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Human Factors Analysis of Air Traffic Safety Based on HFACS-BN Model

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Abstract: Air traffic control (ATC) performance is important to ensure flight safety and the sustainability of aviation growth. To better evaluate the performance of ATC, this paper introduces the HFACS-BN model (HFACS: Human factors analysis and classification system; BN: Bayesian network), which can be combined with the subjective information of relevant experts and the objective data of accident reports to obtain more accurate evaluation results. The human factors of ATC in this paper are derived from screening and analysis of 142 civil and general aviation accidents/incidents related to ATC human factors worldwide from 1980 to 2019, among which the most important 25 HFs are selected to construct the evaluation model. The authors designed and implemented a questionnaire survey based on the HFACS framework and collected valid data from 26 frontline air traffic controllers (ATCO) and experts related to ATC in 2019. Combining the responses with objective data, the noisy MAX model is used to calculate the conditional probability table. The results showed that, among the four levels of human factors, unsafe acts had the greatest influence on ATC Performance (79.4%), while preconditions for safe acts contributed the least (40.3%). The sensitivity analysis indicates the order of major human factors influencing the performance of ATC. Finally, this study contributes to the literature in terms of methodological development and expert empirical analysis, providing data support for human error management intervention of ATC in aviation safety.

Keywords: air traffic control; human factors; aviation safety; HFACS; Bayesian networks; noisy MAX model

1. Introduction

Safety is an important prerequisite for the sustainable and healthy development of the aviation industry [1]. As a critical area of aviation safety, air traffic control (ATC) requires highly skilled operators to work together in a large and complex human–machine system [2]. In an ATC system, air traffic controllers play a central role, and they have to cooperate with the various components of the ATC system to ensure the safety, order, and efficiency of air traffic flow [3]. Like other complex sociotechnical systems, there are always some risks of interference in the system [4]. Uncooperative interactions between controllers and system components hold potential for human errors, leading to safety breakdowns [5]. In fact, during the second half of the 20th century, the technical environment changed and the focus of attention in aviation industrial sectors shifted from technological problems to human factors problems and, finally, to problems with organizations and safety culture [6]. Human error is one of the contributors to more than 70% of aviation accidents [7]. This is demonstrated by a review of the Australian ATC system, which finds that coordination and communication errors contribute most to air traffic incidents [5]. In the UK Airprox incident report, human errors in ATC are related to perception, decision making, communication, and team resource management [8]. ATC-related incident examples include on 1 July 2002, a Tu-154m passenger aircraft (BTC2937) of

Russian Bashkir Air collided with a former DHL Express Boeing 757-200sf cargo plane (DHX611) over the Swiss city of Überlingen, killing all 71 passengers and crew of both aircraft. The main cause of the accident was a Swiss air traffic control center command serious error; on 11 October 2016, a China Eastern Airlines A320 evaded a runway incursion by narrowly passing over the top of an A330 that had crossed into the active runway due to improper situational awareness by both the pilots and tower controllers. As the number of flights increases, air traffic controllers have to learn from these disasters, and an analysis of human factors may be one of the effective ways to learn from such "mistakes" to reduce the number of similar disasters [8]. The International Civil Aviation Organization (ICAO) has been working to improve aviation safety and to apply the latest research on human factors to the global aviation industry. Investigators tend to analyze safety issues from a systematic perspective, including human and organizational factors as well as other factors [9]. In this context, the human factor analysis and classification system (HFACS) emerged. HFACS was originally designed and developed based on the "Swiss-Cheese" model of Reason and the human error framework, which was used to investigate and analyze human error accidents in American military aviation operations [10], and the framework's developers have demonstrated its applicability to commercial and general aviation accident analysis [11]. Moreover, human factors are important for understanding human performance in a variety of transportation sectors, and HFACS was further adapted to investigate ship and railway accidents arising from human errors [12–14]. Celik and Cebi used HFACS to investigate the human factors in the ship accident [15]. Daramola et al. used the HFACS framework to investigate aviation accidents in Nigeria between 1985 and 2010 [16]. Chen et al. used the HFACS framework and Bayesian network to analyze the human factors of crew members behind the aviation accident and evaluate their performance [9]. Zhou et al. searched for human factors affecting aviation safety based on the framework of HFACS through the questionnaire survey of airport staff in Ulaanbaatar, Mongolia. The study focused on the professional opinions of experienced investigators or operators [6].

Through the above review, we found that the existing research can be further improved in the following aspects. First of all, the detailed information about the behavior of air traffic controllers obtained from the accident reports is relatively limited, such as the degree of ATC safety culture, the salary of controllers, whether the ATC supervision plan is complete, etc., which is more or less unavailable in the accident reports [9]. In addition, the reasons behind air accidents seem to be very complex, and the quantitative causal relationship between human factors is usually limited and highly uncertain. Faced with the problem of missing and incomplete data, this paper appliedthe Bayesian network (BN) model, which is one of the most effective theoretical models in the field of uncertain knowledge expression and reasoning. The model can integrate objective information and subjective information from multiple sources, and make an inferential analysis from incomplete, inaccurate, and fuzzy information [17]. Such a combination of HFACS and BN model will advance our full understanding of the underlying causes of ATC safety failure, and the interrelationships among the risk sources and their total effects on ATC performance. In the calculation of a conditional probability table, this paper adopts the noise maximum model, which allows the processing of multi-state nodes in the network [18,19].

The rest of this paper includes the methodology applied in the study, data collection and modeling, results analysis, discussion and conclusion, and further research work.

2. Methodology and Materials

2.1. Human Factors Analysis and Classification System (HFACS)

HFACS is valuable for systematically analyzing the causes of an accident and currently remains at identifying the core risk factors of accidents. It describes four levels of human error: Unsafe acts, preconditions for unsafe acts, unsafe supervision, and organizational influences (Figure 1) [20]. Since its initial development, HFACS has proved to be an effective tool for human error analysis in various fields, such as railway [13], mining [21], and maritime transport [22], as argued previously. This study utilizes the Bayesian network (BN) to construct a quantitative prediction network among different levels of risk factors in HFACS and between risk factors and ATC performance.

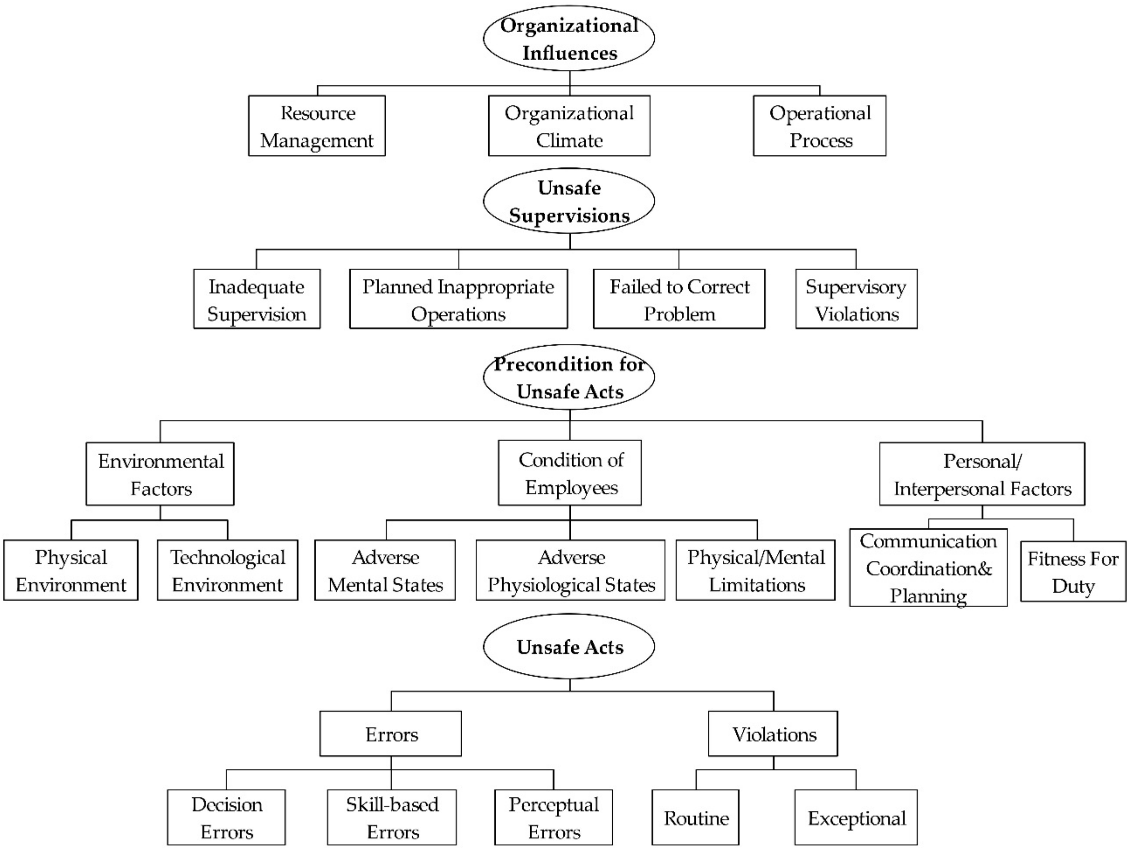

Figure 1. Overview of the human factors analysis and classification system (HFACS).

2.2. Bayesian Network Model

Bayesian network, also known as belief network or causal network, is a probabilistic directed acyclic graphical (DAG) model [23]. Nodes in DAG denote random variables, directed line segments represent conditional dependencies among random variables, and conditional probability tables store joint conditional probabilities between corresponding nodes [24–26]. It is assumed that node B directly affects node A and connects the two nodes with A directed line segment, i.e., B → A, where B stands for "Parents" and A stands for "Children". The connection strength between the two nodes is expressed by conditional probability P (A|B), as shown in Figure 2a. A Bayesian network is formed when variables involved in a system are plotted in a DAG according to a certain causal relationship, as shown in Figure 2b, which is a simple example.

In a BN, any trajectory consists of the connection of the three structures in Figure 3.

BN is especially well suited to safety issues and risk assessment, including the aviation field [27]. Jitwasinkul et al., focusing on personal safety behavior, established the BN model to identify the most critical organizational factors that improve safety behavior [28]. Chen et al. focused on the human error of flight crew behind aviation accidents [9], while Zhou et al. focused on the safety awareness of airport staff [6]. Although these applications are in different settings, it can be concluded that BN can perform human factor and safety analysis, including prediction, diagnosis, decision making, and provide insight into the relationship between variables. This study thus aims to introduce BN as an appropriate method to predict ATC performance and to diagnose human factors in ATC failures.

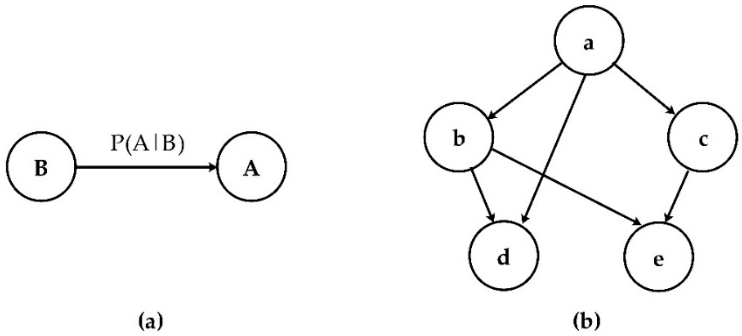

Figure 2. (**a**) Directed acyclic graphs for Bayesian network; (**b**) simple Bayesian network model.

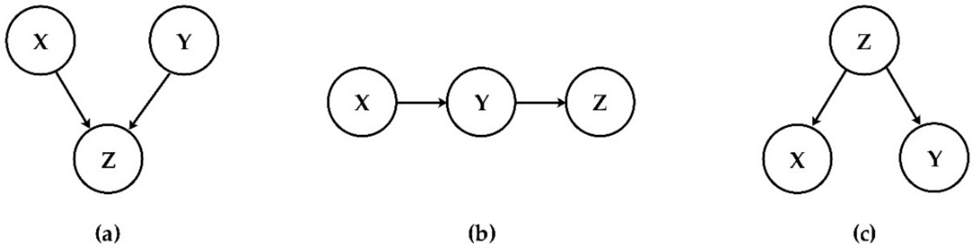

Figure 3. Three basic structures of Bayesian networks. (**a**) Head to head; that is, given the condition of Z, the communication between X and Y is blocked, also known as head-to-head condition independence. It is obvious that variables X and Y have a common result Z. The joint probability can be expressed as P (X, Y, Z) = P(X) P(Y) P (Z|X, Y). (**b**) Head to tail. For a given condition of Y, the communication between X and Z is blocked, which is called head-to-tail condition independent. X, Y, and Z are connected serially, and the corresponding joint probability distribution is P (X, Y, Z) = P(X) P (Y|X) P(Z|Y). (**c**) Tail to tail. For a given condition of Z, the communication between X and Y is blocked, which is called tail-to-tail condition independence. Obviously, X and Y have a common cause. The joint probability is therefore calculated as P (X, Y, Z) = P (Z) P (X|Z) P (Y|Z).

2.3. Noisy MAX Model

In general, the conditional probability table can be obtained from a database or the judgment of relevant experts [29]. However, it is challenging work to directly get all the conditional probabilities for a large-scale network since the number of parameters grows exponentially with the number of parents [30]. At present, the most widely used algorithm is the Noise-OR model proposed by Good [31]. Henrion further extends the model to multivariate variables [32]. Based on Henrion's model and formalizing it, Diez proposed a kind of evidence propagation algorithm "MAX gate" [18]. To focus on the ternary variable BN model, this paper, therefore, adopts the "noisy MAX" dealing with conditional distribution of multiple variables.

In noisy MAX, the child node Y, taken sequentially from 0 to $y_{\max} - 1$, has a total of $y_{\max}$ states, and N parents, $Pa(Y) = \{X_1, \ldots, X_n\}$, representing the causes of Y. The following are two basic axioms of noisy MAX [18]:

$$P(Y = 0|X_i = 0, \forall i) = 1 \tag{1}$$

$$P(Y \le y|x_1, x_2, \ldots, x_n) = \prod_i P(Y \le y|X_i = x_i, X_j = 0, \forall j \ne i) \tag{2}$$

where the X_i are independent of each other.

The parameters for link $X_i \to Y$ are $c_y^{x_i}$, representing the probability of $Y = y$ when parent X_i takes on the value x_i and all other X_j values are 0.

$$c_y^{x_i} = P(Y = y|X_i = x_i, X_j = 0, \forall j \ne i) \tag{3}$$

Define a new parameter:

$$C_y^{x_i} = P(Y \le y | X_i = x_i, X_j = 0, \forall j, j \neq i) = \sum_{k=0}^{y} c_k^{x_i}. \tag{4}$$

Then, Equation (2) can be rewritten as:

$$P(Y \le y | x_1, x_2, \ldots, x_n) = \prod_i C_y^{x_i}. \tag{5}$$

Finally, the CPT is obtained using the following formulas:

$$P(y|X) = \begin{cases} P(Y \le 0|X) & if \quad y = 0 \\ P(Y \le y|X) - P(Y \le y-1|X) & if \quad y > 0 \end{cases} \tag{6}$$

2.4. Research Framework

In order to clearly describe how HFACS and BN effectively combine to predict the performance of ATC, Figure 4 presents the research framework of this paper.

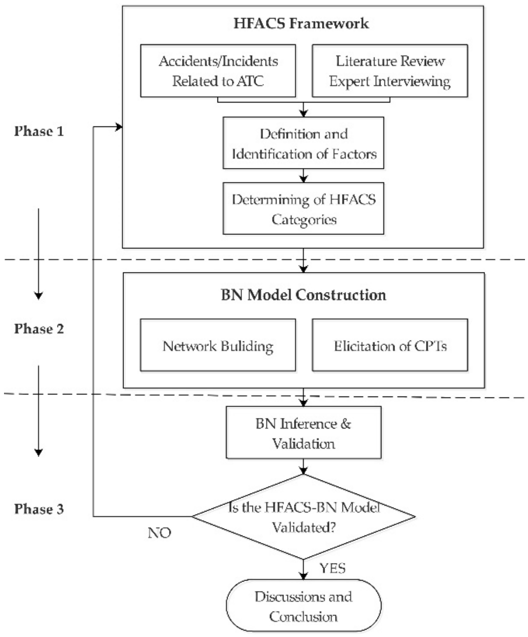

Figure 4. Research framework.

Phase 1. First, an HFACS framework was established for the specific analysis of human factors related to ATC in civil aviation safety. To this end, based on the existing mature HFACS structure, and aviation accident report, we also interviewed the opinions of experts and engineers in relevant fields to select the most important ATC human factors that may lead to aviation accidents. Detailed data information for phase 1 will be provided later in this article.

Phase 2. Next, human factors from the HFACS framework are selected as the node variables of the BN model to establish the influence relationship between different variables involved in the HFACS framework. When the BN model is used for prediction, the prior probability of the root node in the model should be given first. According to the data in the aviation accident reports, and the "Skybrary" database, as well as the results of the questionnaire survey, the conditional probability tables (CPT) among the BN nodes can be generated. CPT calculation results of phase 2 are shown in Section 3.2.

Phase 3. Based on the HFACS-BN model established in the above steps, BN inference and sensitivity analysis were conducted to predict and analyze the most important factors affecting the performance of ATC in the model. Finally, it gives corresponding risk factors intervention measures, and verifies the model to help managers predict aviation safety performance ability.

3. Theoretical Development

3.1. Network Construction

Since 1980, 142 aviation accidents/incidents worldwide related to ATC human factors have been recorded in "Skybrary," accounting for more than 13.6% of the 1045 aviation accidents/incidents in the database in the same period. SKYbrary was initiated by EUROCONTROL in partnership with International Civil Aviation Organization (ICAO), The Flight Safety Foundation and The UK Flight Safety Committee, and work with the Federal Aviation Administration (FAA) to upload the outputs of the Commercial Aviation Safety Team (CAST) to provide reference materials for safety managers. As shown in Figure 5, the time–frequency distribution shows that the number of aviation accidents/incidents related to ATC human factors is on a sharp rise, which is understandable because the leading cause of aviation accidents has shifted from technical problems to human factors; moreover, the number of aircraft fleet and flight frequency are also increasing. The analysis and identification of ATC human factors provide practical insights for organizations on aviation safety and ATC performance management, especially in understanding which key human factors have a significant impact on the performance of controllers, to further improve ATC work and the safety of ATC operations.

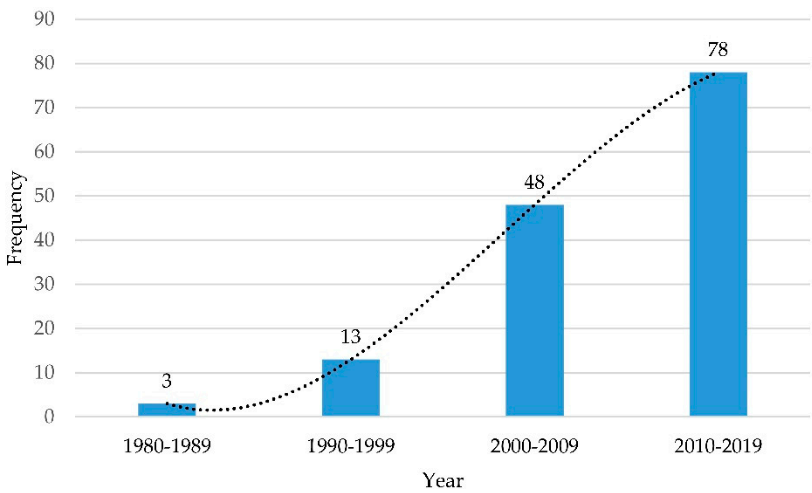

Figure 5. The number of aviation accidents/incidents related to air traffic control (ATC) human factors from 1980 to 2019.

Figure 6 shows the category of ATC human factors and the frequency of each human factor according to Skybrary statistics in 142 aviation accidents/incidents worldwide from 1980 to 2019. As we can see, a total of 14 human factor tags were behind 142 aviation accidents/incidents, and all human factor tags occurred 410 times; where 94 accidents/incidents related to procedural noncompliance and 92 accidents/incidents related to ineffective monitoring, while only 2 and 1 accidents/incidents related to stress and ATC team coordination, respectively. Note that this is because the human factors behind every aviation accident/incident are complex and diverse, as in the case of the 4 April 2016 accident, a Boeing 737-800 crew taking off in normal night visibility from Jakarta Halim were unable to avoid an ATR 42-600 undertow, which had entered their runway after ambiguity in its clearance. Both aircraft sustained substantial damage and caught fire but all those involved escaped uninjured. The accident report involves four kinds of human factor tags, including the ATC clearance error, ATC unit coordination, ineffective monitoring, and procedural noncompliance, hence all human factor tags occurred 410 times.

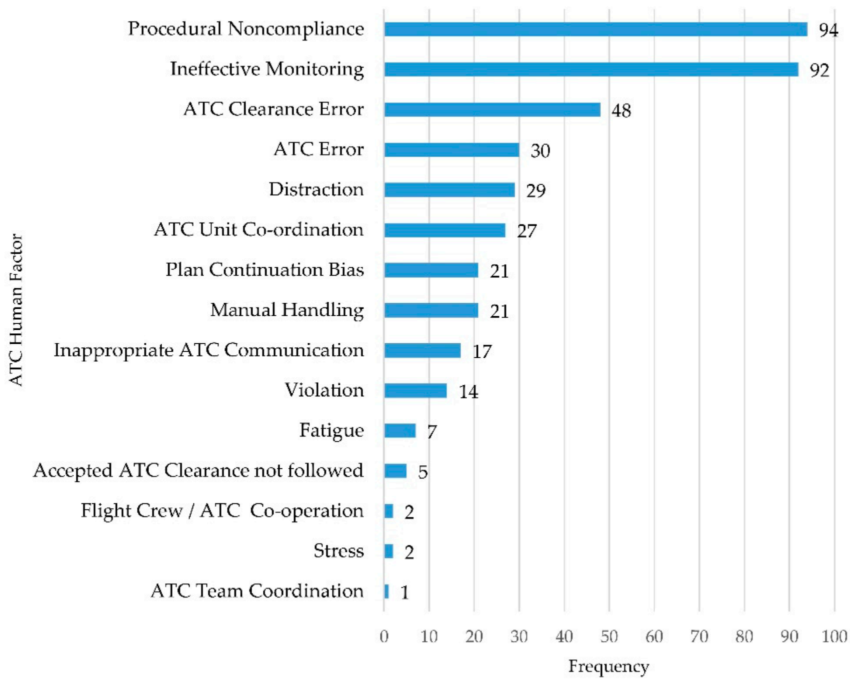

Figure 6. Distribution of ATC human factor tags in aviation accidents/incidents from 1980 to 2019.

Generally, the ATC performance model is a complex system with tightly coupled relationships between nodes. Combined with the opinions of experts in the aviation field, Figure 7 shows the "ATC Performance" model in this paper, which contains four sequential paths affecting the performance of ATC, namely "Organizational Influence", "Unsafe Supervision", "Preconditions for Unsafe Acts", and "Unsafe Acts", and each influence path contains human factors at the corresponding level.

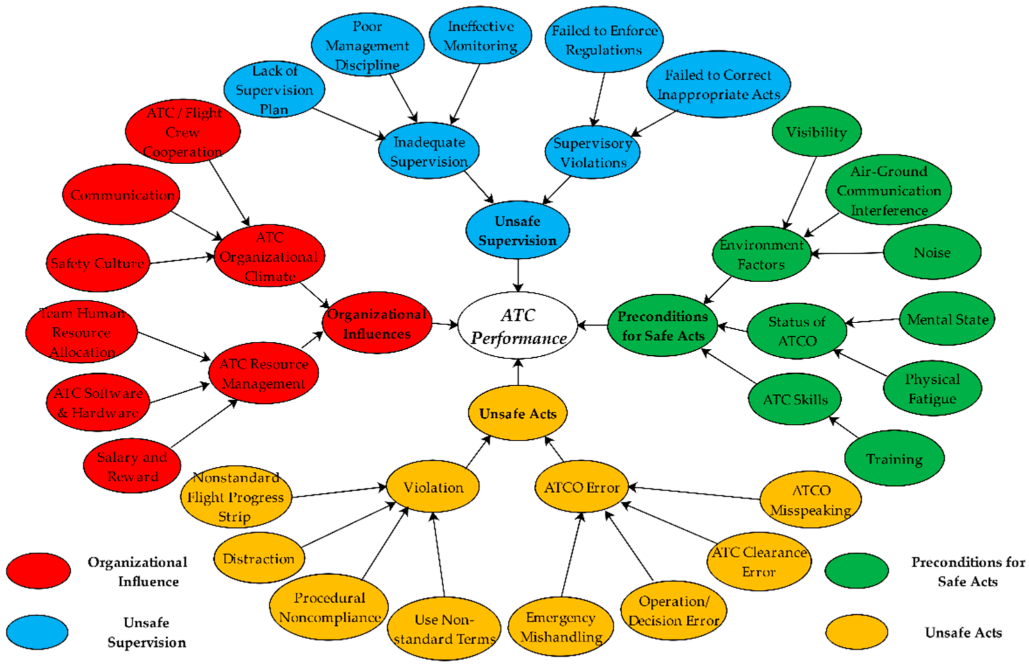

Figure 7. ATC performance model.

In order to better illustrate each node in the ATC performance model, Table 1 describes the source and detailed interpretation of human factors. It is worth mentioning that the ATC human factor tags from Skybrary are not very comprehensive, and most of them are distributed on the two levels of unsafe acts and the preconditions of unsafe acts. However, some human factors related to organizational influence, such as organizational climate, safety culture, or resource allocation, are difficult to be directly recorded in the accident report. However, in previous studies [4,33,34], these factors did affect ATC performance. Therefore, some nodes in the model are not involved in the accident report mentioned above, which are derived from references and expert opinions.

Table 1. Factors description and its sources.

Factors	HFACS Level	Description	Source
Safety Culture	Organizational Influence	It includes the safety policy of the ATC department, safety education, as well as preventive measures	CAA (2003) [35]
Team Human Resource Allocation		The duty of the team members is not clear, the collocation is not reasonable, the work is not coordinated and so on	N.S. Olsen [33]
Salary and Reward		It refers to salary and workload that do not match, employees that are not satisfied with the salary and reward	CAA (2002a) [35]
ATC Communication		Communication between controllers, including briefing on handover	Shappell [36]
ATC/Flight Crew Cooperation		It refers to the communication and coordination between ATCOs and crew members	SKYbrary [37]
ATC Software/Hardware		It includes ATC equipment layout, hardware failure, software interaction and so on	SKYbrary [37]
Lack of Supervision Plan	Unsafe Supervision	ATC supervision is not in place, not comprehensive, not meticulous, etc.	N.S. Olsen [33]
Poor Management Discipline		It means the management style discipline/supervision effect are poor	Experts' opinions
Failed to Enforce Regulations		It leads to an inadequate understanding of the rules by air traffic controllers and may raise safety risks	Zhou [6]
Failed to Correct Inappropriate Acts		It occurs when ATCO does not correct unsafe acts during control	N.S. Olsen [33]
Ineffective Monitoring		It includes monitoring flight path, aircraft systems, operational factors, crew/situational awareness.	ICAO [38]
Visibility	Preconditions for Unsafe Acts	Poor visibility due to weather or environmental conditions, unable to effectively monitor aircraft status	SKYbrary [37]
Air–Ground Communication Interference		Ground–to–air communication frequency is seriously disturbed by the external environment	Experts' opinions
Mental State		Mental, emotional or physical tension, strain or distress	N.S. Olsen [33]
Noise		It includes ambient noise from air traffic controllers, noise from crew members, or other noises in the radio	Experts' opinions
Training		Lack of training materials or inadequate training	Teperi [34]
Physical Fatigue		Factors related to a lack of sleep or long work days	IATA (2006)
Nonstandard Flight Progress Strip	Unsafe Acts	Aircraft call number, departure location, aircraft model and other information are not standard	SKYbrary [37]
Distraction		Distraction refers to the lack of concentration of air traffic controllers, which affects the normal work of ATC	Chang [35]
Use Non-standard Terms		It refers to the use of informal terms in air traffic control activities	SKYbrary [37]
ATC clearance error		There are two types: intended clearance given to wrong aircraft or wrong clearance given to intended aircraft	SKYbrary [37]
Emergency Mishandling		ATCO do not have a good command of special situation handling procedures, poor psychological endurance	ICAO [38]
Operation/Decision Error		Mis operation or decision-making by the ATCO in the control process	N.S. Olsen [33]
ATCO Misspeaking		It refers to careless, absent-minded, insincere control work, resulting in instruction errors	ICAO [38]
Procedural Noncompliance		Not following procedures: FARs, OEM standards, SOPs; It always results in a greater risk for the operation	SKYbrary [37]

3.2. Data Collection

Generally, when the number of parents involved in a BN is large, collecting a conditional probability table (CPT) of each node from the accident/incident reports or experts' opinions is a challenging task. Since the accident reports related to ATC cannot record all the information of each node, it is difficult to deduce CPTs directly from the database. In this paper, the original parameters of CPT are obtained by combining the analysis of aviation accident reports and survey. However, the limitations of the data need to be noted, as the survey related to human factors is susceptible to the influence of statistical factors. These expert estimates, plus the need to be cautious about statistical fluctuations, limit the accuracy of conditional probability estimates [39].

3.2.1. Objective Marginal Probability

The marginal probabilities are obtained by analyzing literature review and ATC accident reports. Two nodes of "ATC Clearance Error" and "Distraction" are taken as examples to illustrate how to obtain the marginal probability from the database. Of the 142 aviation accidents/incidents recorded by the "SKYbrary" between 1980 and 2019, 48 accidents/incidents were related to "ATC Clearance Error," and 29 were related to "Distraction." According to the above 142 relevant records, the marginal probabilities of nodes were calculated, as shown in Table 2.

Table 2. Marginal probabilities for nodes ATC clearance error and distraction.

Node	ATC Clearance Error		Distraction	
State	Yes	No	Yes	No
Number	48	94	29	113
Probability	0.3380	0.6620	0.2042	0.7958

3.2.2. Subjective Conditional Probability

The Noisy MAX model is used to generate conditional probabilities, and the survey is conducted to obtain the original parameters, involving human factors at four levels of HFACS [30]. Each node in the survey has two types of questions, corresponding to the dependencies between parent and child nodes and the countermeasures to be taken. Questions are divided into the following two types:

- Type 1 is used for conditional probabilities assignment, which requires respondents to give conditional probabilities under the condition that only child and parent are considered.
- Type 2 is used for model validation, which requires respondents to select the countermeasures of different nodes that should be taken.

We successfully collected valid questionnaire sheets from 26 air traffic controllers and experts familiar with ATC in China. The Likert scale was adopted to evaluate the survey, with 1 point representing a very low probability and 5 points representing a very high probability, which were used to indicate the influence degree of one node on another node. Taking the node ATC organizational climate in Figure 7 as an example, the Type 1 question amounted to: What is the probability that "Safety Culture = good" results in "ATC Organizational Climate = good"?

Type 2 question: Which of the following measures do you think would reduce human errors and improve ATC performance? Choose several most influential factors or give your opinions. For instance, the corresponding measure lists include regular safety awareness training, improve management discipline, reasonable arrangement work time, strengthening ATC professional skills training, and so on. After the original probabilities were collected and normalized, the noisy MAX model above was used to generate CPT. Table 3 shows an example of CPTS. Out of those 42 sets of questionnaires, 26 sets were valid, reaching a valid response rate of 61.9%. The respondents' backgrounds are described in Table 4.

Table 3. Example of conditional probability table (CPT) inputting.

ATC Organizational Climate	ATC/Crew Cooperation			Communication			Safety Culture		
	Good	Normal	Poor	Good	Normal	Poor	Good	Normal	Poor
Good	0.4776	0.2619	0	0.4468	0.3095	0	0.4762	0.3182	0
Normal	0.3406	0.4048	0	0.3404	0.4286	0	0.3333	0.4318	0
Poor	0.1818	0.3333	1	0.2128	0.2619	1	0.1905	0.25	1

Table 4. Respondents' background.

Item	Frequency	Percent (%)
Gender		
Male	21	80.8
Female	5	19.2
Education		
Bachelor degree	15	57.7
Master	7	26.9
Ph.D.	4	15.4
Position		
Tower control	6	23.1
Approach control	8	30.8
Area control	8	30.8
ATC expert (Dr., Prof.)	4	15.3
Work experience		
<3	3	11.5
3–5	8	30.8
>5	15	57.7
Control mode		
Procedural Control	14	53.8
Radar Control	8	30.8

3.3. Sensitivity Analysis

Sensitivity analysis is a general method to study the influence of inaccurate parameters on model output and to compare the importance of different factors. The analysis based on it will be shown in Section 4.3. The sensitivity function can be used to express the sensitivity change of the posterior probability of the target variable [40]. X is defined as the probability of the variable taking a certain state, Y is a query, then according to the evidence E, the posterior probability S (Y|E) (X) can be expressed as the normalized function of X:

$$s(y|e)(x) = \frac{\alpha x + \beta}{\lambda x + 1}. \tag{7}$$

Here, replace the values of X with 0, 0.5, and 1, respectively, and substitute the posterior probability values of the target variable to determine the values of α, β and λ:

$$\begin{cases} \beta = s(0) \\ \lambda = \frac{\beta - s(0.5)}{s(0.5) - s(1)} - 1 \\ \alpha = s(1) * (\lambda + 1) - \beta \end{cases}. \tag{8}$$

Then, according to the partial derivative of S (Y|E) (X) with respect to X, the sensitivity value of S on X can be obtained:

$$f'(x) = \frac{\partial s(x)}{\partial x} = \frac{\alpha - \beta\lambda}{(\lambda x + 1)^2}. \tag{9}$$

The more sensitive the target variable is to the factor, the more drastic the change of S(Y|E) (X) is with the factor X value.

4. Results

The BN model was implemented in GeNIe software. After the BN model was estimated, sensitivity analysis of probability was carried out by giving evidence of different subsets. In addition, the final target variable "ATC Performance" was performed with bottom-up probability reasoning to calculate the posterior probability of each human factor. Finally, content validity and predictive validity were applied to verify the BN model.

4.1. Key Factors

By setting the human factors in Figure 7 to different states ("Good, Normal, Bad" or "Yes, No"), the percentage of posterior probability increase of the target variable was calculated to measure the importance of different human factors on ATC Performance.

As shown in Table 5, the five most important human factors affecting ATC Performance are training, physical fatigue, mental state, ineffective monitoring, and ATC software/hardware. Obviously, training contributes the most to the performance of air traffic controllers, which means that the professionals interviewed believe that the above human factors are most likely to exist in air traffic accidents related to air traffic controllers. One interesting human factor is ineffective monitoring, which will affect the organization's safety culture, and the attitude, performance, and efficiency of the controllers, ultimately affecting the air traffic safety.

Table 5. Computation results of changing states of influence factors.

No.	Node	State	P (ATC = Good)	State	P (ATC = Good)	State	P (ATC = Good)	Increased Percent
1	Training	poor	0.633	normal	0.656	good	0.662	4.58%
2	Physical Fatigue	poor	0.645	normal	0.657	good	0.661	2.48%
3	Mental State	poor	0.647	normal	0.658	good	0.662	2.32%
4	Ineffective Monitoring	yes	0.654	-	/	no	0.669	2.29%
5	ATC Software/Hardware	poor	0.650	normal	0.657	good	0.660	1.54%
6	Failed to Enforce Regulations	yes	0.652	-	/	no	0.661	1.38%
7	Failed to Correct Inappropriate Acts	yes	0.652	-	/	no	0.661	1.38%
8	ATC/Flight Crew Cooperation	poor	0.652	normal	0.658	good	0.661	1.38%
9	ATC Communication	poor	0.652	normal	0.659	good	0.661	1.38%
10	Noise	high	0.652	normal	0.658	low	0.661	1.38%
11	Safety Culture	poor	0.652	normal	0.659	good	0.660	1.23%
12	Air-Ground Communication Interference	serious	0.653	normal	0.658	slight	0.661	1.23%
13	Visibility	poor	0.653	normal	0.658	good	0.661	1.23%
14	Lack of Supervision Plan	yes	0.653	-	/	no	0.660	1.07%
15	Team Human Resource Allocation	poor	0.654	normal	0.659	good	0.661	1.07%
16	ATC clearance error	yes	0.655	-	/	no	0.662	1.07%
17	Procedural Noncompliance	yes	0.657	-	/	no	0.664	1.07%
18	Operation/Decision Error	yes	0.654	-	/	no	0.660	0.92%
19	Poor Management Discipline	yes	0.654	-	/	no	0.660	0.92%
20	Salary and Reward	low	0.655	middle	0.659	high	0.661	0.92%
21	ATCO Misspeaking	yes	0.655	-	/	no	0.660	0.76%
22	Emergency Mishandling	yes	0.655	-	/	no	0.660	0.76%
23	Nonstandard Flight Progress Strip	yes	0.656	-	/	no	0.660	0.61%
24	Distraction	yes	0.656	-	/	no	0.660	0.61%
25	Use Nonstandard Terms	yes	0.657	-	/	no	0.660	0.46%

4.2. BN Inference

The process of finding the key factors is a top-down probabilistic diagnosis. In Figure 7, the value of the final target variable "ATC Performance" is replaced by 1, and the posterior probability of all parent nodes can be obtained; that is, the so-called bottom-up diagnosis. Here, the probability of "ATC Performance = Bad" is set to 1 to obtain the posterior probability of all nodes. The higher the posterior probability of human factors, the greater the contribution of this factor to aviation accident risk.

Figure 8 shows the marginal probability distribution of the four levels in the HFACS model. Unsafe acts had the greatest influence on ATC Performance (79.4%), while preconditions for safe acts contributed the least (40.3%).

Apparently, as shown in Figure 9, unsafe acts contributes the most to the overall risk of accidents, including violations and air traffic control errors, with a posteriori probability of 71.3% and 52.6%, respectively. This means that the respondents believe that these human factors are most likely to be present in air accidents involving controllers. The second group of factors with more considerable influence belong to unsafe supervision, and preconditions of safe acts level include inadequate supervision, ATCOs states, whose posterior probabilities range between 40% and 65%. The contributions of the other levels to the ATC performance are similar (23%–35%), in which the supervision violation at the level of unsafe supervision and the organizational climate at the level of organizational influence contribute the least to the performance (posterior probabilities are less than 25%).

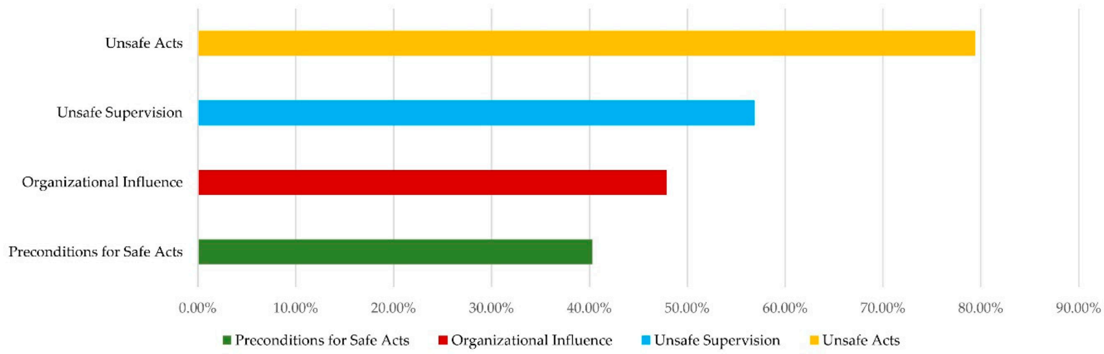

Figure 8. Marginal probability distribution by different levels.

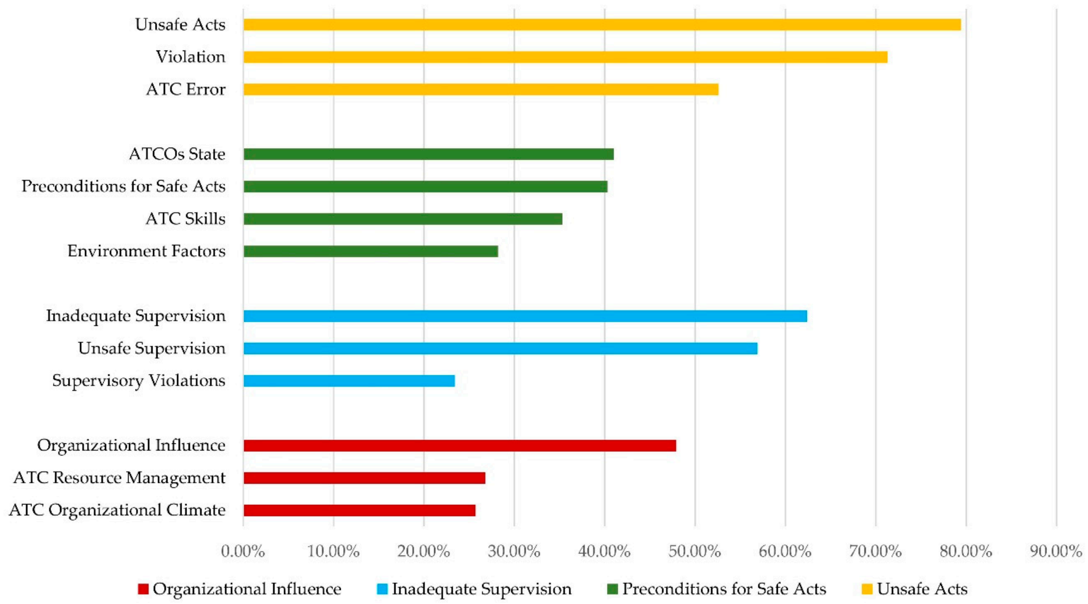

Figure 9. Posterior probabilities from Bayesian network (BN) inferences.

4.3. Model Validation

A BN model without verification is incomplete. This study adopts the following two methods:

- Content validity: In order to check the validity of Content, it is necessary to ensure that the BN network only considers the relevant human factor variables and their relations related to ATC. In this regard, all human factors are derived from the literature review and the viewpoint of front-line ATCOs, who also provide great help for the subsequent input of conditional probability between nodes.
- Predictive validity: The most direct and effective verification method is to compare the diagnosis results of the BN model with the database used, which include countermeasure preferences and sensitivity verification.

Firstly, as mentioned above in Section 3.2.2, there are questions designed for the preference of countermeasures. According to their prior knowledge, the respondents were required to select the six most influential factors from lists that would reduce human errors and improve ATC performance, then compare them with the posterior key human factors calculated by the Bayesian network. Figure 10 shows the countermeasure preferences of 26 frontline ATCOs and relevant experts. Interestingly, "Increase the salary of ATCOs" (chosen by 68.20% of the respondents) is the most popular response.

Higher salaries may have a positive effect on ATC mental state and physical fatigue. Followed by "Reasonable collocation of team members" (53.13%) and "Improve the selection criteria of ATCOs" (41.35%). Understandably, air traffic controllers selected with higher standards tend to have better professional qualities, which can make up for the possible consequences of insufficient training. At the same time, reasonable collocation of team members can also reduce ATC work burden and pressure. In contrast, "Regular safety awareness training" and "Strengthen organizational management" are the least popular measures chosen by 13.32% and 15.53%, respectively. The possible explanation is that respondents are satisfied with the current situation of safety awareness training and organizational management. The above results are roughly consistent with the observations in Section 4.1. However, respondents' preference for countermeasures only indicates their observation and understanding of ATC performance in this region, and cannot be extended to other regions of the world.

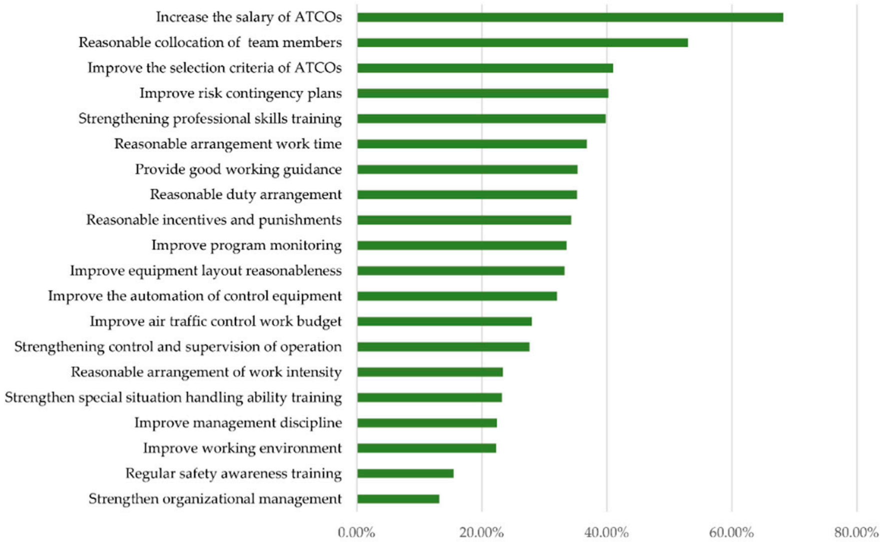

Figure 10. Countermeasure preferences by ATC professionals.

Secondly, the sensitivity analysis of the target node "ATC Performance" was conducted to determine how much uncertainty can be reduced by each human factor. The mathematical function and analysis were shown in Section 3.3. Figure 11 shows the human factors with relatively high sensitivity.

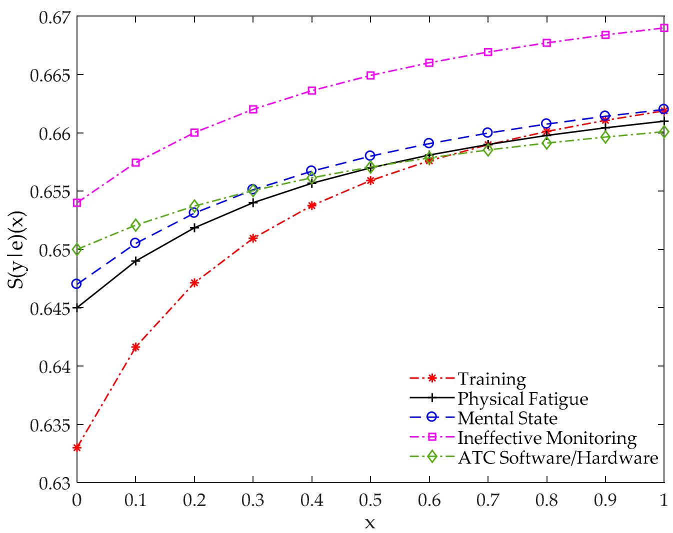

Figure 11. Sensitivity function for different human factors.

The study found that the target variable was relatively sensitive to training, physical fatigue, mental state, ineffective monitoring, and ATC software/hardware. This finding is also consistent with previous observations.

5. Conclusions

As reviewed in Section 1, traditional accident analysis or risk assessment methods are difficult to quantify rare accidents related to aviation safety. HFACS-BN model provides an additional method for identifying the major human factors that may lead to aviation accidents. Through the analysis of 142 aviation accidents/incidents related to ATC human factors worldwide from 1980 to 2019, the ATC performance model identified 25 major human factors (Figure 1). In addition, the subjective data of the human factors perceived by ATCOs are further collected to supplement the objective data of aviation accident report. CPTs are elicited by the noisy MAX model, and two inference methods of probability prediction and probability diagnosis are used to analyze the causal relationship and posterior probability among variables in the BN model.

Concerning the four levels of the HFACS framework, the influence of human factors on various levels is quite different. Unsafe acts (79.4%) and unsafe supervision (56.9%) contribute the most to ATC performance, while preconditions for safe acts (40.3%) has the lowest Influence. Overall, the top five most influential factors for ATC Performance are training, physical fatigue, mental state, ineffective monitoring, and ATC software/hardware; specific values are described in Section 4. The above results further imply that the formulation of aviation safety policy should pay more attention to the supervision level and individual factors. Furthermore, due to the complexity between human factors and accident risk, the coupling relationship and chain reaction between human factors should be fully utilized in the safety-related capacity building for ATCO; for example, reasonable allocation of team members may increase work efficiency and reduce the physical strain.

The contribution of this study is mainly reflected in the following aspects. Firstly, the HFACS framework and BN model are used to provide a systematic and operable method for aviation safety research. Secondly, it makes full use of the ATCO's professional knowledge to overcome the issues of database availability, as mentioned above in Section 3.2.2, to calculate the order of key factors, and to derive effective countermeasures against human errors. Thirdly, the modeling method and data analysis strategy of this study can also be further applied to security research in non-aviation fields. Examples include areas involving human-factor-related accident risk mechanisms such as public transport or mining systems.

This study is, however, not free of limitations, including:

- Almost all accidents have multiple contributory factors and that pilot error is often the probable cause.
- Air traffic control systems vary in size and structure around the world so that where one investigative agency may find ATC, or an associated controller or controllers, responsible for a particular accident, another one may not.
- These data are limited to summarized accident reports based on queried keywords and not based on independent evaluations of all accidents, probable causes, or contributing factors.
- Expert opinions were gathered from one ATC system (i.e., China) and perceptions may not reflect a comprehensive global view.
- The use of expert evaluation and the noisy MAX algorithm to evaluate the prior probability of the root node in the BN model will inevitably involve cognitive bias.

Finally, the current BN model in this study may change with the passage of time and the cognition of various human factors by the frontline ATC. More research should be accumulated in the future to monitor the changes in human factors and causal relationships related to aviation safety, reducing the contribution of human errors to the risk of aviation accidents.

6. Key Points

- "Human error" is an unhelpful yet common explanation for the cause of accidents/incidents in complex activities featuring vast combinations of people and technology (e.g., aviation) [41].
- To better understand the conditions influencing human error in aviation accidents/incidents related to air traffic control, we analyzed the "SKYbrary" database based on the HFACS model and preliminarily identified the human factors affecting ATC performance.
- A subsequent analysis based on BN model combined with accident statistics and expert opinions found that inadequate training, physiological fatigue, and ineffective monitoring were important factors affecting ATC performance continuation aggravated by the lack of regulatory plans.
- Meanwhile, validated the effectiveness of key human factors with the help of sensitivity analysis functions and provided countermeasures to improve ATC performance through surveys of respondents.

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Appendix A

The aviation accident database is an important data source for the construction of the Bayesian network. Based on 142 accidents/incidents related to ATC human factors in 1980–2019 listed on Skybrary, this paper conducts detailed and specific accident analysis, which provides an essential basis for the establishment of CPT. Brief information on the aviation accidents/incidents shown in Table A1.

Table A1. Brief information on air accidents/incidents.

Date	Aircraft Type	Location
	A	
2013	A109	Vicinity London Heliport London UK
2008	A310	Khartoum Sudan
2008	A310	Vicinity Quebec Canada
2009	A318/B738	En-route, Trasadingen Switzerland
2007	A318/B739	Vicinity Amsterdam Netherlands
2011	A319/A321	En-route, west north west of GeneVaSwitzerland
2011	A319/PRM1	En-route, near Fribourg Switzerland
2016	A319	Santiago de Compostela Spain
2010	A319/A319	En-route, South west of Basle-Mulhouse France
2011	A320/A320	Zurich Switzerland
2012	A320/A346	En-route Eastern Indian Ocean
2017	A320/AT76	Yangon Myanmar
2012	A320/B738	Barcelona Spain
2016	A320/B738	Vicinity Delhi India
2013	A320/B739	Yogyakarta Indonesia
2011	A320/C56X	Vicinity GeneVa Switzerland
2014	A320/CRJ2	Port Elizabeth South Africa
2010	A320	Oslo Norway
2000	A320	Toronto Canada
2013	A320	En route, north of Marseilles France
2009	A320	En-route, Denver CO USA
2014	A320	Vicinity Naha Okinawa Japan

Table A1. *Cont.*

2013	A320/B738	Vicinity Delhi India
2013	A320/E190/B712	Vicinity Helsinki Finland
2015	A321/B734	Barcelona Spain
2011	A321/B738	Dublin Ireland
2012	A332/A333	En-route, north West Australia
2004	A332/RJ1H	Vicinity Zurich Switzerland
2014	A343/B763	Barcelona Spain
2012	A343/GLID	En-route, north of Waldshut-TiEngEn southwest Germany
2012	A343	Vicinity Paris CDG France
2009	AS50/PA32	En-route Hudson River NJ USA
1999	AT43	Vicinity Pristina KosoVo
2004	AT45/B733	Munich Germany
1999	AT72/B732	Vicinity Queenstown New Zealand
2009	AT72	Mumbai India
2017	AT75/B739	Medan Indonesia
2014	AT76	Surabaya Indonesia
	B	
2014	B190/B737	Calgary Canada
2008	B190	Vicinity Bebi south eastern Nigeria
1990	B722/BE10	Atlanta GA USA
2004	B732/A321	Manchester UK
1988	B732	En-route, Maui Hawaii
1982	B732	Vicinity Washington National DC USA
1991	B733/SW4	Los Angeles CA USA
2010	B733/Vehicle	Amsterdam Netherlands
2008	B733	Vicinity Helsinki Finland
1996	B734/MD81	En-route, Romford UK
2010	B734	Amsterdam Netherlands
2008	B734	Palembang Indonesia
2015	B734	Sharjah UAE
2010	B734	Vicinity Lyon France
1999	B735	Vicinity Billund Denmark
2013	B735	Vicinity Kazan Russia
2001	B735/B733	Dallas-Fort Worth TX USA
2006	B737/B737	Vicinity Geneva Switzerland
2005	B737	Chicago Midway USA
2011	B737/C212	En-route/maneuvering, near Richmond NSW Australia
2018	B738/A320	Edinburgh UK
2016	B738/AT46	Jakarta Halim Indonesia
2004	B738/B744	Los Angeles USA
2007	B738/CRJ1	New York La Guardia USA
2006	B738/E135	En-route, Mato Grosso Brazil
2013	B738	Alicante Spain
2009	B738	Kingston Jamaica
2017	B738	Sint Maarten Eastern Caribbean
2010	B738	En-route, east of Asahikawa Japan
2010	B738/B734	Johannesburg South Africa
2010	B738/B738	Girona Spain
2012	B738/B738	Vicinity Oslo Norway
2010	B738/B738	Vicinity Queenstown New Zealand
2011	B738/B763	Barcelona Spain
2000	B744/A321	Vicinity London Heathrow UK
2010	B744/Vehicle	Luxembourg Airport Luxembourg
2009	B744	Mumbai India
2007	B744	Sydney Australia
1996	B752	En-route, Vicinity Chancay Peru

Table A1. *Cont.*

2001	B762/A310	Toronto Canada
2002	B762	Vicinity Busan Korea
1998	B763/B744	Amsterdam Netherlands
2007	B763/B772	New Chitose Japan
2014	B763	Addis Ababa Ethiopia
2010	B763/B738	Vicinity Melbourne Australia
2009	B772	St Kitts West Indies
2015	B773/B738/B738	Melbourne Australia
2007	B773	Auckland Airport New Zealand
2016	B773	Dhaka Bangladesh
	C	
1997	C185	Wellington New Zealand
2012	C30J	En-route, northern Sweden
2009	C525/B773	Vicinity London City UK
2004	C550	Vicinity Cagliari Sardinia Italy
2006	CRJ1	Lexington KY USA
2014	CRJ2/A320	Vicinity Port Elizabeth South Africa
2008	CRJ7/C172	Allentown PA USA
2009	CRJ9/Vehicles	Whitehorse YK Canada
2017	CRJ9	Turku Finland
	D	
2012	D328/R44	Bern Switzerland
1990	DC91/B722	Detroit MI USA
1983	DC93/B722	Madrid Spain
1994	DC93	Vicinity Charlotte NC USA
2002	DC95/C206	Toronto Canada
2017	DH8B	Kangerlussuaq Greenland
2013	DH8C/P180	Ottawa ON Canada
	E	
2009	E145/DH8B	Cleveland USA
2011	E145/E135	Chicago O'Hare USA
2016	E190/D328	Basel Mulhouse France
2011	E190/Vehicle	Denver COUSA
2010	E190	Oslo Norway
2016	E195/A320	Brussels Belgium
	F	
2012	F100/EC45	Vicinity Bern Switzerland
2000	F15/B752	En-route, South East of Birmingham UK
2005	F15/E145	En-route, Bedford UK
2016	F50/P28T	Vicinity Friedrichshafen Germany
2014	FA50/Vehicle	Moscow Vnukovo Russia
	M	
1994	MD82/C441	Lambert-St Louis MI USA
2004	MD83	Vicinity Nantes France
2001	MD87/C525	Milan Linate
	P	
2012	PRM1/CRJ2	Nice France
	R	
2009	RJ1H/UNKN	Vicinity Malmo Sweden
2011	RJ85/Vehicle	Gothenburg Sweden

Table A1. *Cont.*

	S	
2011	SF34/AT72	Helsinki Finland
2000	SH33/MD83	Paris CDG France
2012	SU95	maneuvering near Jakarta Indonesia
	T	
2002	T154/B752	En-route, Uberlingen Germany
2011	TBM8	Birmingham UK
	V	
2006	Vehicle/B738	Brisbane Australia
2013	Vehicle/B773	Singapore
2008	Vehicles/B737	Toronto Canada
	W	
1993	WW24	Vicinity John Wayne Airport Santa Ana CA USA

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