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Multi-agent modelling and situational awareness analysis of human-computer interaction in the aircraft cockpit: A case study

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ABSTRACT

The loss of situational awareness by pilots is one of the harshest risk factors leading to catastrophic accidents. In this paper a situational awareness analysis model based on multiple agents is presented to simulate the human-computer interaction process in the aircraft cockpit. From the perspective of human-in-loop, the integrated model consists of modularized pilot agent model, technical system agent model and environment agent model. Following the structured levels of situational awareness, the pilot's cognitive behaviors are modelled based on Adaptive Control of Thought-Rational (ACT-R) theory and Bayesian network, with the triggering inputs from the visual and auditory sensory channels. Considering the effects of overlapping information from different channels, the formation and evolution mechanism of the pilot's situational awareness is analyzed in a probabilistic inference manner. The tests of input-output characteristics prove that the model can well reflect the distribution and resist the uncertain fluctuation of different cognitive elements. The safety issues based on two simplified real risk scenarios, under the background of the incidents/accidents related with Boeing 737-8 (MAX), were analyzed. The mechanism of accident evolution along with the possible preventive measures were discussed. It is concluded that an early control priority transmission from the technical system to the pilots and the display of direct prompt messages could make a difference in avoiding the serious risk.

1. Introduction

With the increasing application of new technologies in the field of automation and intelligence in the aircraft cockpit, the traditional human-machine interaction has gradually evolved to human-computer interaction. The interaction process has a large amount of information and many interactive nodes, which may lead to the pilot's loss of situational awareness.

According to the Aviation Safety Network (ASN) statistics, the number of aircraft departures worldwide in 2019 has reached 39 million. Since 2000, the number of aircraft accidents per million flights worldwide has been declining. In the past five years, this data has basically remained at about 0.5 flights per million flights. Although the overall level of civil aviation safety has improved significantly, from 2000 to 2019, the number of global aircraft accidents and fatalities showed significant fluctuations. With the continuous increase in the scale of civil aviation, the future situation of civil aviation safety remains uncertain.

According to Boeing statistics, the number of accidents caused by human factors accounted for about 80% of the total number of

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accidents, and mechanical reasons accounted for only 20%, which is almost the inverse compared to the early time of the aviation industry [1]. Furthermore, in the field of general aviation, accidents directly caused by pilot errors account for about 70% of the total accidents [2]. A joint survey conducted by Federal Aviation Administration (FAA) and National Aeronautics and Space Administration (NASA) on issues arising from automation pointed out that the design of automation should take full account of how the flight crew communicate with the automation system, how the flight crew understand the automation system, and the importance of the automation system feedback [3]. To overcome the limits of automation, flight crew resource management may an aera to focus on [4]. NASA's Human Research Program also analyzes the risks that may be induced by inadequate human-computer interaction, and points out that the risk of human error can be significantly reduced by understanding the influencing factors and taking appropriate measures [5].

Above all, now that the problem of mechanical failures has been greatly guaranteed by technological development, the improvement of human-computer interaction in the aircraft cockpit will be the key to reducing the risk of accidents and promoting the level of aviation safety.

It is widely accepted that situational awareness (SA, also spelled as "situation awareness") is defined as the perception of the elements in the environment, the comprehension of their meaning, and the projection of their status in the near future [6, 7]. Consistent with the definition, SA is usually divided into three taxonomies of levels when tracing the sources of SA errors in aviation [8]. The approaches to assess SA can be divided into two categories: qualitative methods and quantitative methods [7]. The qualitative analysis methods are based on the evaluation scales carrying the subjective comments either from the users or the third-party observers [9–11]. The main drawbacks to them are the variable individual differences and low credibility of evaluation results, which depend on the experience and expertise of subjects to a great extent. The quantitative analysis methods mainly include psycho-physiological measures, computer-aided simulations and probabilistic approaches [12–14]. Due to the fact that developing new SA measures tends to hit a bottleneck, most recent studies put their emphasis on the application of sophisticated approaches to assess whether the changes in design or new technologies integrated in the cockpit will actually improve SA. Stanton et al. [15] measured the pilots' SA by assessment questionnaire to test if the use of a novel Head Up Display (HUD) can improve the performance in degraded visual conditions. Li et al. [16] evaluated a newly-designed augmented visualization Primary Flight Display (PFD) by comparing the changes in SA, with the help of eye movements and workload scales. Whether the new design can reasonably allocate limited cognitive resources became a key factor in their work. Davis et al. [17] used 10-point scale to estimate SA for the design of sensor data visualization. Cak et al. [18] studied how the individual differences such as divided attention, inhibition, working memory and expertise may affect SA by means of multiple subjective measures. However, neither qualitative methods with rating scales nor quantitative methods with psycho-physiological indicators can avoid the negative effects of individual differences. The challenge lies in how to select a sufficient number of representative subjects whose feedbacks can be accepted by the authorities (e.g., FAA) and the remaining majority of users (e.g., airline pilots).

To make up for these shortcomings, computer-aided and probabilistic approaches have been widely used in SA modelling and simulation. On the one hand, computer-aided approaches represented by multi-agent modelling have received much preference due to the autonomy, reusability and ability of supporting distributed simulation in related studies. Adriaensen et al. [19] put forward a distributed modelling framework for joint cognition between human and technical agents, from a socio-technical system perspective. Kridalukmana et al. [20] extended the multi-agent SA model to make it applicable in collaborative driving. Although their work breaks through traditional modelling methods in the field of SA to form a systematic, flexible, and universal framework for describing human-computer interaction, their focus is on describing the information transmission relationship of interaction-related agents. The structured levels of SA are not strictly inherited from the definition. Nor did they take into account the impact of multi-channel inputs on SA in complex interactive scenarios. On the other hand, probabilistic approaches, including Bayesian networks and Petri nets among others, are commonly applied in quantifying SA related performance such as safety and reliability. McAnally et al. [21] modelled human SA by representing the declarative knowledge of air force pilots based on Bayesian networks, but there was considerable variability in predicting the behaviors. De Rosa et al. [22] used analytical games to collect knowledge data for SA assessment. The data collected from experiments were used for parameter training and knowledge was acquired based on Bayesian inference. Wang et al. [23] classified human cognitive error under the framework of SA, and constructed a Bayesian network to quantify the system reliability considering the man-machine coupling effects. Wang et al. [24] pointed out that Timed Petri Nets (TPN) can provide quantitative results to represent SA, including personal characteristics and task performance. Due to the fact that the formation process of SA is directional, undirected probabilistic models represented by Markov nets are not suitable to solve this problem. It means that, in a typical probabilistic SA model, the subsequent node will only be affected by the previous one. Even so, directed Markov models such as Markov chains will also not be applicable when two or more sources of SA need to be fused together. In the aviation domain, when considering the combination of agents and probabilistic approaches for SA modelling, there has not been any noticeable research in addition to Stroeve's work on runway incursion [25–27] which quantified the risk by Monte Carlo simulations. Therefore, it can be said that this paper is a continuation of multi-agent modelling in aviation and aims at realizing the problem of probability quantification of the pilot's SA from a systematic perspective.

The remainder of this paper is divided into five sections. Section 2 gives a general description of the human-computer interaction in the aircraft cockpit from the perspective of multiple agents. Section 3 outlines the conceptual structures of the agent models. Section 4 models the pilot's cognitive behaviors (refers in particular to situational awareness) based on Bayesian network and tests the input-output characteristics of the model. Section 5 analyzes the safety issues based on two typical risk scenarios and discusses the mechanism of accident evolution along with possible preventive measures. Finally, conclusions and future work are addressed in Section 6.

2. Agent-based description of human-computer interaction

From the perspective of human-in-loop, human-computer interaction in the aircraft cockpit involves three types of agent aggregations, including

- pilots (captain & first officer),
- cockpit (technical systems), and
- environment.

Fig. 1 illustrates the interactions among these aggregations, and the arrows show how information flows in such a human-computer-environment system.

2.1. General description

The stakeholder interactions in the aircraft cockpit mainly take place among the pilots, the technical systems and the environment.

2.1.1. Pilots

In most cases, flight operating tasks (flight crew duties) are assigned to the captain (CA) and the first officer (FO) with dynamic changes following different phases of flight. Undeniably, several types of aircraft still reserve flight engineers on board (e.g., B747-100/200/300) and short-hop flights may only need one pilot to perform (typically for general aviation). The agents talked about here only cover the condition that the captain and first officer collaborate with each other to execute flight tasks, which is the mainstream working mode existing in most commercial aircrafts nowadays.

Pilots shall perform flight tasks following Standard Operating Procedures (SOPs) published by their airline. SOPs are compiled according to flight phases and offer step-by-step instructions from a technical and operational point of view. Flight Crew Operations Manual (FCOM) is one of the main sources of SOPs and provides basic guidance on the compilation of other manuals to ensure the continuing airworthiness of aircraft. In other words, FCOM is a reflection of the design and manufacturing features. However, it is not approved or enforced by aviation administration and thus can not be applied directly in flight. Despite of that, FCOM's close connection with aircraft development and huge influence on flight operation have underscored its importance in aviation field.

The main parts of FCOM contain normal procedures sequenced by phases of flight and supplementary procedures classified by unexpected conditions. In preflight and postflight phases, roles are allocated between the captain and first officer. Whereas in flight phases, roles are allocated between Pilot Flying (PF) and Pilot Monitoring (PM). That is to say, the roles pilots play in the cockpit depends mainly on what procedures they operate during flight, and the roles of PF and PM may change as required during a flight under the captain's authorization. On consideration of the professional and experiential differences between the two pilots, situational awareness (SA) and task performance (TP) will show distinctions under different role allocations.

2.1.2. Technical systems

One of the most notable features in intelligent cockpit is the integration of advanced airborne systems. Airborne systems involve those equipment and systems which pilots can manipulate, read, listen to and talk with through multi-channel interactive technologies during flight, including control, display, warning and communication systems. As influential agents in the interaction network constructed later, their availability and status need to be highly concerned. Availability denotes the condition whether certain airborne system can meet the pilots' performing needs and is fully determined by its task reliability. Status denotes the effect degree of certain airborne system in a given task scenario and is determined by its failure effects in aircraft level.

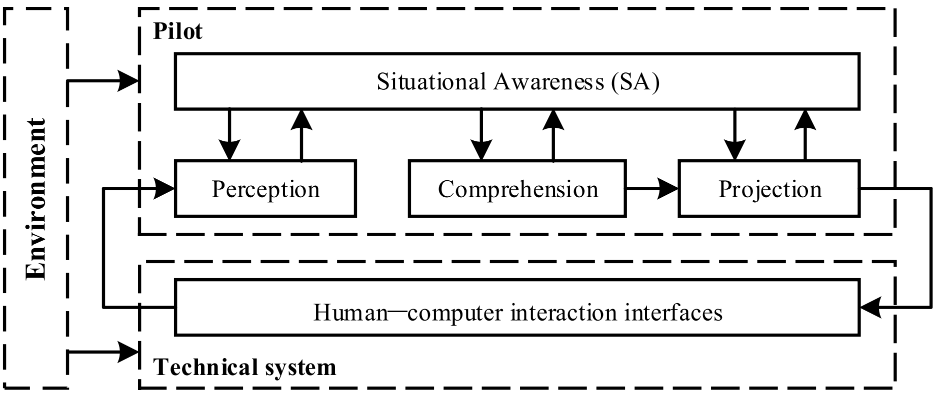


Fig. 1. Relationships between different agent aggregations in the aircraft cockpit described from the perspective of human-in-loop and cognitive science.

2.1.3. Environment

There are two main attributes concerning human-computer interaction inside the cockpit, one denoting flight phases and the other denoting performance modes. Typical flight phases for civil aircraft contain taxi, takeoff, climb, cruise, descent, approach and landing. Typical performance modes for civil aircraft contain normal, abnormal and emergency condition. Different combinations of certain flight phase and performance mode set the background for human-computer interaction analysis, which can be added into scenarios for modelling the interaction process. Current statistical data show that takeoff and landing are essential phases during which accidents are most likely to occur. Stirred by these basic data, human-computer interaction network model can simulate the probabilities of consequential risks.

2.2. Basic assumptions

The LNI610 airline accident involved a Boeing 737-8 (MAX) [28] was taken as a case to illustrate the interactions between the pilots and the technical systems, along with the aviation environment and cockpit environment acting as influencing factors. The process of human-computer interaction in this accident was simplified by

- omitting the interactions between fight crews and air traffic controllers (ATC),
- neglecting the accident causes outside the flight deck (e.g., maintenance, safety culture, organization, etc.) except environmental factors, and
- limiting the relevant technical systems to flight control system, sensors, flight assistant system, display system and warning system.

Fig. 2 further extends Fig. 1 with the detailed structures inside each agent aggregation and formalizes the interaction relationships between different agents.

3. Modularized agent models

Vrije Universiteit Amsterdam and National Aerospace Laboratory NLR offered a library of model constructs for agent-based modelling of risk assessment in Air Traffic Management (ATM) [29]. The library contains 11 model constructs covering the most common human factors in socio-technical systems, which provides the computational ways for agent-based hazard analysis. Although it was originally designed for ATM, most model constructs in it have universal applicability, such as those for decision making, situational awareness, and visual attention. On their basis, the agents described in Section 2 can be modularized using modified constructs.

3.1. Pilot agent model

The pilot agent model is an integration architecture combining the task level (TL) and the cognition level (CL). TL origins from the flight operation tasks, including but not limited to task identification, task scheduling and task execution. CL describes the simplified cognition process to form situational awareness, including but not limited to perception, comprehension, projection. The model structure is shown in Fig. 3.

The pilot agent belongs to the learning-inference agent class. Its ability of active learning and decision reasoning will be exampled

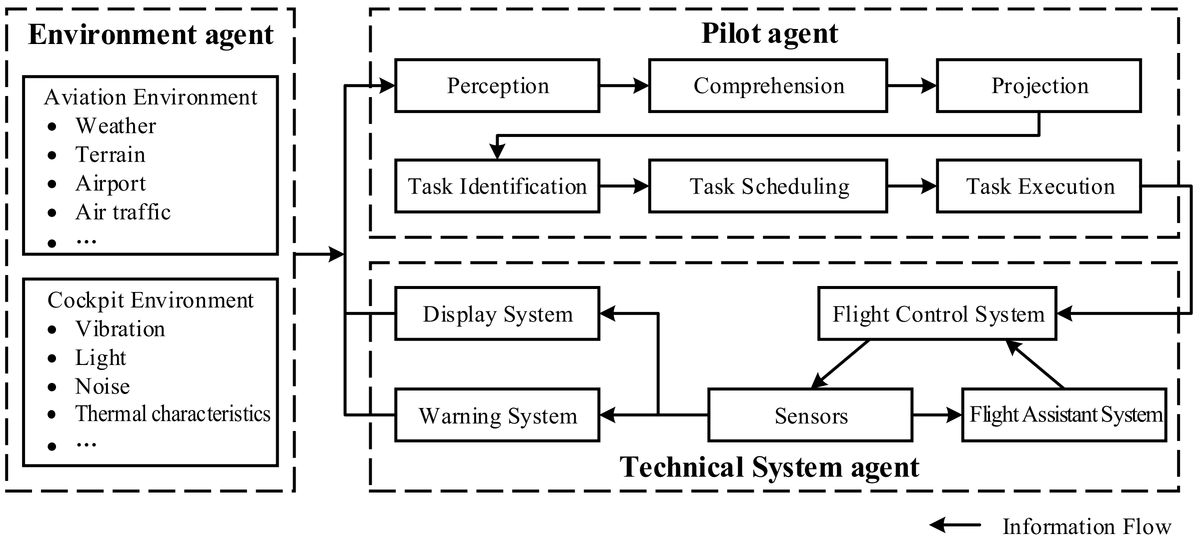


Fig. 2. Detailed and formalized interaction relationships between different agents.

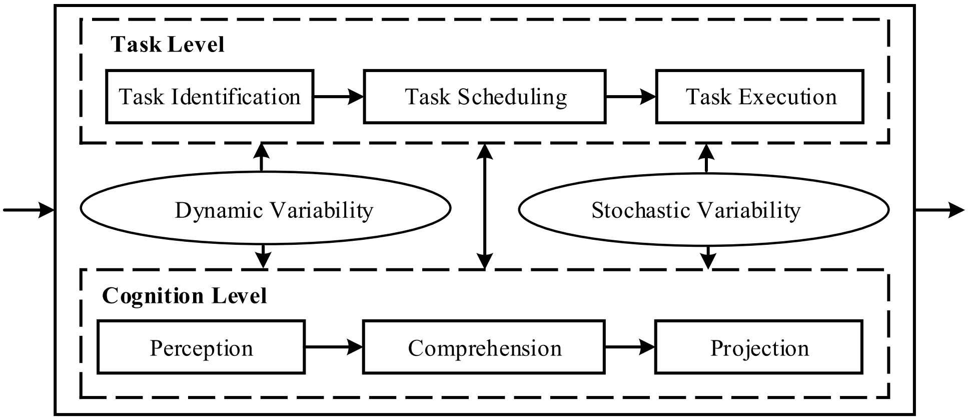


Fig. 3. The structure of pilot agent model.

in Section 4 and 5.

3.2. Technical system agent models

For simplification, here the technical systems mainly refer to the flight assistant system, flight control system, sensor system, display system and warning system. According to the differences in information processing and intelligence degree, the above-mentioned systems are further classified into 3 categories.

3.2.1. Perception-decision type

In the context of this paper, the perception-decision type of technical system refers to the flight assistant system. More specifically, it denotes the systems that own the control priority under some preconditions, e.g., the Maneuvering Characteristics Augmentation System (MCAS) equipped in Boeing 737-8 (MAX).

3.2.2. Perception-reaction type

The perception-reaction type of technical system includes sensor system, display system and warning system. When perceiving the changing characteristics of information, they will output characters, pictures or sound by predefined ways. Their working conditions will be dually influenced by stochastic variability and dynamic variability.

3.2.3. Stimulus-response type

This paper refers the perception-reaction type of technical system to the flight control system. Its input-output relation is strictly constrained by flight dynamics equations and mainly affected by dynamic variability.

For the first type of technical systems, the structure of its agent model is shown in Fig. 4.

The flight assistant system represented by MCAS, with a degree of intelligence, is authorized with control priority right at the beginning of design. For this type of system, the Situational Awareness module describes the ability to perceive the information delivered from other systems (e.g., sensors) or environment, to judge the current situation (e.g., flight state) and to predict what could happen in the near future (e.g., tend to dive or climb). The inputs of the MCAS agent model can be expressed by

$$\mathrm{SA}(\alpha,\ \mathrm{pilotmode}) \tag{1}$$

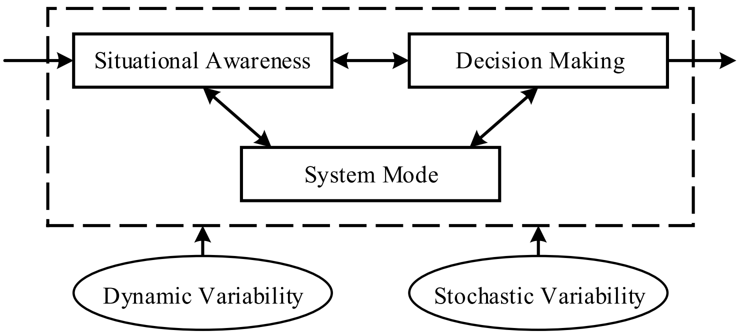


Fig. 4. Perception-decision technical system agent model.

where α denotes the angle of attack and *pilotmode* denotes whether the current pilot state is manual or auto. It is based on this judgment that decisions will be made by the Decision Making module according to the reasoning rules. For example, in the accident, MCAS judged the angle of attack was too large by the signals transmitted from air data sensors, so it restrained the aircraft from climbing based on the decision-making rules. Conclusions can be drawn from the severe consequence that the decisions made by this type of technical system are not necessarily correct and could even invalidate the flight crew's error correction.

It also can be seen that the third type of technology system represented by the flight control system is downstream of the control chain formed by the first type of technical system. The third type can only act on the instructions of high-level technical systems, which belongs to the "stimulus-response" mode of operation, so there is no SA module in its agent model.

Besides, the System Mode module describes the functioning of the technical system, such as failure conditions, system settings, etc. The Dynamic Variability module describes the variability due to dynamic processes, and the Stochastic Variability module describes the variability of the system performance due to measurement or analytical error, noise jamming, etc. [30] They represent the same meaning in the agent models of the second and third types of technical systems.

For the second type of technical systems, the structure of its agent model is shown in Fig. 5.

The second type of technical systems is represented by the sensor system, the display system and the warning system. Compared with the first type, the SA in its agent model is weaker. By sensing the information transmitted by other systems, it responds accordingly to the requirements of information processing, display, and alarm. It does not generate any control-end output to other systems, that is, without the decision capabilities.

The sensor system consists of aircraft state sensors and external world sensors. The inputs of its agent model can be expressed by

$$\mathrm{SA}(\alpha,\ yaw,\ pitch,\ roll,\ velocity,\ \ldots) \tag{2}$$

where α denotes the angle of attack, *yaw* denotes the angle of yaw, *pitch* denotes the angle of pitch, *roll* denotes the angle of roll and *velocity* denotes airspeed.

The information processed by the sensor system agent will be transmitted to the flight assistant system, the display system and the warning system.

The inputs of the display system agent can be expressed by

$$\mathrm{SA}(flightpara,\ alert\mathrm{inf}o,\ \ldots) \tag{3}$$

where *flightpara* denotes the flight parameters and *alertinfo* denotes the alert information.

The information processed by the display system agent will be encoded by different characters or pictures on the human-computer interaction interface.

The inputs of the warning system agent can be expressed by

$$\mathrm{SA}(flightpara,\ \ldots) \tag{4}$$

where *flightpara* denotes the flight parameters.

The Decision Making module in the warning system agent model determines whether the feature value exceeds the limit and triggers an alarm. Alarm modes include warning tone and display.

For the third type of technical systems, the structure of its agent model is shown in Fig. 6.

The third type of technical system, represented by flight control system, is simplified here to a "stimulus-response" structure that only transfers control relations through dynamic constraints. As a result, it only contains the System Mode module and Dynamic Variability module.

3.3. Environment agent model

The environment agent model describes the context of the human-computer interaction, including aviation environment and cockpit environment. The environment agent model is made up of a "Contextual Condition" module, which is shown in Fig. 7. The environment agent is functioned as an input model, so only the situation will be considered that the inputs of other agents are disturbed due to environmental factors.

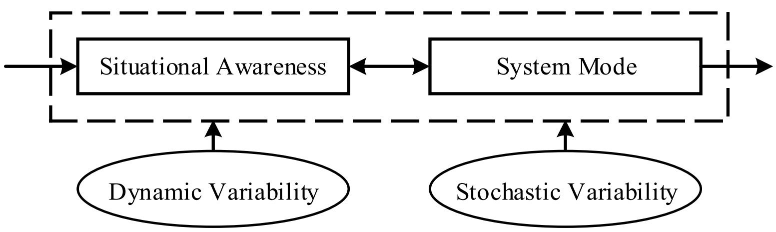


Fig. 5. Perception-reaction technical system agent model.

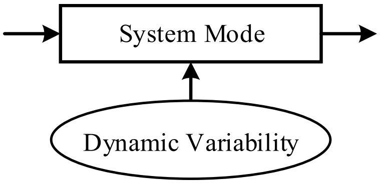


Fig. 6. Stimulus-response technical system agent model.

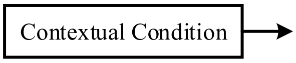


Fig. 7. Environment agent model.

4. Modelling of cognitive behaviors

4.1. Triggering factor: air data sensor failure

Flight accidents attributed to the failure of air data sensors are continuing to threaten flight safety [31]. The air data sensor system integrates the measures of static pressure, total pressure and outside air temperature to compute the air data parameters, including the angle of attack which was thought to play an essential role in the Boeing 737-8 (MAX) accident.

Typical air data sensor failure modes include stuck, gain loss, constant deviation, sinusoidal oscillation, complete failure, etc. [32–34] They can be expressed as the functional forms on time series as follows, where $f(t)$ represents the original sensor signal before the failure and $f_{\mathrm{modeX}}(t)$ represents the sensor signal after the failure. The time in the expressions starts from the moment of failure.

For the sensor stuck failure,

$$f_{\mathrm{mod}\,e1}(\mathrm{t}) = \mathrm{c}_1 \tag{5}$$

where c_1 is constant and denotes the fixed deviation.

For the gain loss failure,

$$f_{\mathrm{mod}\,e2}(\mathrm{t}) = \mathrm{c}_2.f(t) \tag{6}$$

where c_2 is the coefficient and $0<c_2<1$.

For the constant deviation failure,

$$f_{\mathrm{mode3}}(t) = f(t) + \mathrm{c}_3 \tag{7}$$

where c_3 is constant and denotes the deviation from the input signal.

For the sinusoidal oscillation failure,

$$f_{\mathrm{mode4}}(\mathrm{t}) = \mathrm{c}_4.\sin(\omega\mathrm{t} - \mathrm{c}_5) + f(t) \tag{8}$$

where c_4 denotes the amplitude, c_5 denotes the phase difference and ω denotes the angular frequency.

For the complete failure,

$$f_{\mathrm{mode5}}\left(t\right) = \begin{cases} f(t), & \mathrm{t} = 0 \\ 0, & \mathrm{t} \neq 0 \end{cases} \tag{9}$$

When analyzing the impact of air data sensor failures on display, warning and situational awareness, the fault isolation or control law switch of flight control will not be considered [35].

4.2. Visual and auditory warning

Alerting information is usually transmitted through the auditory and visual channels during human-computer interaction. Warnings in the auditory channel are in the form of prompt tone. For example, the Enhanced Ground Proximity Warning System (EGPWS) alerts to the abnormal slope, airspeed, altitude, terrain, and descent rate using specific phonetic phrases. The output forms of the visual channel include warning light, warning flag and highlighted symbols. Alerting information in the auditory and visual channels are usually adopted simultaneously, so the formation of pilots' situational awareness needs to consider the effects of both channels.

In the accident case, "IAS DISAGREE" and "ALT DISAGREE" indications appeared, and then "FEEL DIFF PRESS" warning light came on. In addition, EGPWS reported on abnormal slope, altitude, airspeed, etc. It should be noted that alarms and system failures do not always directly correspond to each other, unless all necessary indicators have been fully installed. The implicit alert in the accident was actually "AOA DISAGREE". However, it was not activated by the system, so lacking enough direct information prevented the pilots from accurately knowing the current status of the aircraft and recovering from failure. Due to the inaccurate information feedback from the warning system, the situational awareness of the flight crew was suppressed unexpectedly, which became a key factor in inducing subsequent risk events. The reflection on this accident should not be limited to human errors. Instead, this is a disaster caused by design issues, which should essentially be attributed to the need for airworthiness certification focusing on the human-computer interaction.

4.3. Situational awareness model

Existing research has not yet formed a unified and standardized conceptual model for situational awareness. Different researchers have proposed multiple quantification and modelling methods of situational awareness based on different scenario settings. The representative studies are as follows.

Hooey et al. [36] proposed the concept of Situation Elements (SEs), which decomposes the pilot's cognitive situation into information characterized by several discrete elements. Thereby, they defined situational awareness as the ratio of detected/comprehended SEs to required/desired SEs:

$$\mathrm{SA} = \frac{\mathrm{SE_s\ detected/comprehended}}{\mathrm{SE_s\ required/desired}} \tag{10}$$

This quantification method focuses on the proportion of statistical data. However, it is difficult to handle those implicit cognitive elements that cannot be independently characterized during segmentation. For example, the pilots usually need to infer implicit faults by synthesizing multiple explicit information. Besides, the pilots may face a dilemma when facing recognition objects with a strong coupling relationship, such as the alert messages with both voice and image prompts. It is hard to decide whether the prompts belong to one SE or several SEs.

Secondly, it is also difficult to accurately measure whether a certain SE is understood or not when performing a cognition mission. Even through interviewing the pilots or completing the questionnaires after the mission, the disadvantages of overly subjective dependence cannot be avoided.

Wickens and Liu et al. [37, 38] proposed the methods of establishing situational awareness with visual attention. The premise is that the pilot noticing event *i* occurs is equivalent to his/her attention being allocated to event *i*. This premise is consistent with the reality in most cases, but in some cases the pilot fell into "inattentional deafness" [39, 40]. That is to say, although the pilots noticed the existence of auditory or visual alerts, they did not develop the desired situational awareness due to environmental or mission distractions, or because of their choice to violate routine procedures.

Another limitation of this type of method is that it only considers the formation mechanism of the pilot's situational awareness on the visual channel, and ignores the impact of the information overlap on the multiple channels. The reason for this problem may be that compared to other sensory channels, the visual attention resources in the cockpit are easier to be quantified by means of information flow, and the information received by the pilot through vision is also easier to measure through physiological instruments (such as eye trackers).

Considering the effects of overlapping information in the visual channel and auditory channel, this paper establishes a situational awareness model based on Bayesian theorem, and analyzes the formation and evolution mechanism of the pilot's situational awareness in a probabilistic inference manner.

According to the definition of situational awareness, the model's processing flow is divided into three stages: Perception, Comprehension, and Projection, as shown in Fig. 8. The visual channel and auditory channel represent the data inputs of the model. P_v and P_a indicate the pilot's initial perception of the input information on each channel respectively. C_v and C_a indicate the pilot's understanding of the information on each channel based on the initial perception respectively. C_j represents the pilot's fusion understanding of all channel information. P_j represents the motion sequence generated by the situational awareness based on the decision making and planning.

4.3.1. Single-channel perception & comprehension

Based on the ACT-R theory [41], the process of single-channel perception and comprehension in this situational awareness model

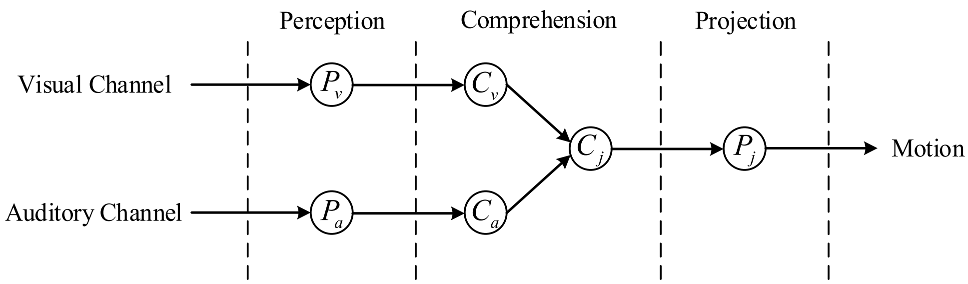


Fig. 8. The process flow of forming situational awareness

was modelled. The method of cognitive resource allocation in this theory was initially developed for its visual module, while here in this study it will be extended to analyze both visual and auditory channels to make it universal.

Following the ACT-R theory, the perception process of the visual or auditory can be abstracted as the activation of the corresponding channel [42], denoted as A, and the calculation formula is

$$A = A_0 + \sum w_j S_j \tag{11}$$

where A_0 is the baseline activation value; w_j is the importance of the element j for completing visual/auditory cognitive goals; S_j is the associative strength between cognitive element j and the visual/auditory sense, which is related to the stimulus facts formed by the characteristics (size, color, strength, etc.) and number of element j.

According to the learning equation [42], A_0 can be approximately calculated by

$$A_0 = Const + 0.5\ln(InfoNum) \tag{12}$$

where *InfoNum* denotes how many times the information has been presented, and *Const* depends on the frequency of presentation, which can be set to 0 here.

The associative strength S_j can be estimated by

$$S_j = S_0 - \ln(FactNum_j) \tag{13}$$

where $FactNum_j$ is the number of facts associated with element j, and S_0 is the upper limit value estimated by experience, which is generally preferable to be 2.

To sum up, the calculation formula (11) can be rewritten as

$$A = 0.5\ln(InfoNum) + \sum wj\left(2 - \ln\left(FactNum_j\right)\right) \tag{14}$$

where the meanings of the variables are the same as those mentioned above.

Besides, the theory sees the comprehension process on the single channel as a retrieval of cognitive resources in the declarative memory. The probability of success in comprehension (that is, the probability of successful retrieval of the corresponding cognitive resource) can be expressed by

$$\Pr(C_{v/a}) = \frac{1}{1 + e^{-(A-\tau)/s}} \tag{15}$$

where $C_{v/a}$ presents successful comprehension in visual or auditory channel; τ is the threshold of the activation response, and only when A is greater than this value will the retrieval behavior occur; the parameter s represents the influence of noise interference during the retrieval process, which is usually set to 0.4.

4.3.2. Joint comprehension based on Bayesian inference

Psychological experiments showed that in a series of tasks such as perception, decision making and action, people's behavioral characteristics can be described by near-optimal Bayesian inference. Under the premise of knowing the probability distribution of prior knowledge, the joint probability distribution of posterior knowledge can be obtained through Bayes' Rule [43]. After the pilot comprehends the information P_v and P_a perceived on the visual channel and the auditory channel, the corresponding comprehension utility C_v and C_a are formed, and will be fused based on Bayes' theorem by

$$\Pr(s|C_v, C_a) \propto \Pr(C_v|s)\Pr(C_a|s)\Pr(s) \tag{16}$$

where s indicates the stimulus source (warning information).

Bayesian networks, also known as belief networks, are extended based on Bayes' theorem. A Bayesian network is a directed acyclic graph (DAG) which is composed of nodes representing variables and directed edges connecting these nodes [44]. Bayesian networks are widely used for human factors analysis typically in aviation safety, plant operations, offshore and marine industries [45–48]. The themes of these studies mainly include identification of critical factors and risk analysis. The advantages of using Bayesian networks are mainly manifested in that they can clearly express the hierarchical causal structures between complex factors by building formal models, and can well deal with the uncertainty and coupling of the relations.

Constructing a Bayesian network contains three phases. First, the nodes and directed edges should be defined according to the process flow of forming situational awareness. Afterwards, the conditional probability distribution can be determined based on the causal relations between different nodes. In this paper, the data for conditional probability distribution is procured through numerical modelling which will be clarified later. Finally, the probabilistic results of successful comprehension and projection, $\Pr(C_j)$ and $\Pr(P_j)$, can be obtained through Bayesian inference.

It is assumed that the state of the "comprehension" behavior only exists in the binary form of being "comprehended" and " not comprehended", so the state of the nodes in the Bayesian network is only true or false. This indicates that there will be no unfinished states to be concerned, such as "to be comprehended" or "not to be comprehended". This discretization method of binary states is commonly used in human factor analysis based on Bayesian networks [46, 49], especially for describing the effects or results of human states and behaviors. On the contrary, the continuous processing method of parameters is suitable for describing physical properties of machines [49]. Fig. 8 is further abstracted into the form of a Bayesian network, as shown in Fig. 9, where: node 1 represents the stimulus s; node 2 represents the comprehension C_v on the visual channel; node 3 represents the comprehension C_a on the auditory channel; node 4 indicates the joint comprehension C_j; and node 5 indicates the projection P_j for future actions.

It is generally considered that there are three approaches to obtain conditional probability data in for human factors analysis, including statistical analysis, expert interviews and numerical simulation [50]. Among them, the numerical simulation method is suitable for the situation where little accident data is available and experts' subjective opinions have low credibility. It can be used to simulate different scenarios and generate various types of data for Bayesian networks [51]. In the research of this paper, on the one hand, there are not enough accident statistics to be detailed to the cognition level; on the other hand, the subjective judgments are difficult to distinguish different formation stages of situational awareness. As a result, numerical modelling based on a combination of ACT-R theory and empirical values is chosen to procure conditional probabilities for Bayesian inference.

Using the calculation methods provided in Section 4.3.1, the conditional probability distribution of comprehending the warning information under the visual and auditory stimulus, each denoting $\Pr(\mathrm{Cv}|\mathrm{s})$ and $\Pr(\mathrm{Ca}|\mathrm{s})$, can be determined. By constructing the Bayesian network, the joint probability distribution $\Pr(\mathrm{s}|\mathrm{Cv},\mathrm{Ca})$ can be obtained under the conditions of C_v and C_a for comprehending the initial stimulus.

In the Bayesian network, for node 1, p_1=Pr(s). The states of node 2 and node 3 are affected by the input of node 1, and their conditional probabilities are shown in Tables 1 and 2, respectively.

The state of node 4 is affected by the inputs of node 2 and node 3, and the conditional probabilities are shown in Table 3.

The probability distribution of node 5 is only affected by the input of node 4, which is shown in Table 4.

With the reasoning engines provided by Bayesian network modelling tools, such as the joint tree reasoning engine, belief propagation reasoning engine, etc., given the trigger probability of the failure, the probability distribution laws of joint comprehension and projection in the situational awareness model can be obtained.

4.3.3. Simulink-based modelling

Based on the above analysis, a situational awareness model as shown in Fig. 10 was constructed on the Simulink platform. The input of the model is the visual and auditory stimuli formed by the warning information, and the output of the model is the joint probability distribution Pr(C_j) and the joint probability distribution Pr(P_j).

The input-output characteristics of the model will be tested below. The conditional probability distribution of each node listed in Tables 1–Table 4 is closely related to human error in the pilot's cognitive process. The trigger of human error has individual differences and is susceptible to environmental factors. As a result, it always shows strong randomness in statistical measures. How to determine the probabilities of human error under different situations is one of the focuses of human reliability research. Since that is not the main point of this paper, it is assumed that the conditional probability of each node in the Bayesian network obeys the normal distribution. The probability distributions of the input variables are shown in Table 5.

According to the different values of Pr(C_v) and Pr(C_a), the test components are classified into "high-high", "high-low", and "low-low".

4.3.4. Output characteristics with "high-high" inputs

Taking $\Pr(\mathrm{Cv}|\mathrm{s})\sim\mathrm{N}(0.8,0.01)$ and $\Pr(\mathrm{Ca}|\mathrm{s})\sim\mathrm{N}(0.7,0.01)$ as inputs, under the stimulation of the warnings, and subject to the constraints of the conditional probability distribution of each node in the formation of situational awareness, the statistical distribution chart and fitting chart of Pr(C_j) are shown in Fig. 11 (a), (b) respectively.

The fitting results show that Pr(C_j) obeys a normal distribution with a mean value of 0.4050 and a standard deviation of 0.0102. The root mean square error RMSE is 2.35 with the maximum frequency being 33. The confidence level for this fitting is 95%.

The statistical distribution chart and fitting chart of Pr(P_j) are shown in Fig. 12 (a), (b) respectively.

The fitting results show that Pr(P_j) obeys a normal distribution with a mean value of 0.5705 and a standard deviation of 0.0103. The root mean square error RMSE is 2.58 with the maximum frequency being 34. The confidence level for this fitting is 95%.

4.3.5. Output characteristics with "high-low" inputs

Taking $\Pr(\mathrm{Cv}|\mathrm{s})\sim\mathrm{N}(0.8,0.01)$ and $\Pr(\mathrm{Ca}|\mathrm{s})\sim\mathrm{N}(0.3,0.01)$ as inputs, under the stimulation of the warnings, and subject to the constraints of the conditional probability distribution of each node in the formation of situational awareness, the statistical distribution chart and fitting chart of Pr(C_j) are shown in Fig. 13 (a), (b) respectively.

The fitting results show that Pr(C_j) obeys a normal distribution with a mean value of 0.1745 and a standard deviation of 0.0066. The root mean square error RMSE is 2.41 with the maximum frequency being 34. The confidence level for this fitting is 95%.

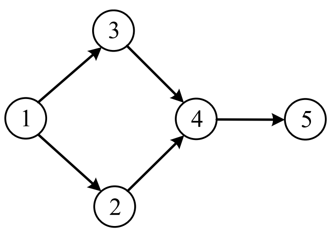


Fig. 9. A Bayesian network representing the situational awareness model.

Table 1
Conditional probability distribution of Node 2.

State of Node 1	p_2
True	$\Pr(Cv\|s)$
False	$\Pr(Cv\|\overline{s})$

Table 2
Conditional probability distribution of Node 3

State of Node 1	p_3
True	$\Pr(Ca\|s)$
False	$\Pr(Ca\|\overline{s})$

Table 3
Conditional probability distribution of Node 4

State of Node 2	State of Node 3	p_4
True	True	$\Pr(Cj\|Cv, Ca)$
True	False	$\Pr(Cj\|Cv, \overline{Ca})$
False	True	$\Pr(Cj\|\overline{Cv}, Ca)$
False	False	$\Pr(Cj\|\overline{Cv}, \overline{Ca})$

Table 4
Conditional probability distribution of Node 5

State of Node 4	p_5
True	$\Pr(Pj\|Cj)$
False	$\Pr(Pj\|\overline{Cj})$

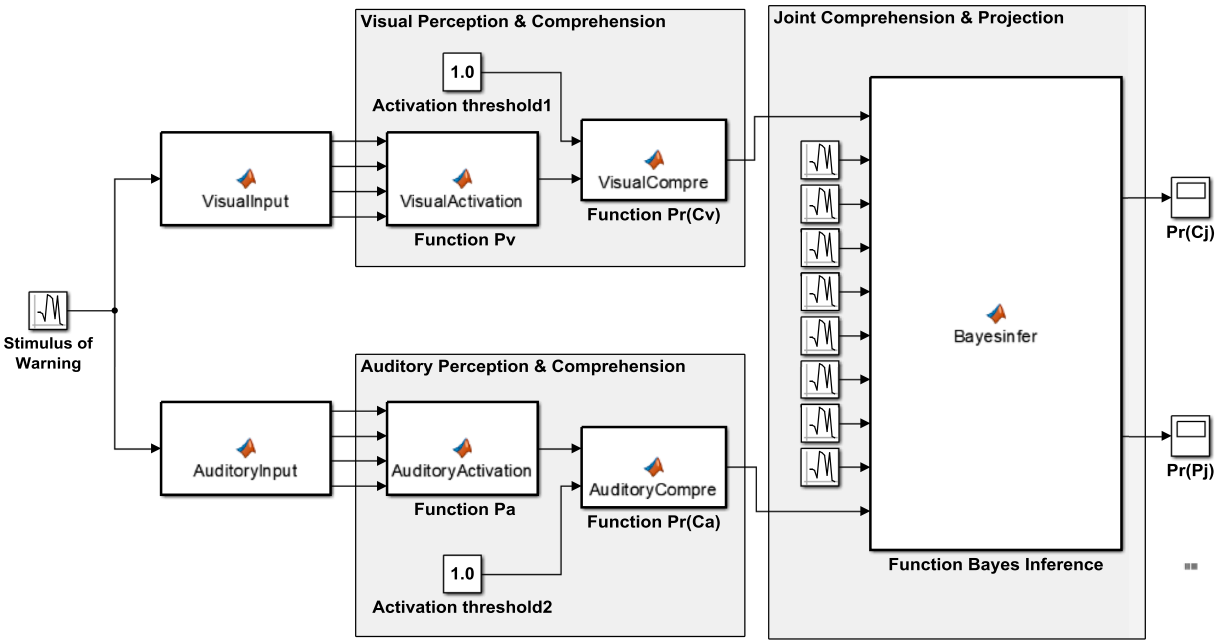
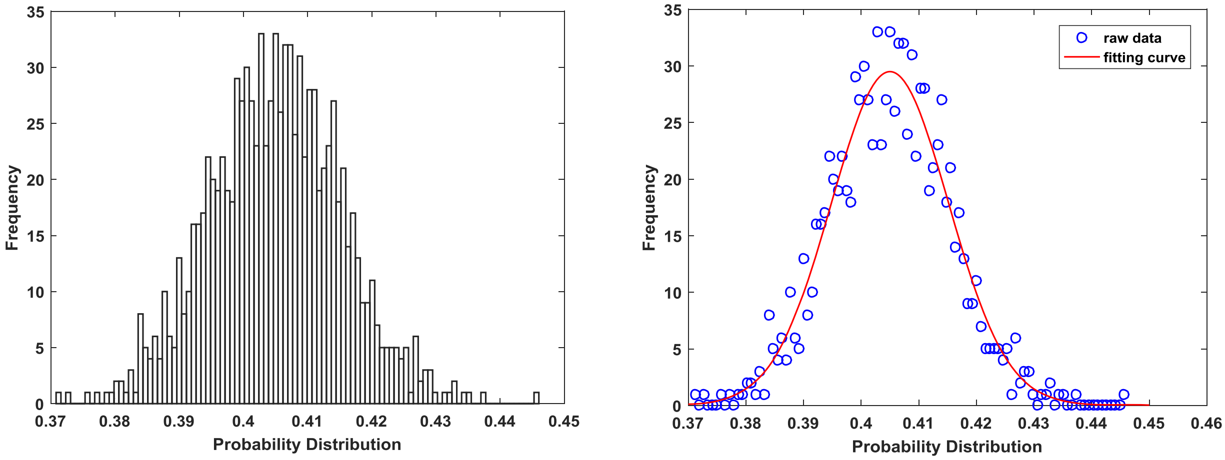


Fig. 10. Simulink-based situational awareness model under the stimulus of warning.

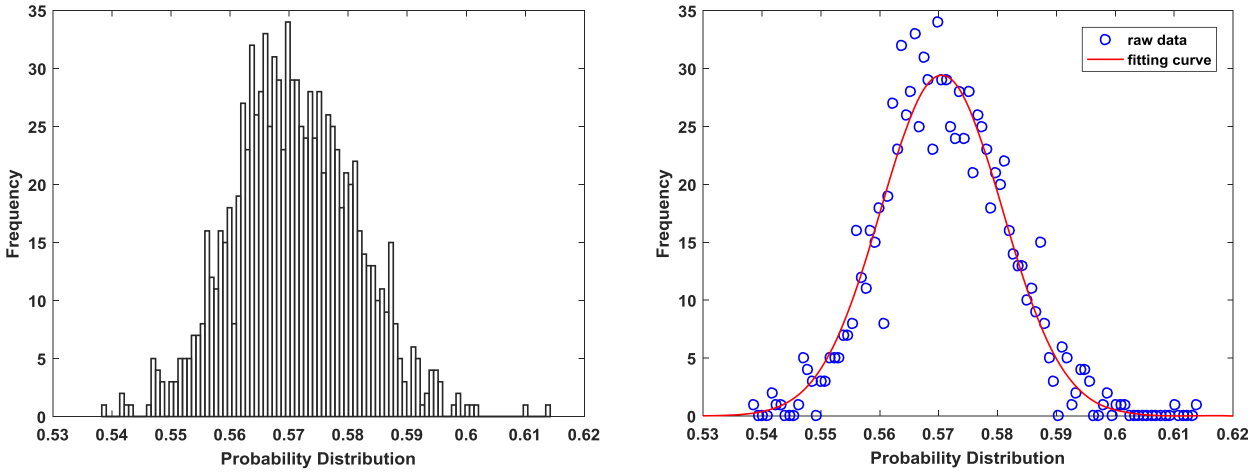
Table 5
Probability distributions for testing arguments of the Simulink model

Node	Argument	Probability Distribution
1	$\Pr(s)$	N(0.8, 0.01)
2	$\Pr(\mathrm{Cv}\mid \mathrm{s})$	Determined by the probability of successful comprehension ($\Pr(C_v)$) on the visual channel.
	$\Pr(\mathrm{Cv}\mid \overline{\mathrm{s}})$	N(0.1, 0.01)
3	$\Pr(\mathrm{Ca}\mid \mathrm{s})$	Determined by the probability of successful comprehension ($\Pr(C_a)$) on the auditory channel.
	$\Pr(\mathrm{Ca}\mid \overline{\mathrm{s}})$	N(0.1, 0.01)
4	$\Pr(\mathrm{Cj}\mid \mathrm{Cv}, \mathrm{Ca})$	N(0.9, 0.01)
	$\Pr(\mathrm{Cj}\mid \mathrm{Cv}, \overline{\mathrm{Ca}})$	N(0.8, 0.01)
	$\Pr(\mathrm{Cj}\mid \overline{\mathrm{Cv}}, \mathrm{Ca})$	N(0.5, 0.01)
	$\Pr(\mathrm{Cj}\mid \overline{\mathrm{Cv}}, \overline{\mathrm{Ca}})$	N(0.1, 0.01)
5	$\Pr(\mathrm{Pj}\mid \mathrm{Cj})$	N(0.9, 0.01)
	$\Pr(\mathrm{Pj}\mid \overline{\mathrm{Cj}})$	N(0.1, 0.01)



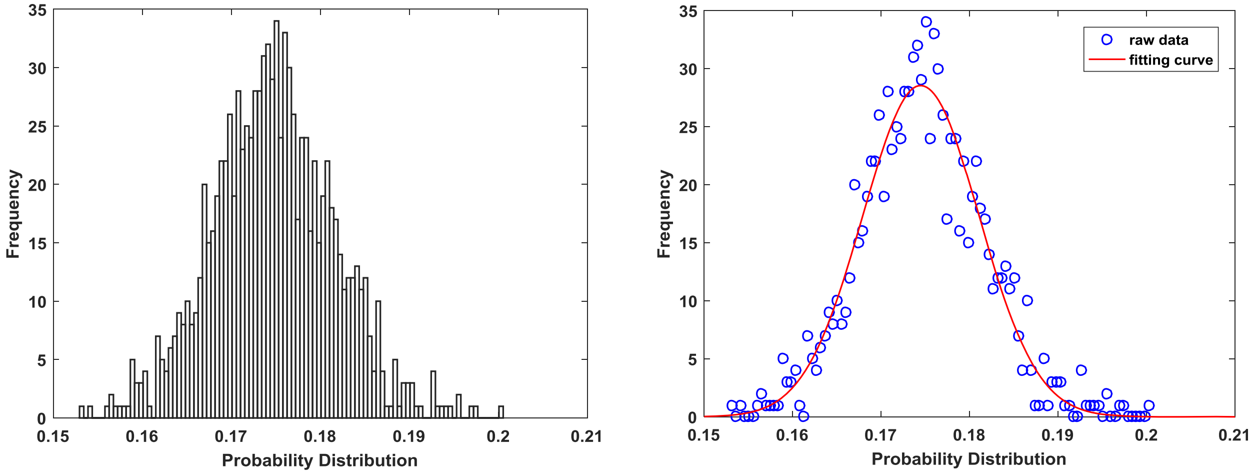
(a) (b)

Fig. 11. Statistical distribution chart and fitting curve chart of $\Pr(C_j)$



(a) (b)

Fig. 12. Statistical distribution chart and fitting curve chart of $\Pr(P_j)$.



(a) (b)

Fig. 13. Statistical distribution chart and fitting curve chart of $\Pr(C_j)$.

The statistical distribution chart and fitting chart of $\Pr(P_j)$ are shown in Fig. 14 (a), (b) respectively.

The fitting results show that $\Pr(P_j)$ obeys a normal distribution with a mean value of 0.4390 and a standard deviation of 0.0087. The root mean square error RMSE is 3.60 with the maximum frequency being 36. The confidence level for this fitting is 95%.

4.3.6. Output characteristics with "low-low" inputs

Taking $\Pr(\mathrm{Cv}|\mathrm{s})\sim N(0.2,0.01)$ and $\Pr(\mathrm{Ca}|\mathrm{s})\sim N(0.3,0.01)$ as inputs, under the stimulation of the warnings, and subject to the constraints of the conditional probability distribution of each node in the formation of situational awareness, the statistical distribution chart and fitting chart of $\Pr(C_j)$ are shown in Fig. 15 (a), (b) respectively.

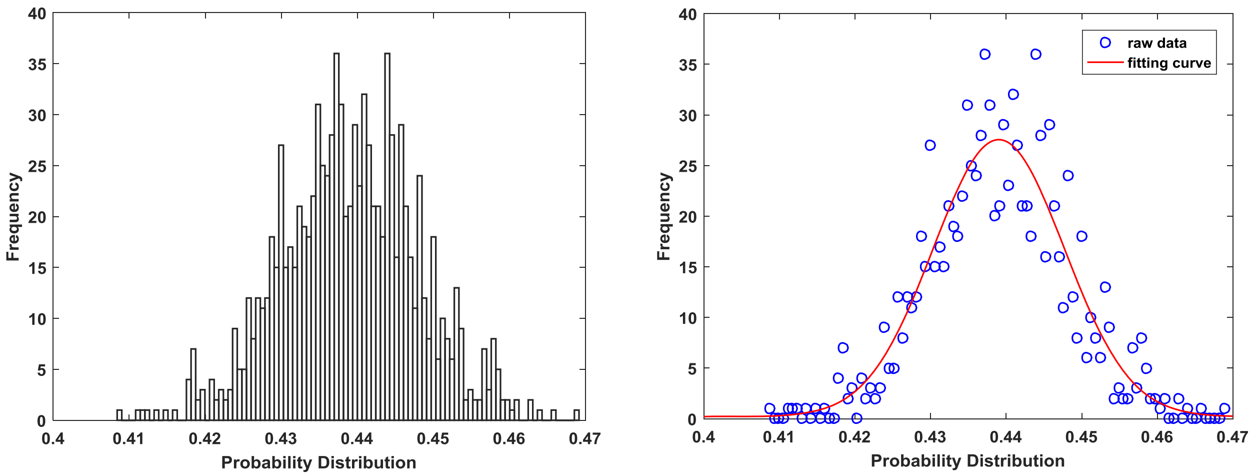
The fitting results show that $\Pr(C_j)$ obeys a normal distribution with a mean value of 0.1028 and a standard deviation of 0.0050. The root mean square error RMSE is 3.24 with the maximum frequency being 35. The confidence level for this fitting is 95%.

The statistical distribution chart and fitting chart of $\Pr(P_j)$ are shown in Fig. 16 (a), (b) respectively.

The fitting results show that $\Pr(P_j)$ obeys a normal distribution with a mean value of 0.4891 and a standard deviation of 0.0096. The root mean square error RMSE is 2.99 with the maximum frequency being 37. The confidence level for this fitting is 95%.

Through the above examples of testing the input-output characteristics, it can be seen that the outputs of the model can transfer the distribution characteristics of the input data. The situational awareness model can capture the uncertain fluctuation characteristics of the input data, and achieve a high level of accuracy.

Based on the above testing cases, sensitivity analysis can also be carried out to measure the effects of $\Pr(\mathrm{Cv}|\mathrm{s})$ and $\Pr(\mathrm{Ca}|\mathrm{s})$ on the system outputs $\Pr(C_j)$ and $\Pr(P_j)$, which can be quantified by a sensitivity indicator defined as



(a) (b)

Fig. 14. Statistical distribution chart and fitting curve chart of $\Pr(P_j)$.

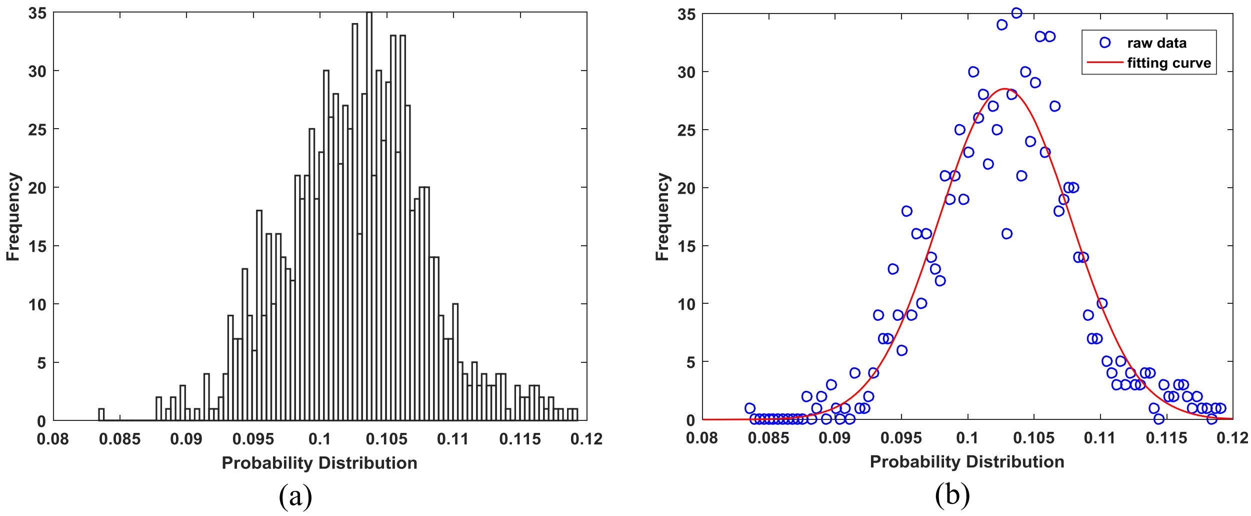


Fig. 15. Statistical distribution chart and fitting curve chart of $\Pr(C_j)$.

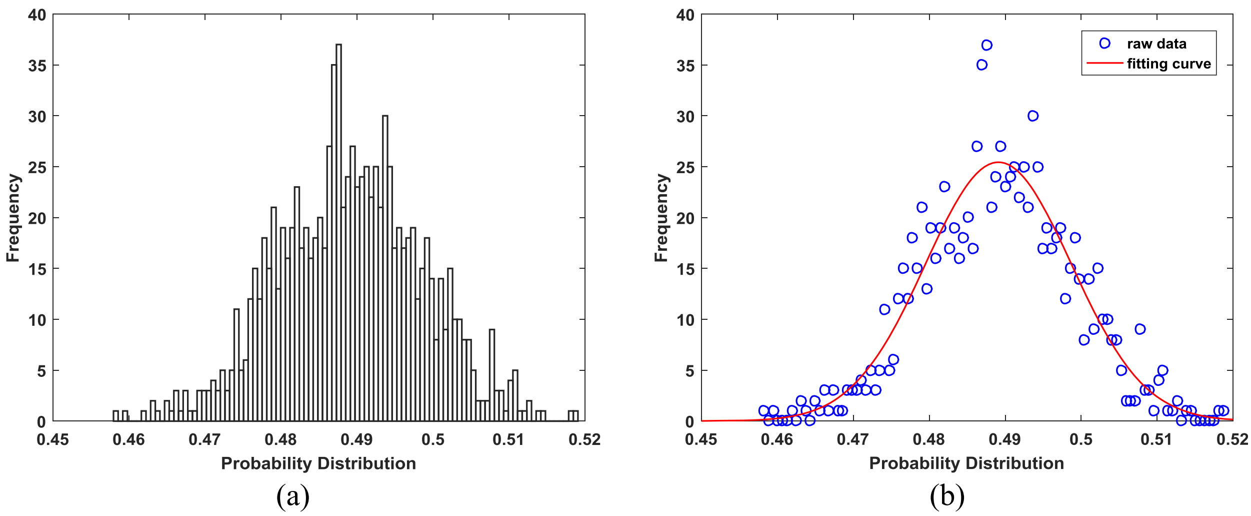


Fig. 16. Statistical distribution chart and fitting curve chart of $\Pr(P_j)$.

$$SI = |y_H - y_L| / 2\Delta x \tag{17}$$

The above definition of *SI* is adapted from the previous work of Loucks et al. [52] where y_H and y_L are defined as functions of the input parameter *x*. $y_H = f(x0 + \Delta x)$ and it measures the system output with a positive change Δx over its baseline input value x_0. Similarly, $y_L = f(x0 - \Delta x)$ and it measures the system output with a negative change Δx downward from its baseline input value x_0. In this sensitivity analysis, the value of x_0 is taken as 0.5, and the results are shown in Table 6.

Sensitivity analysis results show that, on the whole, the input parameter $\Pr(\text{Ca}|\text{s})$ has greater influence on the outputs than $\Pr(\text{Cv}|\text{s})$. Moreover, the output parameter $\Pr(C_j)$ is more susceptible to inputs than $\Pr(P_j)$. The analysis results are consistent with the general knowledge related to human-computer interaction design in the aircraft cockpit, which is embodied in the following aspects. Firstly, it

Table 6
Sensitivity analysis results of the situational awareness model

Parameters Inputs (*x*)	Outputs (*y*)	y_H	y_L	Δx	*SI*	Corresponding testing cases
$\Pr(\text{Cv}\|\text{s})$	$\Pr(C_j)$	0.1745	0.1028	0.3	0.1195	"high-low" and "low-low"
	$\Pr(P_j)$	0.4390	0.4891	0.3	0.0835	
$\Pr(\text{Ca}\|\text{s})$	$\Pr(C_j)$	0.4050	0.1745	0.2	0.5763	"high-high" and "high-low"
	$\Pr(P_j)$	0.5705	0.4390	0.2	0.3288	

is more likely for the pilots to perceive the existence of auditory warnings than visual ones, which is also the reason why emergency warnings are usually designed in auditory forms. Secondly, the comprehension stage in the process of forming situational awareness is built upon the cognitive processing of multi-channel perceptual information. The comprehension stage is considered more complex than the projection stage, for that there is no extra information processing task in the projection stage. As a result, the sensitivity analysis results also prove the rationality of the model.

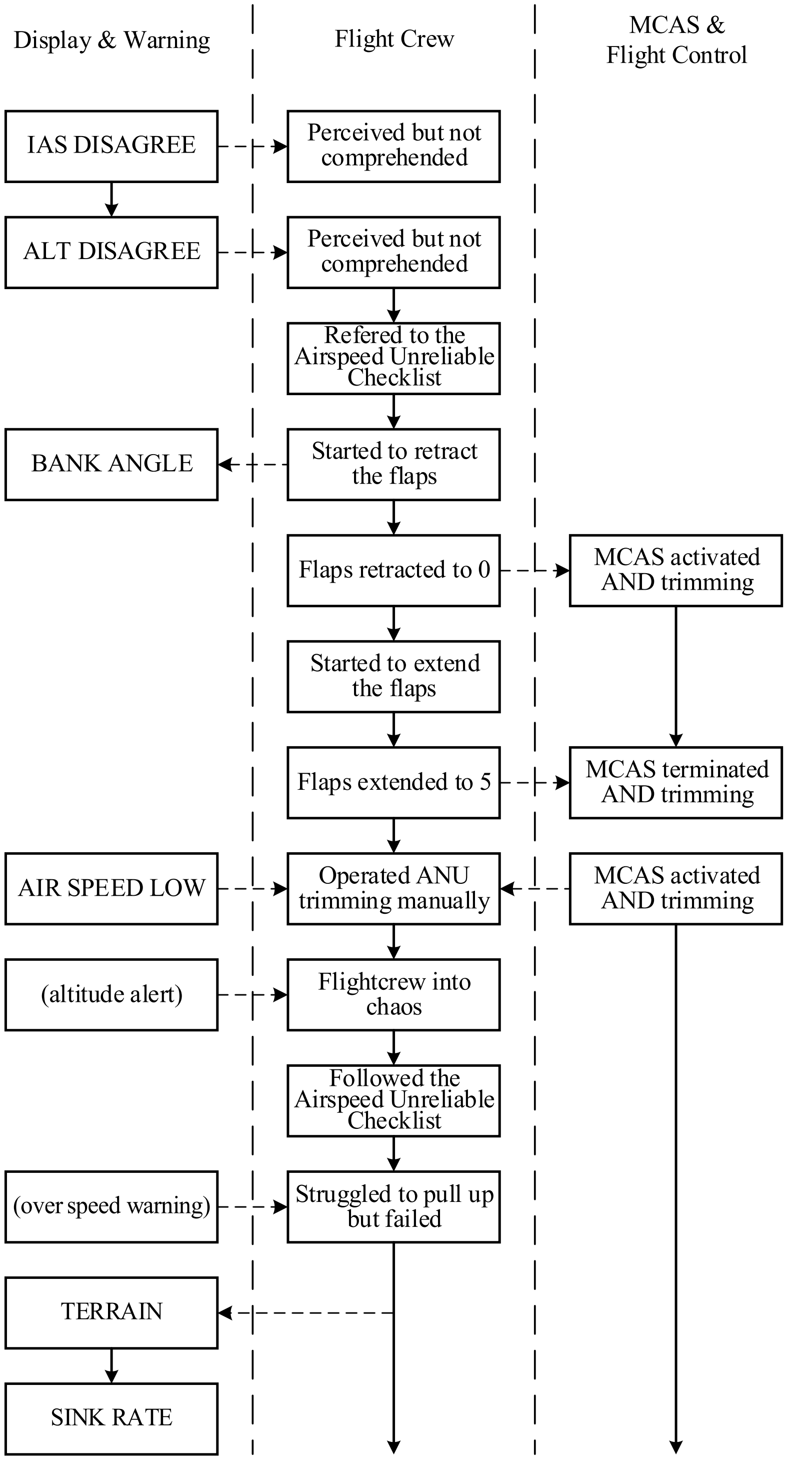


Fig. 17. The event series related to human-computer interaction in Scenario 1.

5. Integrated simulation and safety analysis: a case study

5.1. The risk scenarios concerning human-computer interaction

One of the human-computer interaction risk analysis scenarios (denoted as Scenario 1) selected in this section is derived from the simplification and abstraction of the Boeing 737-8 (MAX) accident. One of the main inducements of the accident was caused by the wrong AOA data. The MCAS system misjudged the current aircraft status, and issued flight control instructions that were higher than the flightcrew's control authority. The pilots lost situational awareness due to a combination of multiple factors (such as failing to receive the key failure information received, failing to understand what caused the aircraft to dive, etc.). Thus, the control authority of the aircraft could not be intercepted successfully by them in the game between human and computer. The key developments related to human-computer interaction in Scenario 1 are shown in Fig. 17.

In addition, other pilots encountered a similar problem (recorded as Scenario 2) when using the accident aircraft on another flight. Different from the crashed flight, the pilots quickly located the cause of the warnings. By cutting off the stabilizing surface automatic trimming (STAB TRIM) function and switching to manual trimming, the control authority was successfully intercepted and the disastrous consequences were avoided. The pilots never experienced the loss of situational awareness in this series of decision-making actions. In contrast, the key developments related to human-computer interaction in Scenario 2 are shown in Fig. 18.

5.2. Integrated simulation based on multi-agents

The agents in the integrated simulation environment mainly include the pilot agent, flight assistant system agent, air data sensor agent, display system agent, and warning system agent. In addition, uncertain factors such as the introduction of disturbances to the socio-technical system by the environment agent are also considered Impact on simulation results.

For the risk scenarios in Section 5.1, the assumptions to carry out the integrated simulation include:

- The visual warning information only includes indicated airspeed disagree (IAS DISAGREE) and altitude disagree (ALT DISAGREE). The first warning triggered by the failure of the air data sensor is IAS DISAGREE. The visual warning information is highlighted in text form on the bottom of the Primary Flight Display (PFD).
- The auditory warning information includes only bank warning (BANK ANGLE), low airspeed warning (AIR SPEED LOW), altitude warning (pre-set target altitude during flight), overspeed warning, terrain warning (TERRAIN), and descent rate warning (SINK RATE). The auditory warning information is output in the form of broadcast voice or prompt sound.
- Regardless of forgetting the perceived and comprehended information due to memory decline over time, the means of revealing the evolution of this phenomenon include the learning functions and forgetting function in the field of psychology.
- Set the STAB TRIM as the switcher between the flight assistant system and pilot control authority. The flight assistant system has higher control authority than the pilot when the switch is on, and the pilot control authority is higher than the flight assistant decision system when the switch is off.
- The P(P_j) output by the situational awareness model determines the possibility that the pilot is driven to take corrective action, that is, the STAB TRIM switch is turned off to intercept the control authority. If the switch is turned off, the warning information will no longer increase. If the switch is not turned off, the number of warning messages will continue to increase until all the warnings are generated.

The event of sensor failure was set to obey the probability distribution of N(0.2, 0.01). $\Pr(\mathrm{Cv}|\mathrm{s})$ and $\Pr(\mathrm{Ca}|\mathrm{s})$ changed dynamically with the inputs of the visual and auditory channel. The values of the remaining variables were set in accordance with Section 4.3.4. The simulation time was 100 time units, and the cumulative numbers of visual and auditory warnings during the simulation process are shown in Fig 19.

On the 10th time unit, a warning was triggered by a sensor failure. On the 12th time unit, the visual warnings were all displayed, and the auditory warnings continued to increase with the deduction of the situation, and reached the peak value on the 25th time unit. According to Bayesian reasoning, with the continuous increase of the warning information, the changes in the probability of successful comprehension of the audiovisual information, $\Pr(C_j)$, and the probability of taking the correct actions, $\Pr(P_j)$, are shown in Fig. 20 (a), (b).

5.3. Comparison and discussion

In this part, the risk effects with or without certain factors in the loop of interaction will be discussed and compared with those in Section 5.2. Besides, comparison with past studies will also be carried out to draw the highlights and limitations of this study.

5.3.1. Control priority: an early transmission from system to pilot

If the pilot takes the correct actions in advance, that is, the flight control authority is intercepted from the flight assistant system by turning off the STAB TRIM switch, the development phases of the situation will be similar to the scenario described in Scenario 2, Section 5.1. The variable settings in this process are consistent with those in Section 5.2, and the cumulative numbers of visual and auditory warnings are shown in Fig. 21.

On the 6th time unit, the pilot took the correct action and successfully obtained the control authority. After that, the number of

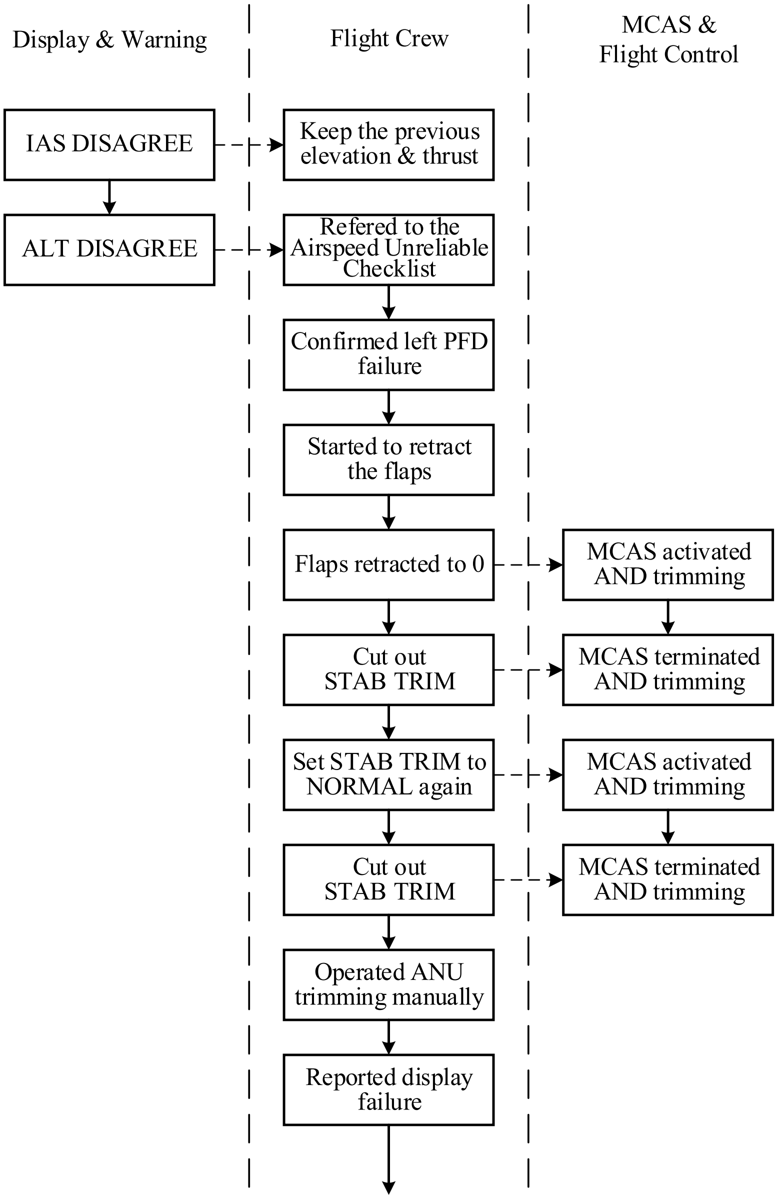


Fig. 18. The event series related to human-computer interaction in Scenario 2.

warnings no longer increased. In this scenario, the changes in the probability of successful comprehension of the audiovisual information, $\Pr(C_j)$, and the probability of taking the correct actions, $\Pr(P_j)$, are shown in Fig. 22 (a), (b).

Comparing the results shown in Figs. 20 and 22, it can be seen that the earlier transfer of flight control authority from the technical system side to the pilot side can effectively curb the evolution of the situation to an uncontrollable direction. By avoiding excessive warning messages to concentrate the pilot's attention resource allocation, it has played a positive role in accurately judging the current situation and avoiding the risk of losing situational awareness, which is consistent with the scenario described in Scenario 2 in Section 5.1.

5.3.2. *Direct prompt message: AOA disagree warning*

One of the important reasons for the loss of situational awareness is that the pilot cannot quickly locate the cause of the failure from the warning prompt information. Thus, it is difficult to take targeted measures to isolate the failure and avoid catastrophic consequences. Warning information such as ALT DISAGREE and IAS DISAGREE failed to indicate the direct cause of the risk event, and the lack of the key alarm information of inconsistent AOA led the flightcrew to immerse themselves in tedious troubleshooting procedures. As the situation became uncontrollable, the probability of successful disposal gradually decreased.

The AOA DISAGREE display warning was introduced in the simulation environment. The logical sequence of triggering was after

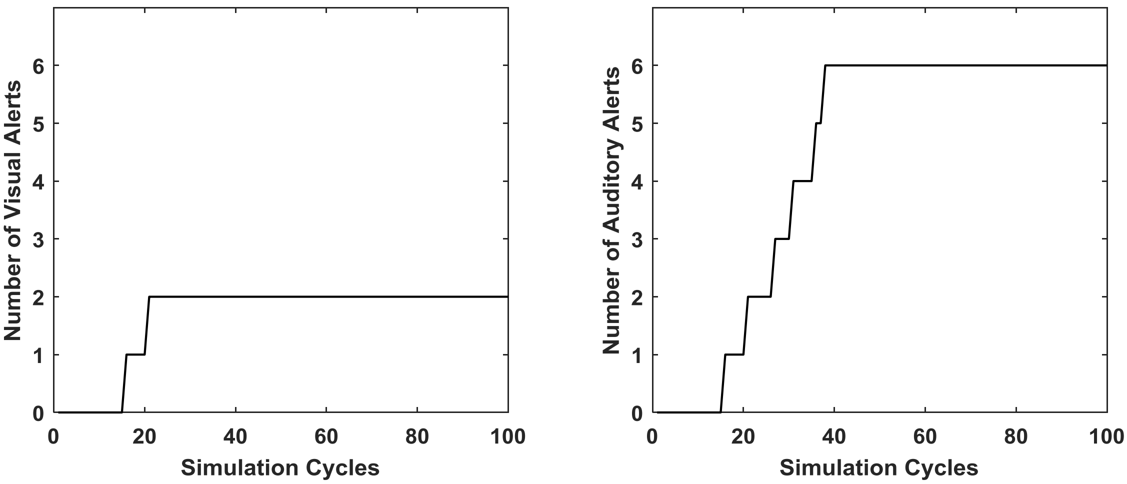


Fig. 19. The relationship between numbers of visual/auditory alerts and simulation cycles.

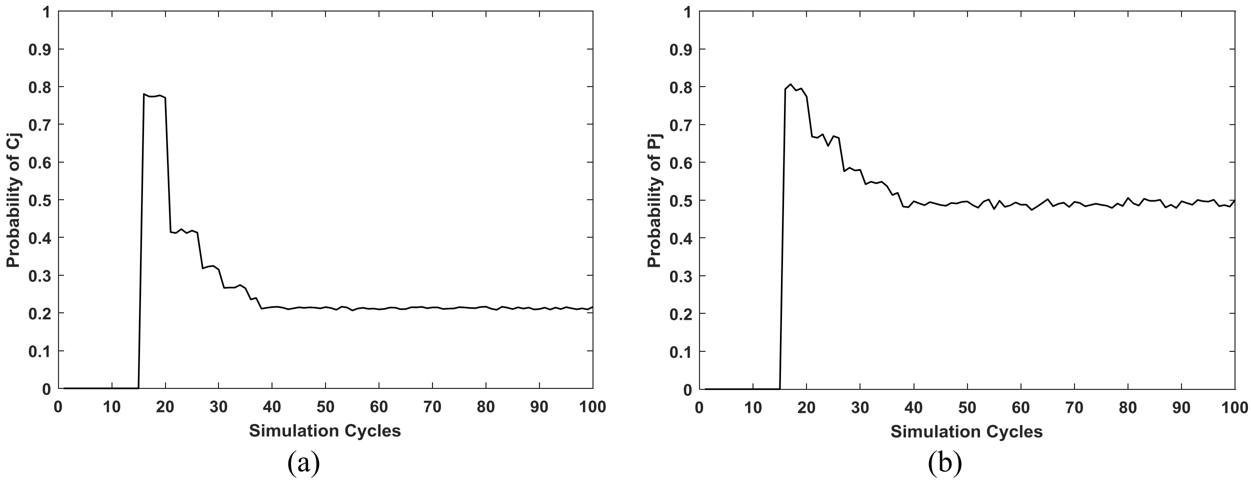


Fig. 20. The relationship between probability of C_j, P_j and simulation cycles.

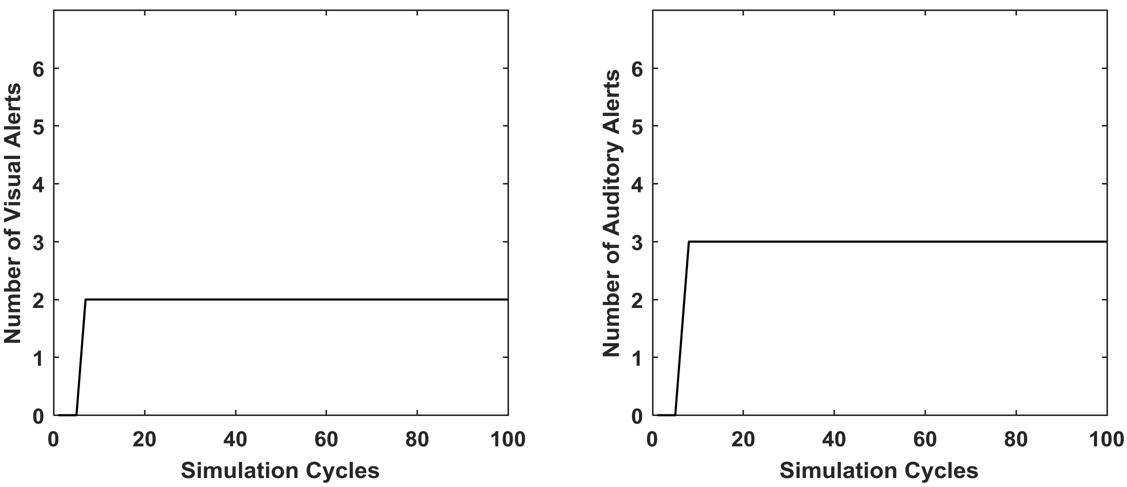


Fig. 21. The relationship between numbers of visual/auditory alerts and simulation cycles.

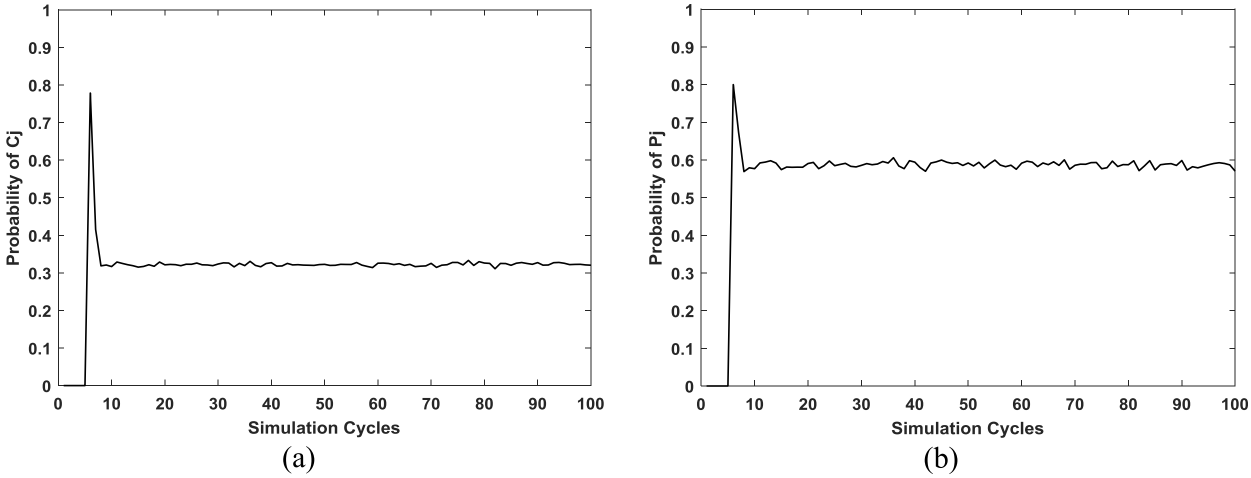


Fig. 22. The relationship between probability of C_j, P_j and simulation cycles.

the two existing visual warning information. The number of facts contained in it was set to 1, indicating that the warning information was directly pointed to the AOA sensor failure. So, there was no need for pilots to convert information multiple times. The weights of the three visual warning contents were set to 0.2, 0.2, and 0.6.

Similarly, for comparison with Scenario 1, the initial settings of the variables during simulation are consistent with those in Section 5.2. The cumulative numbers of visual and auditory warnings are shown in Fig. 23.

The warning was triggered on the 3rd time unit. The AOA DISAGREE alarm information was displayed on the 12th time unit. The logical sequence of other visual and auditory warning information is the same as that in Section 5.2.

According to Bayesian reasoning, the changes in the probability of successful comprehension of the audiovisual information, $\Pr(C_j)$, and the probability of taking the correct actions, $\Pr(P_j)$, are shown in Fig. 24 (a), (b).

According to cognitive theory, the increase of cognitive factors will cause the extra allocation of additional cognitive resources, which will further increase the difficulty of forming the key elements of situational awareness such as desired comprehension and decision-making. Comparing the results shown in Figs. 20 and 24, it can be seen that the probabilities of $\Pr(C_j)$ and $\Pr(P_j)$ are higher than the scenario described in Scenario 2, although the visual warnings are more in this simulation. At this time, the displayed warning information is more important and direct than the original one, which is reflected in the weight and number of facts. The results show that the AOA DISAGREE warning information can also play a positive role in accurately judging the current situation and avoiding the risk of losing situational awareness for the pilots.

5.3.3. Comparison with past studies

Comparing this work with past studies will be carried out from two aspects. Firstly, in the aspect of SA assessment, the comparison will be made with qualitative and quantitative methods typical in aviation [7]. Secondly, in the aspect of Bayesian modelling, the comparison will be drawn with the methods developed by statistical data and expert experience in other human-computer systems

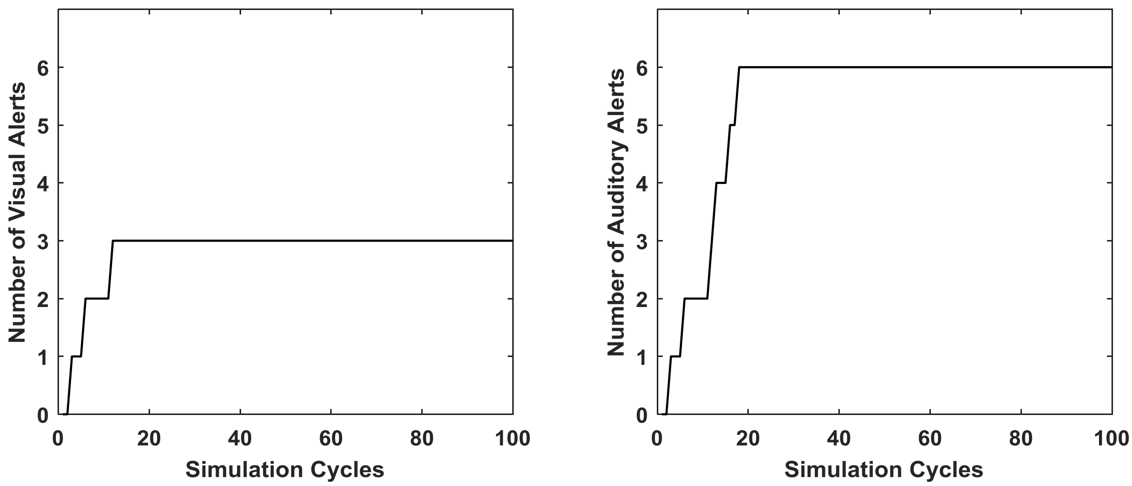


Fig. 23. The relationship between numbers of visual/auditory alerts and simulation cycles.

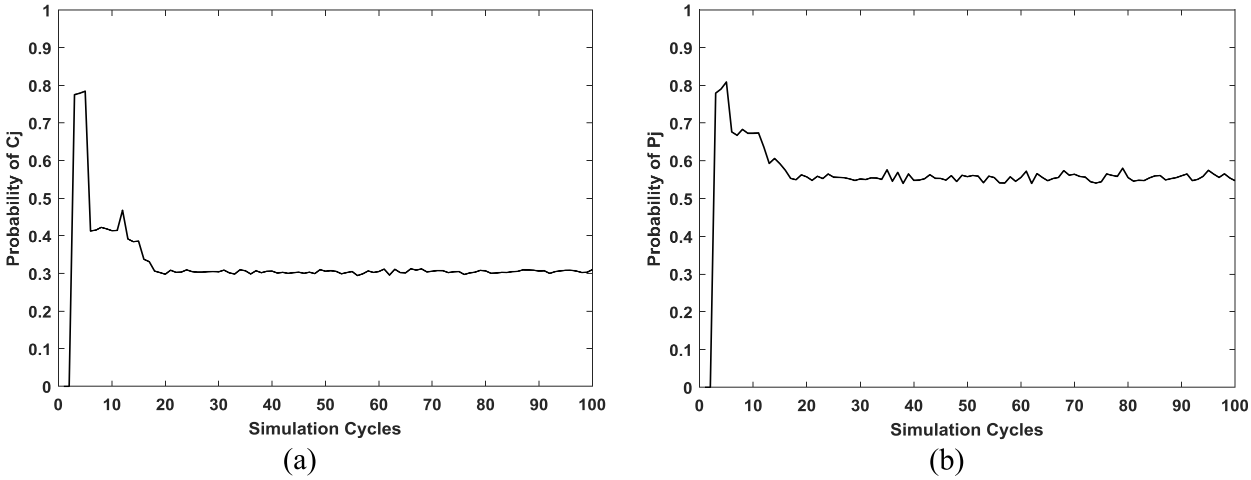


Fig. 24. The relationship between probability of C_j, P_j and simulation cycles.

[50]. Table 7 shows the comparison results, as well as the highlights and limitations of this work.

By comparison, it can be seen that the main advantage of the methods proposed in this work is the flexible ability to construct different simulation scenes from a deep perspective of cognition. They are not limited to the hardware or software conditions and the severity of risks. For generalizing the model to more human-computer or human-machine systems, the types of stimulus in visual or auditory channel should be re-defined. Besides, the conditional probabilities should be updated by any of the three above-mentioned approaches. What can remain the same as the proposed model include the general structure of forming situational awareness and the calculating methods of cognition related parameters based on ACT-R. The model can provide an in-depth analysis of complex accident causes, and find solutions to identifying the risk inducing mechanism of key factors. Then back to the design stage, it is expected that designers will give more consideration to these key factors which may result in potentially dangerous events by prediction of future to some extent.

6. Conclusions and future work

In this paper, an agent-based model is proposed for analyzing the cognitive behaviors during human-computer interaction in the

Table 7
Comparisons between this work and past studies

Aspect	Method	Highlights	Limitations
SA assessment	Qualitative methods	Ease of implementation with rating scales. Easy to process the evaluation data.	Completely depending on the subjective judgment. Unable to capture the dynamic changes of SA in real time.
	Quantitative methods	Dynamically and continuously capturing the physiological characteristics concerning SA.	Requiring psychophysiological monitoring devices. Difficult for heterogeneous data processing.
	Methods proposed in this work	Providing an insight into the cognition level. Suitable for the assessment situation where it is difficult to create a huma-in-the-loop scene.	Having a complex modelling process. Requiring certain simplification and assumption on the basis of real scenes.
Probabilistic approaches	Markov models	Predicting the future state of a node only by the current state rather than any past states. Able to model the undirected interrelations between different nodes by Markov nets.	Not appliable to model the directional formation process of SA especially with two or more sources to be considered.
	Petri nets	Quantifying the features of SA including task performance by duration of transitions.	Unable to represent the duration of transitions in forming SA due to the unobservable features of different phases.
	Bayesian networks used in this work	Clearly expressing the hierarchical causal structures between complex factors and well dealing with the uncertainty and coupling of directed relations.	Having challenges in determining the inference rules and conditional probabilities for Bayesian modelling.
Methods of procuring data for Bayesian modelling	Methods based on statistical data	Accurately obtaining the probability distribution of the real events.	Relying on a large number of accident reports or records. Not available in the absence of data.
	Methods based on expert experience	No need to collect statistics from a large number of accident reports. Suitable for the situation of insufficient accident data.	Completely depending on the subjective judgment. Having difficulty in determining the probabilities accurately.
	Methods proposed in this work	Combining ACT-R theory and empirical values to procure probabilities for numerical modelling. Building multiple simulation scenes flexibly.	Necessary to accurately analyze the ACT-R input parameters in different scenes. Many preparations for the preliminary work of modelling.

aircraft cockpit. In more details, the model contains the pilot agent module, the technical system agent module and the environment agent module. The kernel of the pilot agent module, situational awareness, is modelled based on ACT-R theory and Bayesian network. Under the tests of input-output characteristics, it proves that the model can transfer the distribution characteristics and uncertain fluctuation of different visual or auditory cognitive elements. Sensitivity analysis results show that the conditional probability of comprehending the warning information under the auditory stimulus has greater influence on the outputs than that under the visual stimulus. The probability of successful joint comprehension is more susceptible to inputs than that of successful projection. Two scenarios concerning the human-computer interaction were taken as examples to illustrate the importance of early control priority transmission and direct prompt messages in avoiding the serious risk. Comparison with past studies show that the methods proposed in this work have advantages in constructing different simulation scenes for quantitative SA analysis, from a deep perspective of cognition.

Future work will concentrate on the refined modelling of human-computer interaction. More interaction channels will be integrated into the simulation model such as tactile channel and gesture channel. This is driven by the introduction of novel interactive methods such as the touch screen and gesture recognition into the aircraft cockpit. Non-binary states of the nodes in Bayesian networks will be considered to describe the SA formation process by introducing multi-category or continuous parameters.

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