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Structural Equation Modeling for Airspace Optimization: The Analysis of Causal Factors Influencing Aviation Safety

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Abstract

Increased flight volumes necessitate urgent reforms in Airspace Management (ASM) to mitigate risks of fatalities and near-misses. In order to enhance aviation system safety, the International Civil Aviation Organization (ICAO) mandates that state parties must conduct the Universal Safety Oversight Audit Program (USOAP) to continuously monitor civil aviation. This research aims to identify critical factors influencing Thailand's ASM by employing experimental design and Structural Equation Modeling (SEM) to analyze influences and relationships among communication, surveillance, navigation, Air Traffic Management (ATM), and ASM. The methodology includes stimulation and a questionnaire-based survey conducted with aviation professionals and mapping out their answers to find the influences, relationships, and importance of the different factors. The results were validated using various statistical tools. The findings indicate signi1ficant direct and indirect effects on ASM, emphasizing that effective communication and robust surveillance are essential for safety and operational efficiency. This study highlights the need to increase the ASM framework, providing actionable insights for optimizing air traffic control in response to the growing air traffic demand. Furthermore, SEM for Airspace optimization can be applied internationally to significantly reduce accidents and incidents in the future.

Keywords: airspace optimization; structural equation modeling; communication; safety; air traffic management

1. Introduction

The COVID-19 pandemic initially disrupted air travel, but with decreasing severity and widespread vaccination, international travel has resumed with increased volumes globally. As a result, this has caused high traffic densities in airspace, control areas, approach control areas, and airport areas (aerodrome control area). Furthermore, statistical analysis of commercial aviation accidents from 1985 to 2020 indicated that the approach and landing phases are the most critical and often lead to accidents. Additionally, the occurrence of air incidents is high during the departure and arrival phases of flights, with a higher likelihood during the approach phase. These phases are significant because they require high demands for the aircrew in terms of navigation, aircraft configurational changes, and communication with air traffic controllers who are dealing with the congested airspace [1].

To mitigate the number of incidents during approach flight phases, innovative arrival approach procedures were proposed using a Point Merge route network called Multi-Level

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Point Merge to meet the requirements of parallel runway operations. This system strongly reduces vectoring and increases safety by reducing traffic congestion in the Terminal Maneuvering Area (TMA). Additionally, it simplifies runway allocation and supports trajectory control solutions. This system demonstrates good dynamic sequencing efficiency in TMA and performs efficiently in managing both arrival and departure phases [2]. This design approach procedure is considered a crucial factor in ASM in this study.

Moreover, over the past 20 years, the International Civil Aviation Organization (ICAO) has reported a concerning increase in global aircraft accidents and incidents related to air navigation systems, which require immediate attention. A report on global air safety since 1990 emphasizes the need for all state members to maintain rigorous safety standards. Thus, the ICAO required state parties to conduct the Universal Safety Oversight Audit Program (USOAP), which is in accordance with the Standard and Recommended Practices and the State's safety oversight obligation. The aim of this is to consider whether the state can establish a safety oversight to implement the critical elements of the program with efficiency and consistency [3,4]. The eight audit areas defined by the ICAO-USOAP are as follows:

1. Primary aviation legislation and specific operating regulations.
2. Civil Aviation Organization.
3. Personnel Licensing and Training.
4. Aircraft Operations.
5. Airworthiness of Aircraft.
6. Aircraft Accident and Incident Investigation.
7. Navigation System Services.
8. Aerodromes and Ground Aids.

The most critical problem related to accidents is at the safety and reliability level. Based on the air traffic data analyzed from Thailand's Automatic Dependent Surveillance-Broadcast reception system between December 2019 and March 2024, it was found that the air traffic has doubled in multiple airspace sectors. With the steady increase of aircraft entering and exiting the airport proximity zone and TMA, which is considered a conflict hot spot, requiring effective ASM to manage all the traffic. Additionally, based on various studies, Thailand had experienced a significant increase in the number of near-misses, rising from 39 in 2018 to 66 in 2021 [5]. The increase in the risk rate was almost two-fold, making it one of the major obstacles to the development of airspace optimization. To tackle this issue, it is crucial to analyze which airspace engineering systems contribute most to the problem and find solutions, aligning with the deficiencies identified by the ICAO [6].

The ICAO has defined Communication Navigation Surveillance (CNS)/Air Traffic Management (ATM) systems as "systems that employ digital technologies, including satellite systems, together with various levels of automation, applied in support of a seamless global Air Traffic Management system". In other words, ATM is the dynamic and integrable management of air traffic services, airspace, and air traffic flow to help improve air navigation. This is achieved by enhancing the handling, transferring of information, extending surveillance, and improving navigational accuracy. The results will be a reduction in separation between aircraft, allowing for increased airspace capacity. The CNS/ATM concept is addressed as shown in Figure 1 [7].

Due to the complexity and the involvement of numerous factors associated with ASM in ATM, many research efforts have been dedicated to applying optimization theory to airspace design [8]. ASM optimization consists of modeling an operational problem with a mathematical model for which an optimization algorithm is applied to identify the best set of decision variables in the state space before they are implemented in the operational

domain. Furthermore, this approach allows researchers to describe, explain, and predict various relationships within complex systems.

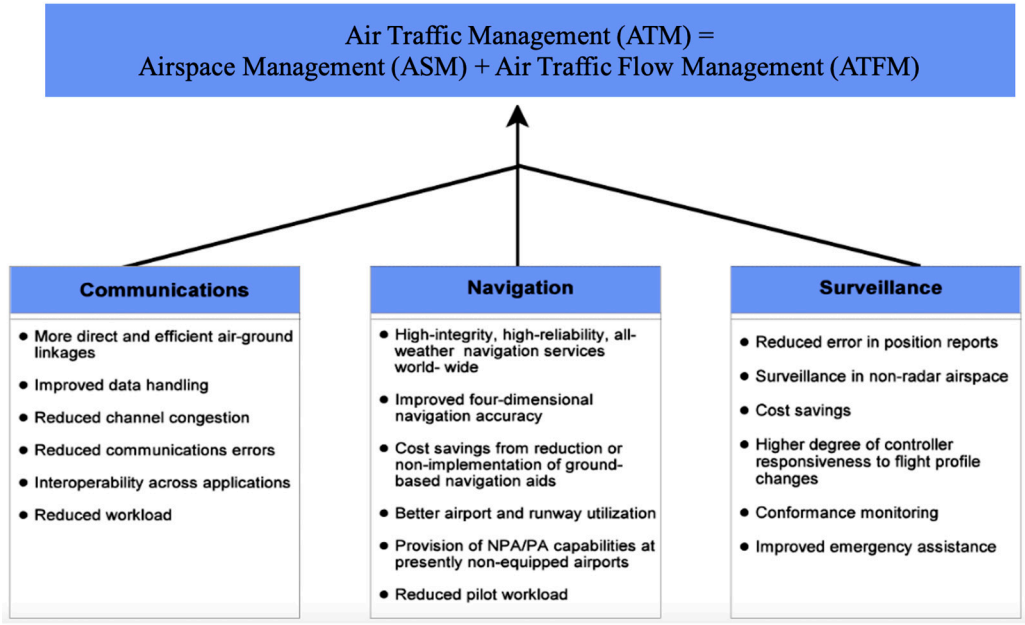


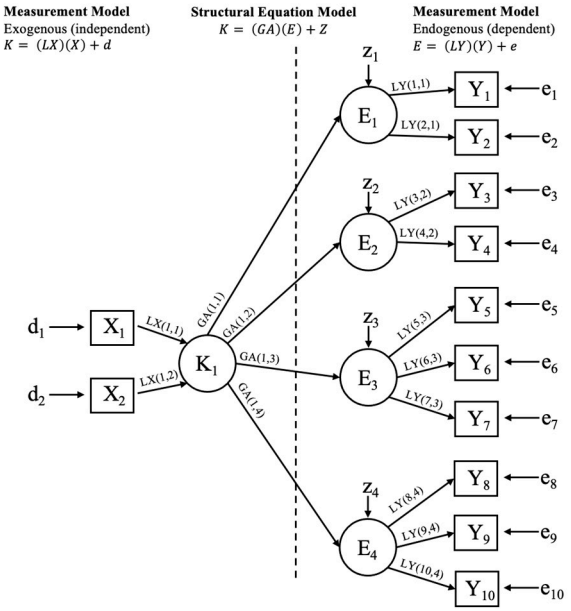
Figure 1. The ICAO's definition of the ATM concept, which includes airspace and air traffic flow management, as well as communication, navigation, and surveillance systems.

According to research, no phenomenon can be considered independent of any other phenomenon. This means that both independent and dependent variables are influenced by and can influence others. Thus, a research model should include several variables with direct and indirect effects and appear to be a set of mathematical equations that demonstrate the relationships between all variables and reflect reality. This can be achieved with Structural Equation Modeling (SEM) since it is a multi-variate statistical analysis technique that uses both factor and regression equation analysis to analyze the relationship between variables [9]. As a result, SEM is widely used to analyze and identify errors associated with the complex system. Examples include the study of human factors or safety based on data collected from questionnaires and interviews.

There are two types of relationships in SEM: simple correlation or covariance and causal effect of influence. SEM is a powerful model that can be used to explain the cause of accidents and increase the safety of ATM as it assists in identifying the associated root causes and the main influential factors [10]. SEM is computed using the Linear Structural Relation (LISREL) software designed by Jöreskog and Sörbom, which comprises two key models: the measurement model and SEM [11]. The measurement model illustrates the relationship between latent (unobservable) and manifest (observable) variables in the format of an equation for both exogenous (left) and endogenous (right) variables. That is, it defines how well manifest indicators reflect the underlying latent variables, whereas SEM illustrates the linear structural relationship among latent variables within the model. The LISREL concept is addressed as shown in Figure 2, along with the symbols and their corresponding meaning.

Circles represent both independent and dependent latent variables, while squares denote observed variables X and Y. Specifically, X variables (denoted as X_1 to X_2) correspond to the operationalization of abstracts and constructs that cannot be directly measured. Alternatively, Y variables (Y_1 to Y_{10}) reflect dependent constructs that are influenced by exogenous factors through structural relationships within the model. Together, the X and Y variables allow for the empirical estimation of the theoretical constructs and their interrela-

tionships, enabling robust testing of complex causal hypotheses. The arrows and associated coefficients describe the strength of the causal relationship between the independent variables and measurement errors, with the arrowhead indicating the direction of influence. Double-headed curved arrows represent the correlation between variables. On the left side of the measurement model, the equation for exogenous variables (K = (LX)(X) + d) indicates that the latent exogenous variable K consists of the associated manifest variable (X) multiplied by the loading factor (LX), plus some measurement error (d). The loading factor describes how strongly each manifest variable is related to the latent variable. Conversely, on the right side of the measurement model, the equation for the endogenous variable (E = (LY)(Y) + e) shows that the latent variable (E) is determined by the loading factor (LY) multiplied by the manifest variable Y plus some measurement error (e). Finally, SEM (K = (GA)(E) + Z) states that the exogenous latent variable (K) is equal to the multiplication of the influence coefficient (GA), with the latent endogenous (E) plus some associated error term (Z) [12].



Symbols	Meaning
Squares	Manifest variables
Circles	Latent variables
d,e	Error term associated with manifest variables
X	Manifest exogenous variable
LX, LY	Factor loading between manifest and latent variables
K	Latent exogenous variable
GA	Influence coefficient between latent variables
E	Latent endogenous variables
Z	Error term associated with latent variables
Y	Latent endogenous variables

Figure 2. SEM model illustrating the relationships between manifest and latent variables for both independent and dependent systems. The table on the right shows the symbols and their corresponding meanings. The dashed line partitions the exogenous and endogenous variables. The arrowheads show the direction of influence.

Thus, the objectives of this research are to analyze the key components and patterns involved in safe and efficient airspace optimization, to identify safety factors, and to examine the direct and indirect factors influencing ASM through the use of SEM analysis. The findings of this research will provide guidelines for improving the ASM system to enhance safety and efficiency in accordance with the national and international strategy. The remainder of this paper is organized as follows: Section 2 presents the methodology of this research, Section 3 presents the results of the methodology applied to the Bangkok case study, which could be implemented further internationally, and Section 4 provides the discussion. Finally, Section 5 concludes the research.

2. Materials and Methods

By analyzing the causal effects of airspace optimization factors that contribute to the increase in accidents and incidents using SEM, the following criteria can be achieved:

1. Analysis of key elements and patterns for safely and effectively managing airspace.

2. Identifying the direct and indirect causal safety factors that influence airspace and ATM.
3. Determining guidelines for improving the ASM system, making it safer and more efficient according to the national and international strategy.

The methodology employed in this study starts with conducting extensive literature research based on ICAO-USOAP and ATM concepts to identify all the variables that contribute to the increase in accidents and incidents and safety. Subsequently, the findings were converted into interview questions. Additionally, air traffic data is based on the monitoring of automatic dependent surveillance broadcasting signals and using the distance and altitude detection system between automatically controlled aircraft. Recognizing that data collected through research and interviews could potentially introduce biases, therefore this study also conducted experiments by simulations.

After, data was collected from experiments and interviews, a regression analysis and confirmation factor analysis (CFA) was conducted in accordance with Bollen's principles [13], followed by using the LISREL software (version 8.7) for SEM computation, which can be divided into six steps:

1. Model specification.
2. Model identification.
3. Parameter estimation.
4. Assessment of the model goodness of fit (evaluating the congruence between empirical data and linear structural equation model). This helps to check the validity of the model by comparing the variance–covariance matrix derived from the empirical data.
5. Model modification.
6. Interpretation.

2.1. Simulation and Experiments

Preliminary research was conducted with a focus on the ASM global concept and current safety problems faced in Thailand. The search keywords included communication, surveillance, navigation, ATM, and ASM. Furthermore, to verify the findings regarding the increase in the number of near-misses [5], a simulation method was used for cross-verification.

Experiments were conducted using "The System Automatically Detects the Separation Distance and Altitude between controlled aircraft" software, which functions as an auxiliary mechanism to detect 'hotspots' in complex airspace [14–16]. This system simulates aircraft to automatically approach each other, while applying the ICAO guidelines on the minimum horizontal separation standard of 5 nautical miles (NM) in the control area and 3 NM in the TMA and vertical separation of 1000 feet. [7]. Thus, communication, navigation, surveillance, airspace, and other influencing factors could be observed. In addition, by mapping the simulation results to the flight procedure position of specific instruments such as terminal control areas, control zones, and airspace around the airport (with the influence of ATM on ASM), this study ensures that data is collected from aviation data sources (COMM), making the influence of COMM on SUR, NAV, and ASM more real than the bias of the interviewer. By using SUR, it has influence on ASM. The above-mentioned causal relationship approach supports the analysis of the SEM. Therefore, this allows the integration of key issues that will be resolved during the interview and incorporates the verification process to support subsequent SEM analysis.

2.2. The Design of a Research Questionnaire

Based on the findings, the key components and their associated variables are described below (Figure 3):

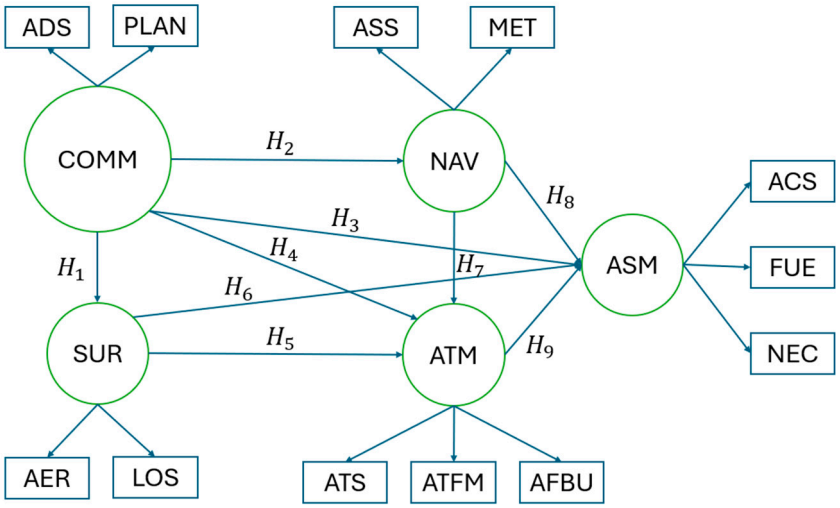


Figure 3. Mapping of the relationships among the systems studied (COMM, SUR, NAV, ATM, and ASM) and their respective variables, with arrowheads indicating the direction of influence. Squares represent manifest variables, and circles represent latent variables.

1. Communication systems, hereafter referred to as COMM, encompass a set of technologies that enable the effective exchange of information to ensure efficient operations, which include:
    a. Advisory and surveillance, hereafter referred to as ADS, provides real-time position reporting and tracking of aircraft.
    b. Advanced airspace usage planning, hereafter referred to as PLAN, facilitates the optimization, allocation, and scheduling of airspace resources.
2. Surveillance systems, hereafter referred to as SUR, encompass technologies and procedures used for monitoring the aircraft's positions and movements, which include:
    a. Air Traffic Control (ATC) along flight routes and close proximity operations, hereafter referred to as AER, supports continuous monitoring of aircraft along enroute corridors and during operations in congested airspace.
    b. Surveillance service for alerts and loss of separation in flight operations, hereafter referred to as LOS, provides timely alerts to prevent conflicts and mitigate risks when aircraft are too close to one another.
3. Navigation systems, hereafter referred to as NAV, are systems and methods used to guide an aircraft along a safe and efficient flight path, which include:
    a. Satellite systems for aviation and knowledge of efficient flight operations, hereafter referred to as ASS, is the utilization of Global Navigation Satellite Systems (GNSSs) for precise positioning.
    b. Weather and clear design of arrival and departure points, hereafter referred to as MET, is the integration of meteorological information with structured entry and exit points to enhance predictability.
4. ATM systems ensure safe, orderly, and efficient flow of air traffic:
    a. Air Traffic Services (ATS) for control of air traffic at airports and in terminal areas provides separation, sequencing, and control of aircraft during airport and terminal operations.
    b. Flight procedures using Performance Based Navigation (PBN) and real-time flight management, hereafter referred to as ATFM, enable efficient use of airspace through advanced flight planning and optimized routing.

c. CNS and arrival and departure systems, hereafter referred to as AFBU, are the integration of CNS technologies to manage aircraft movements and ensure coordination between enroute and terminal phases of flight.

5. ASM is the process of organizing, designing, and allocating airspace to optimize its capacity:
   a. Airspace design and aircraft systems, hereafter referred to as ACS, involve structuring and aligning airspace with aircraft capabilities.
   b. Forecast information on volume and timing for landing and takeoff within the airspace, hereafter referred to as FUE, is the delivery of predictive data on traffic demand to support capacity planning and runway scheduling.
   c. Near-miss airborne operations and entry into runways, hereafter referred to as NEC, focus on monitoring and preventing runway incursions and potential airborne conflicts.

As shown in Figure 3, COM, NAV, and SUR influence both ATM and ASM, consistent with ICAO's definition of the ATM concept (Figure 1). Additional links from COM to SUR and NAV illustrate that communication is required to relay information between the two systems, consistent with findings from ICAO and EUROCONTROL. These causal direction justifications are summarized in Table 1.

Table 1. Causal direction justification of the studied variables.

Hypothesis	Path	Reference
H_1	COMM → SUR	[7,17]
H_2	COMM → NAV	[7,17]
H_3	COMM → ASM	[7,17]
H_4	COMM → ATM	[7,17]
H_5	SUR → ATM	[7,17]
H_6	SUR → ASM	[7,17]
H_7	NAV → ATM	[7,17]
H_8	NAV → ASM	[7,17]
H_9	ATM → ASM	[7,17,18]

The reliability of the studied variables was evaluated using Cronbach's alpha. All variables satisfied the commonly accepted threshold of $\geq$0.70, as presented in Table 2. Moreover, all values exceeded 0.80, indicating good to excellent levels of internal consistency reliability [19].

Table 2. Calculated Cronbach's alpha for COMM, SUR, NAV, ATM, and ASM to assess reliability.

Variables	Calculated Cronbach's Alpha
COMM	0.864
SUR	0.882
NAV	0.861
ATM	0.924
ASM	0.910

Once the key concepts and their components had been identified, the next step was to develop a questionnaire that covered all the relevant variables. The questionnaire

was a design based on a 5-point rating scale and can be broken down into the following seven sections:

1. Demographics and workload: this section includes gender, age, education, career, work experience, average workload, fatigue, stress, health conditions, and rest periods.
2. Satisfaction with Aeronautical Information Service and Management: this section includes communication and related issues, navigation and related issues, surveillance issues, and meteorological services and associated problems.
3. Satisfaction with ATS: this section includes area control service, approach control service, aerodrome control service, altering service, air traffic advisory service, and flight information service.
4. Satisfaction with ASM: this includes standard instrument departure, standard instrument arrivals, instrument approach procedures, airspace design, and the flexible use of airspace.
5. Satisfaction with airspace sector design: this section concerns PBN.
6. Air traffic flow and capacity management: this section includes advanced airspace planning, airspace capacity management, accurate forecasting of aircraft landing and takeoff times, and the design of entry and exit points to manage air traffic flow efficiently for aircraft landing at airports such as Suvarnabhumi and Don Mueang International Airports.
7. Training and knowledge: this section assesses aviation training and knowledge related to CNS, PBN, ATS, ATM, ASM, ATFM, satellite systems, aviation system block upgrade, aircraft system, loss of control in-flight, controlled flight into terrain, loss of separation, near collision, runway excursion, and runway incursion.

Before the questionnaire was implemented in interviews, an expert was recruited to review and validate the content and the appropriate language. The full questionnaire is provided in Supplementary Material S1 file.

2.3. Participant Recruitment

The use of a 5-point rating scale questionnaire together with interviews is an example of a mixed-method research approach, as it combines the collection of both qualitative and quantitative data to help answer complex research questions and strengthen the findings [20]. Also, according to Hair et al. [21], the number of data points should be at least 15–20 times the number of parameters being studied for normal distributed data. Given that this study includes 12 observable variables (ADS, PLAN, AER, LOS, ASS, MET, ATS, ATFM, AFBU, ACS, FUE, and NEC), the sample size should be around 180–250 and collected by conducting a semi-structured interview method via a questionnaire. As a result, a total of 215 individuals from the aviation field with more than 5 years of domestic and international work experience were recruited during 2023–2025. Since the research focuses on providing insights from the perspective of service participants, the study recruited air traffic controllers, pilots, and engineers. Participants were selected using probability sampling techniques, specifically stratified and simple random sampling. The following organization, which represents a stratum, was grouped based on similar characteristics:

1. Aeronautical Radio of Thailand Ltd.
2. Academic support professionals.
3. Transportation commission of the senate.
4. Airlines.

Simple random sampling was used to pick out the participants from these strata. Each stratum contributed approximately the same to total 215 individuals.

2.4. Regression Analysis

Since one of the objectives of this research was to analyze key elements associated with ASM, a regression analysis was conducted using the Statistical Package for Social Science software (version 26) [22].

2.5. Mathematical Computation Procedures

A CFA was conducted first to ensure the relationship between the variables and subsystems is statistically significant. SEM was computed using the LISREL software to analyze the direct and indirect variables of the whole system. Additionally, numerous statistical tools were then used to evaluate both the CFA and SEM models, which can be grouped into three categories: model fit indices, regression analysis, and tests for distribution and normality, as shown in Table 3. Model fit indices assess how well a model reproduces the observed data, ensuring that the associated equations accurately represent the underlying phenomena. Regression analysis indices validate the relationships among variables and key assumptions. Furthermore, distributional and normality indices confirm the assumptions required for SEM and CFA methods, ensuring reliable parameter estimation. Without these three major groups of indices, the evaluation of the proposed model's fit would be incomplete, and the results of SEM and CFA could be misleading.

Table 3. Statistical tools and definitions used to evaluate CFA and SEM models, including model fit indices, regression diagnostics, and normality tests to ensure valid, reliable, and well-fitting results.

Statistical Tool	Definition
Model fit indices: evaluate the fit of a statical model	
Goodness of Fit Index (GFI)	Measure of fit between hypothesize model and observed covariance matrix
Adjusted Goodness of Fit Index (AGFI)	Corrects the GFI by penalizing for inclusion of excessive parameters
Root Means Square Error of Approximation (RMSEA)	Measure estimated discrepancy between population and model-implied population covariance matrices per degree of freedom
Root Means Square Residual (RMR)	Measure the average difference between observed and predicted covariances
Standard Root Mean Square Residual (SRMR)	Measure the average difference between observed and predicted correlations
Comparative Fit Index (CFI)	Analyze the model's fit by examining the discrepancy between data and hypothesized model
Average Variance Extracted (AVE)	Estimates the amount of common variance among latent construct indicators
Composite Reliability (CR)	Measures the internal consistency of a set of items amongst latent constructs
Regression analysis: evaluate model validity and detect multicollinearity among predictors	
Durbin–Watson Statistics	Test for autocorrelation in residuals
Variance Inflation Factor (VIF)	Assesses multicollinearity among independent variables
Distribution and normality test: assess data normality and distribution characteristics	
Skewness (SK)	Measure the asymmetry of the distribution (0 indicates symmetric, positive indicates right skew and negative indicate left skew)
Kurtosis (KU)	Measures "tailedness" of the distribution (normal distribution has kurtosis of 3)

Table 4 shows the requirement of eight fitness indices that need computing when utilizing SEM. These fitness indices comprise parsimonious, absolute, and incremental fits, which show how well this model fits with the data. Parsimonious fit assesses the discrepancy between the observed and model-implied covariance matrices relative to model complexity. Absolute fit uses various measures to evaluate how well the hypoth-

esized model reproduces the observed data, independent of other models. Incremental fit compares the hypothesized model to a baseline or null model. Together, these indices confirm whether the SEM is statistically valid, well-fitting, and interpretable, providing confidence that the model structure accurately represents the underlying relationships among constructs.

Table 4. SEM fit indices with their recommended thresholds and interpretation, showing how each measure evaluates the adequacy of the model and whether its reliably represents the observed data.

No.	Name of Category	Index Name	Criteria	Interpretation
1	Parsimonious Fit	χ^2/df	<2.00 [23,24]	Model fits with data.
2	Absolute Fit	*p*-value	>0.05 [23,24]	Model is consistent.
3		RMSEA	<0.08 [24]	Model consistent with empirical data.
4		GFI	>0.95 [11]	Model is harmonious.
5		RMR	≤0.05 [25]	Model has squared average of remainder.
6		SRMR	≤0.05 [25]	Model is consistent.
7	Incremental Fit	AGFI	>0.95 [26]	Model is harmonious when adjusted.
8		CFI	>0.95 [27]	Measurement consistent with empirical data.
9	Construct Validity	AVE	≥0.50 [28]	Indicates satisfactory convergent validity
10		CR	≥0.70 [28]	Indicates satisfactory internal consistency

According to Holmes-Smith P et al. [23], at least these fitness indices from each of the three categories should be computed to understand how the model is linked to the data. If the SEM model did not satisfy these criteria, the model would need to be adjusted. Model adjustments were made by refining the structure based on these fit indices until the model aligned well with the observed data. These steps helped to enhance both the reliability and validity of the final model.

3. Results

3.1. Participant Demographic

The use of large sample sizes helps to ensure that the estimated parameter values are stable and highly reliable. However, researchers still aim to use the smallest possible sample size that can produce results as accurate as those obtained from a large sample. This is to maximize research efficiency, saving time and budget while still achieving valid and trustworthy results. In addition, with SEM analysis, the sample size should not be less than 100, therefore, a total of 215 participants were sampled from 250 individuals to analyze the influencing factors in the model [21]. In the first section of the questionnaire, which gathered general participant information, the findings showed that 85.4% of respondents were male, 27.1% were aged between 41 and 50 years, 61.9% held a bachelor's degree, and 18.6% were pilots.

3.2. Linear Regression Analysis

Table 5 summarizes the results from regression analysis conducted to evaluate the direct impact of the independent variables (COMM, NAV, SUR, and ATM) on the dependent variable (ASM).

Table 5. Regression analysis of four independent factors (COMM, NAV, SUR, and ATM) and their effects and relative importance on the dependent variable (ASM).

Dependent variable (Y)		ASM	
Independent variable (X)		$COMM (X_1)$ $NAV (X_2)$ $SUR (X_3)$ $ATM (X_4)$	
Prediction: goodness of fit			
Multiple R		0.996	
R^2		0.992	
Adjusted R^2		0.991	
Standard error		0.05954	
Analysis of variance	**Degree of freedom**	**Sum of square**	**Mean square**
Regression	4	31.776	7.944
Residual	73	0.259	0.004
F-test = 2240.934		Significant level = 0.000	
Durbin–Watson		1.865	
Explanation: variables in the equation			
Independent variable	**Unstandardized coefficients (b)**	**Standardized coefficients (Beta)**	**t-value**
$COMM (X_1)$	0.549	0.850	80.846
$NAV (X_2)$	0.153	0.237	22.572
$SUR (X_3)$	0.138	0.214	20.318
$ATM (X_4)$	0.263	0.408	38.799
Constant (B_0)		3.814	
Collinearity diagnostics	**Tolerance**	**VIF**	**Condition index**
$COMM (X_1)$	1.000	1.000	1.000
$NAV (X_2)$	1.000	1.000	1.000
$SUR (X_3)$	1.000	1.000	1.000
$ATM (X_4)$	1.000	1.000	1.000

The Multiple R value of 0.996 indicated a strong correlation between the independent and dependent variables. The R^2 and adjusted R^2 values of 0.992 and 0.991 suggest that approximately 99% of the variance in ASM can be explained by the independent variables. The standard error of 0.0595 indicates the average distance from the observed values to the regression line; in other words, a lower value indicates a better fit for the data.

Four degrees of freedom for regression reflected the number of independent variables, while the 73 residuals represent the remaining data points. The regression value of 31.776, computed from the sum of squares, explains the variability of the model. Conversely, the residual value of 0.259 indicates that the variability is not explained by the model. The F-test yielded 2240.934, a high value which indicates that Y has an influence on X. It shows that the four independent variables studied (COMM, NAV, SUR, and ATM) can explain the overall influence on the dependent variable (ASM).

The Durbin–Watson statistic, which tests for autocorrelation in the residuals, has a value of 1.865, suggesting no autocorrelation and indicating a good model fit. The unstan-

dardized coefficient (b) indicates the amount of change in Y for a one-unit change in the predictor, holding all other variables constant. The standardized coefficient (Beta) indicates the relative importance of each predictor, with COMM having the highest influence, followed by ATM, NAV and SUR. The t-value, which is the ratio of the coefficient to its standard error, serves the same purpose as the F-test but these values show the individual's significance to X.

Factor analysis was used to group related raw data together by using the principal component analysis method before running the linear regression analysis. Therefore, the variables with high factor loading also caused the VIF value to be 1.000. This value indicates that there are no multicollinearity issues, meaning the predictors do not correlate too highly with each other.

The regression analysis can be expressed by the following equation:

$$\hat{y} = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 \quad (1)$$

where $\hat{y}$ represents ASM, X_1 is COMM, X_2 is NAV, X_3 is SUR, and X_4 is ATM. When b's and X's were substituted with the values from Table 3, the equation becomes:

$$\hat{y} = 3.814 + 0.549(\text{COMM}) + 0.153(\text{NAV}) + 0.138(\text{SUR}) + 0.263(\text{ATM}) \quad (2)$$

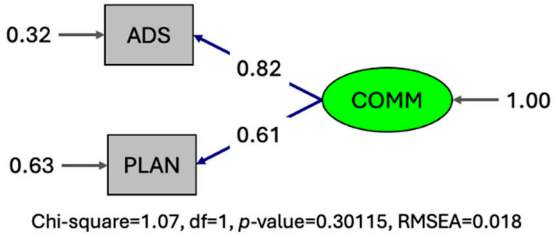
From Equation (2), the coefficients of all independent variables are positive, which indicate that the results of the regression analysis of the system influencing ASM for safety and efficiency, ranked in order, are as follows: aviation COMM system (X_1), ATM system (X_4), NAV system (X_2), and SUR (X_3), all of which have statistical significance.

3.3. Confirmation Factor Analysis

Before the development of the SEM model, CFA was conducted on each variable to ensure that the sub-variables (shown in Figure 3) are statistically significant.

3.3.1. Communication

Figure 4 demonstrates the relationship COMM has on ADS and PLAN. The number on the arrow is the factor loading, which shows the strength of the relationship. This means that ADS (0.82) is more significant to COMM than PLAN (0.61). The values to the left of the grey boxes represent error terms, which are 0.32 for ADS and 0.63 for PLAN. On the right side of the green oval, the value of 1.00 associated with COMM indicates that the variance is fully accounted for. The SK values were 0.143 and 0.111. The KU values were −0.769 and −0.785. All the SK and KU values are close to zero, indicating that the observed variables are normally distributed. Fit indices for this model fit with the empirical data, indicated by the chi-square value of 1.07 with 1 degree of freedom. The *p*-value of 0.30 is more than 0.05, meaning that the model is acceptable. Lastly, the RMSEA is 0.018, which is close to zero, further indicating good alignment with the empirical data.



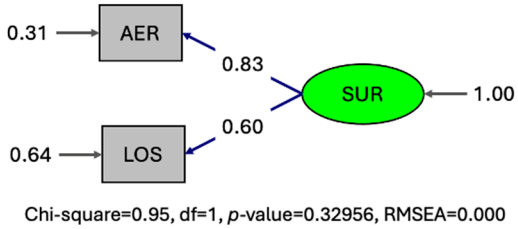
Statistical analysis of the COMM system

Variable	SK	KU
ADS	0.413	−0.769
PLAN	0.111	−0.785

Figure 4. CFA model showing the influence of ADS and PLAN on COMM (**left**) and statistical analysis results (SK and KU values) used to assess the normality of the system (**right**). The gray square represents manifest variables, and the green circle represents latent variables.

3.3.2. Surveillance

Figure 5 shows the relationship of SUR on AER and LOS, with the latter variable being less significant, as shown by the factor loading of 0.60 compared to 0.83. The variance is fully accounted for (1.00), and the error term is similar to that of Figure 4 of 0.31 (AER) and 0.64 (LOS). The SK values of 0.085 and 0.093 and KU values of −0.486 and −0.504, all of which are close to 0, indicating that the variables are normally distributed. The chi-square value is 0.95 with 1 degree of freedom, which does not differ significantly from zero, suggesting that the model aligns with empirical data. The *p*-value (0.33) is more than the threshold of 0.05, indicating that the model is acceptable. An RMSEA value of 0.000 confirms that the model fits well with the empirical data.



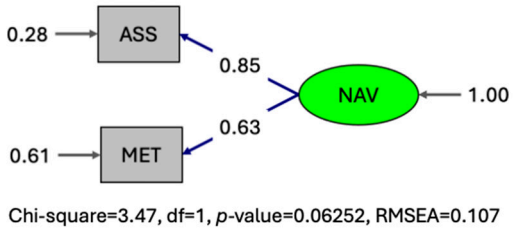
Statistical analysis of the SUR system

Variable	SK	KU
AER	0.085	−0.486
LOS	0.093	−0.504

Figure 5. CFA model showing the influence of AER and LOS on SUR (**left**) and statistical analysis results (SK and KU values) used to assess the normality of the system (**right**). The gray square represents manifest variables, and the green circle represents latent variables.

3.3.3. Navigation

Figure 6 shows the relationship NAV has on ASS and MET. ASS (0.85) has more influence and lower error (0.28) towards NAV compared to MET with an influence of 0.63 and an error term of 0.61. Both the SK (0.095 and −0.004) and KU values (−0.293 and −0.796) approach zero, which suggests that the observed variables conform to a normal distribution. The chi-square value of 3.47 with 1 degree of freedom indicates that the chi-square differs from zero insignificantly, suggesting that the research model fits the empirical data. The *p*-value (0.06) indicates that the model is acceptable, and finally, the RMSEA is 0.107, which is close to zero, indicating that the model aligns well with the empirical data.



Statistical analysis of the NAV system

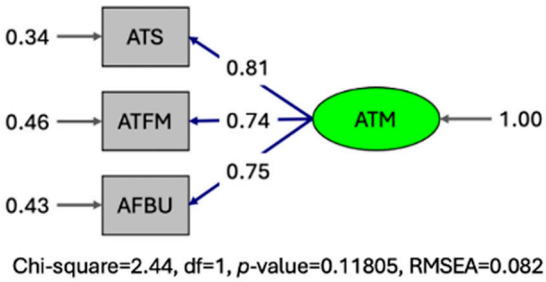
Variable	SK	KU
ASS	0.095	−0.796
PLAN	−0.004	−0.293

Figure 6. CFA model showing the influence of ASS and MET on NAV (**left**) and statistical analysis results (SK and KU values) used to assess the normality of the system (**right**). The gray square represents manifest variables, and the green circle represents latent variables.

3.3.4. Air Traffic Management

Figure 7 illustrates the relationship ATM has with ATS, ATFM, and AFBU. The ATS correlation value of 0.81 has the highest influence on ATM, followed by AFBU with a value of 0.75, and ATFM with a value of 0.74. This order is also the same for the errors associated with each variable. SK values are between 0.128 and 0.308, indicating that the observable variables exhibit a distribution close to normal. Moreover, the KU values between −0.815 and −0.868 also suggest the same assumption. The chi-square value is 2.44 with 1 degree of freedom, indicating that the chi-square differs from zero significantly, showing that the

research model fits. The *p*-value of 0.118 confirms that the model is acceptable. The RMSEA is 0.082, which is close to zero, indicating that the model aligns well with the empirical data.



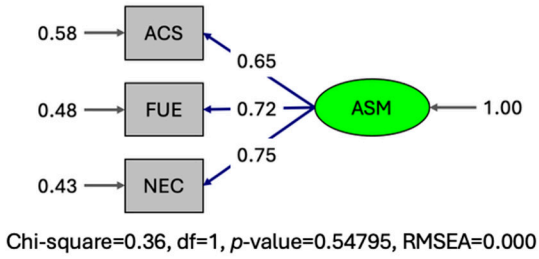
Statistical analysis of the ATM system

Variable	SK	KU
ATS	0.128	−0.868
ATFM	0.308	−0.718
AFBU	0.209	−0.815

Figure 7. CFA model showing the influence of ATS, ATFM, and AFBU on ATM (**left**) and statistical analysis results (SK and KU values) used to assess the normality of the system (**right**). The gray square represents manifest variables, and the green circle represents latent variables.

3.3.5. Airspace Management

Figure 8 shows the relationship ASM has with ACS, FUE, and NEC. NEC has the highest correlation value of 0.75, followed by FUE with a value of 0.72, and finally, ACS with a value of 0.65. This order is also the same for the errors associated with each variable. The SK value is between 0.105 and 0.245, indicating that the observable variables exhibit a distribution close to normal. Moreover, the KU value, which is between −0.622 and −1.075, also suggests the same assumption. The chi-square value is 0.36 with 1 degree of freedom, indicating that the research model fits the empirical data. The *p*-value of 0.548 is higher than the threshold of 0.05, showing that the model is acceptable. An RMSEA of 0.000 indicates that the model aligns well with the empirical data.



Statistical analysis of the ASM system

Variable	SK	KU
ACS	0.220	−1.075
FUE	0.245	−0.622
NEC	0.105	−0.873

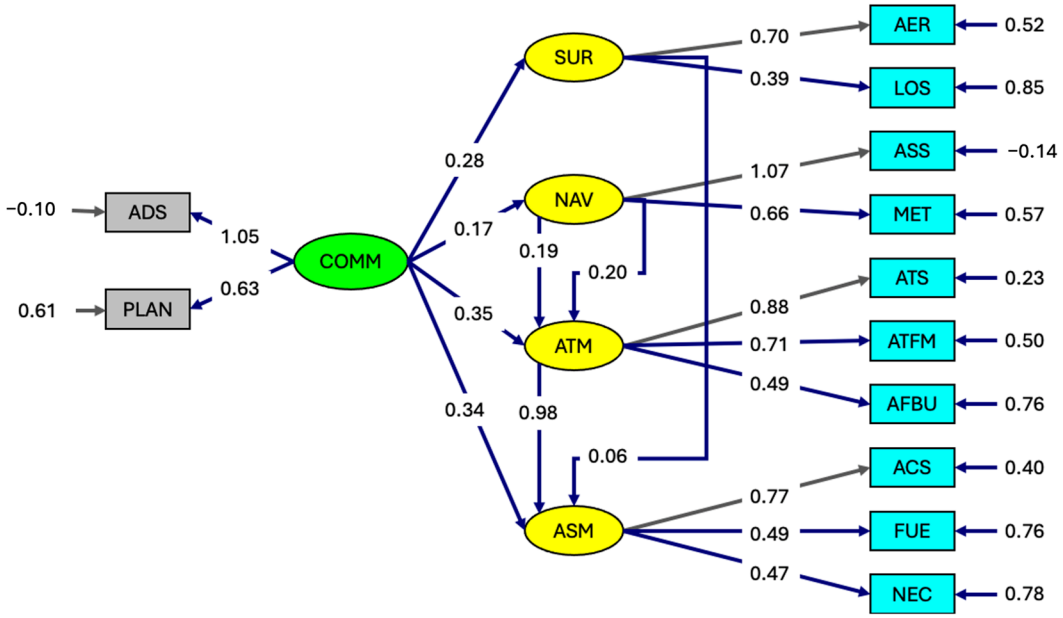
Figure 8. CFA model showing the influence of ACS, FUE, and NEC on ASM (**left**) and statistical analysis results (SK and KU values) used to assess the normality of the system (**right**). The gray square represents manifest variables, and the green circle represents latent variables.

3.3.6. Overall Relationship

After conducting the CFA on the individual variables and their sub-variables to check the associated relationships, it was found that they were all statistically significant since they all achieved a *p*-value of more than 0.05. The next step is to combine the individual systems together to form a single SEM model, as shown in Figure 9A. The exogenous latent variable is COMM, and its manifested variables are ADS and PLAN. On the other hand, four endogenous variables (SUR, NAV, ATM, and ASM) were studied along with 12 manifested variables. The statistical calculation (Figure 9B) shows that only RMSEA and SRMR are acceptable when compared with the level of acceptance. This means that this model is a good representation of the data; however, the other six statistical computations do not satisfy the acceptance level. Therefore, necessary adjustments must be made by adding relationships between the error terms associated with endogenous manifested variables. These adjustments were made based on the LISREL software modification

instructions, which state the two elements that need to be modified to ensure the model fits the statistical tests.

(**A**)



(**B**)

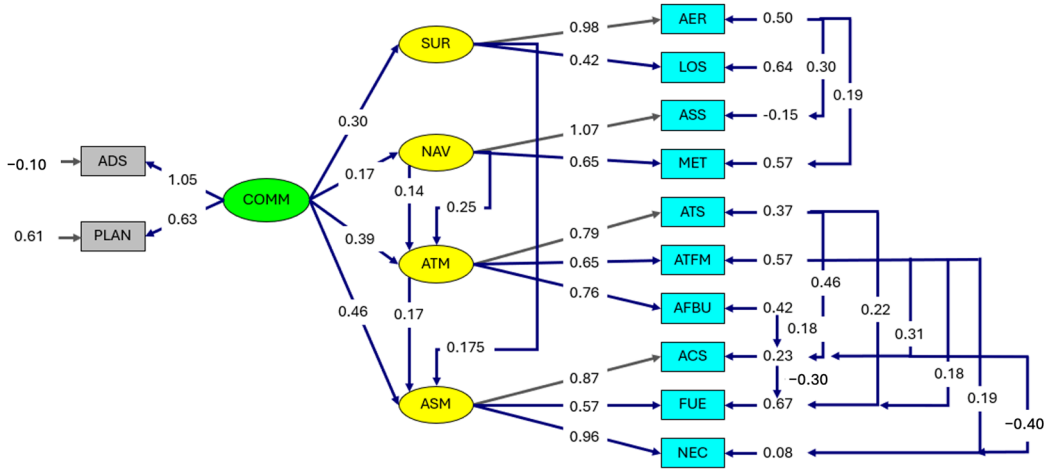
Tests	Level of acceptance	Obtained value	Results
χ^2/df	< 2.00	118.72	Unacceptable
p-value	> 0.05	0.000	Unacceptable
RMSEA	< 0.08	0.141	Acceptable
GFI	> 0.95	0.84	Unacceptable
RMR	< 0.05	0.11	Unacceptable
SRMR	< 0.05	0.11	Acceptable
AFGI	> 0.95	0.73	Unacceptable
CFI	> 0.95	0.83	Unacceptable

Figure 9. (**A**) SEM model for airspace optimization and (**B**) statistical calculations to check the model's acceptability. The gray squares represent exogenous manifest variables, and the green circles represent exogenous latent variables. The blue squares represent endogenous manifest variables, and the yellow circles represent endogenous latent variables. The arrowheads show the direction of influence.

Adjustments were made to Figure 9A through a process known as modification, in which relationships between the error terms of the dependent manifested variables are added. This is an iterative process that involves identifying parameters that could be added to improve model fit, re-running the software, and evaluating whether the revised model is reliable. The adjusted model, including the curve arrows between error terms resulting from the modification process, is shown in Figure 10A. The statistical calculations (Figure 10B) also showed drastic improvements as all eight criteria are acceptable.

AVE and CR were calculated to evaluate the quality of a measurement model to determine if the indicators correctly measure the intended latent constructs. The calculated results are shown in the Table 6, where the AVE is more than or equal to 0.50, and the CR is more than or equal to 0.70. As a result, these variables converge on the same target as well as being reliable and consistent with each other.

(**A**)



(**B**)

Tests	Level of acceptance	Obtained value	Results
χ^2/df	< 2.00	1.6508	Acceptable
p-value	> 0.05	0.0090	Acceptable (using χ^2/df conditions)
RMSEA	< 0.08	0.0000	Acceptable
GFI	> 0.95	0.9800	Acceptable
RMR	< 0.05	0.0360	Acceptable
SRMR	< 0.05	0.0360	Acceptable
AFGI	> 0.95	0.9500	Acceptable
CFI	> 0.95	1.000	Acceptable

Figure 10. (**A**) Adjusted SEM for airspace optimization and (**B**) statistical calculation to check the model's acceptability. The gray squares represent exogenous manifest variables, and the green circles represent exogenous latent variables. The blue squares represent endogenous manifest variables, and the yellow circles represent endogenous latent variables. The arrowheads show the direction of influence.

Table 6. Calculated AVE and CR values for COMM, NAV, SUR, ASM, and ATM.

Latent Variables	AVE *	CR *	Results
COMM	0.57	0.69	Acceptable
NAV	0.78	0.87	Acceptable
ASM	0.54	0.78	Acceptable
SUR	0.67	0.86	Acceptable
ATM	0.75	0.85	Acceptable

* Level of acceptance for AVE is ≥0.50 [28] and CR is ≥0.70 [28].

The diagram demonstrates that COMM has a direct positive influence on ASM, ATM, SUR, and NAV, respectively. Additionally, COMM exerts a positive indirect influence on ATM through NAV, which in turn has a positive indirect effect on ASM via ATM. Consequently, these relationships highlight that both the COMM and NAV systems play a significant role in efficiently managing airspace through their respective pathways. The summary of the direct, indirect, and total effects for all variables is indicated in Table 7. The direct effect is found by the factor loading between two variables, and the indirect effect is the multiplication of the factor loading pathway.

Table 7. Summary of strength and types of effects of the studied variables as shown by the adjusted SEM model.

Variables	Influence Coefficient	Types of Effect
COMM on SUR	0.30	Direct
COMM on NAV	0.17	Direct
COMM on ATM	0.39	Direct
COMM on ASM	0.46	Direct
COMM on ASM through SUR	$0.30 \times 0.175 = 0.0525$	Indirect
COMM on ASM through NAV and ATM	$0.17 \times 0.14 \times 0.17 = 0.004046$	Indirect
COMM on ATM through NAV	$0.17 \times 0.14 = 0.0238$	Indirect

COMM has a direct effect on SUR, NAV, ATM, and ASM with an influence coefficient equal to 0.30, 0.17, 0.39, and 0.46, respectively. COMM also has many indirect effects. For instance, COMM has an indirect effect on SUR through ASM with an influence coefficient of 0.0525. COMM has an indirect effect on ASM through NAV and ATM with an influence coefficient of 0.004046. Lastly, COMM has an indirect effect on ATM through NAV with an influence coefficient of 0.0238.

In other words, communication failure can directly affect other components studied, as well as having a cascading effect that starts at the NAV level and propagates towards ATM and ASM. When communication is lost, the pilot and ATC cannot receive updated information such as the real-time position of the aircraft, altitude changes, or reroutes. Therefore, NAV becomes more procedural and pre-planned, reducing the flexibility of ATC. This may lead to delays or increased separation, which reduces the ASM capacity and flexibility to maintain safety.

3.4. Mathematical Expression of the Overall Relationship

3.4.1. Relationship Between Dependent Latent (E) and Manifest (Y) Variables and Error (E)

The matrix below shows the manifest variable (Y) as columns, observed variable (E) as rows, and LY is the relationship between the two. For example, LY(1,1) indicates the factor loading of SUR on AER, whereas LY(2,1) is SUR on LOS. From Figure 10A, the values on the line from variables E to Y are the LY values. If there is no relationship between the two, the values will be blank.

$$
\begin{array}{c}
\\
\text{AER(Y1)} \\
\text{LOS(Y2)} \\
\text{ASS(Y3)} \\
\text{MET(Y4)} \\
\text{ATS(Y5)} \\
\text{ATFM(Y6)} \\
\text{AFBU(Y7)} \\
\text{ACS(Y8)} \\
\text{FUE(Y9)} \\
\text{NEC(Y10)}
\end{array}
\begin{bmatrix}
\text{SUR(E1)} & \text{NAV(E2)} & \text{ATM(E3)} & \text{ASM(E4)} \\
\text{LY}(1,1) & \text{LY}(1,2) & \text{LY}(1,3) & \text{LY}(1,4) \\
\text{LY}(2,1) & \text{LY}(2,2) & \text{LY}(2,3) & \text{LY}(2,4) \\
\text{LY}(3,1) & \text{LY}(3,2) & \text{LY}(3,3) & \text{LY}(3,4) \\
\text{LY}(4,1) & \text{LY}(4,2) & \text{LY}(4,3) & \text{LY}(4,4) \\
\text{LY}(5,1) & \text{LY}(5,2) & \text{LY}(5,3) & \text{LY}(5,4) \\
\text{LY}(6,1) & \text{LY}(6,2) & \text{LY}(6,3) & \text{LY}(6,4) \\
\text{LY}(7,1) & \text{LY}(7,2) & \text{LY}(7,3) & \text{LY}(7,4) \\
\text{LY}(8,1) & \text{LY}(8,2) & \text{LY}(8,3) & \text{LY}(8,4) \\
\text{LY}(9,1) & \text{LY}(9,2) & \text{LY}(9,3) & \text{LY}(9,4) \\
\text{LY}(10,1) & \text{LY}(10,2) & \text{LY}(10,3) & \text{LY}(10,4)
\end{bmatrix}
=
\begin{bmatrix}
\text{SUR(E1)} & \text{NAV(E2)} & \text{ATM(E3)} & \text{ASM(E4)} \\
0.98 & & & \\
0.42 & & & \\
 & 1.07 & & \\
 & 0.65 & & \\
 & & 0.79 & \\
 & & 0.65 & \\
 & & 0.76 & \\
 & & & 0.87 \\
 & & & 0.57 \\
 & & & 0.96
\end{bmatrix}
$$

Each manifest (Y) variable has an associated error (e) term, which reflects the proportion of variance in the observed variable not explained by the latent factor. Accordingly,

10 manifest variables correspond to 10 error terms, displayed diagonally in the matrix. Blank cells indicate no error covariance between variables. For interpretation, for example, e1 (AER) has a value of 0.50, meaning that 50% of the variance in AER is unexplained by its associated latent factor (SUR). This suggests that while SUR accounts for part of AER, the remaining variance is influenced by other factors. In contrast, the error variance for e2 (LOS) is 0.89, indicating that 89% of the variance is unexplained by SUR. This high error suggests that LOS is a weak indicator of SUR, as most of its variability arises from outside influences. In other words, AER is more strongly associated with SUR, while LOS contributes little to representing SUR in the model.

	e1	e2	e3	e4	e5	e6	e7	e8	e9	e10
e1	0.50									
e2		0.64								
e3			0.15							
e4				0.57						
e5					0.37					
e6						0.57				
e7							0.42			
e8								0.23		
e9									0.67	
e10										0.08

From the two matrices above, each latent variable (E) and its associated manifested variable (Y) and error term (e) can be written as shown below for each of the four main systems (SUR, NAV, ATM, and ASM).

$$\begin{gathered}\text{SUR consist of LY } (1,1) \text{ AER and LY } (2,1) \text{ LOS} \\ \text{SUR consist of } 0.98(\text{AER}) \text{ and } 0.42(\text{LOS})\end{gathered} \tag{3}$$

$$\begin{gathered}\text{NAV consist of LX } (3,2) \text{ ASS and LX } (4,2) \text{ MET} \\ \text{NAV consist of } 1.07(\text{ASS}) \text{ and } 0.65(\text{MET})\end{gathered} \tag{4}$$

$$\begin{gathered}ATM \textit{ consist of } LY\ (5,3)\ ATS,\ LY\ (6,3)\ ATFM, \textit{ and } LY\ (7,3)\ AFBU \\ ATM \textit{ consist of } 0.79(ATS),\ 0.65(ATFM), \textit{ and } 0.76(AFBU)\end{gathered} \tag{5}$$

$$\begin{gathered}ASM \textit{ consist of } LY\ (8,4)\ ACS,\ LY\ (9,4)\ FUE, \textit{ and } LY\ (10,4)\ NEC \\ ASM \textit{ consist of } 0.87(ACS),\ 0.57(FUE), \textit{ and } 0.96(NEC)\end{gathered} \tag{6}$$

3.4.2. Relationship Between Independent Latent (K) and Manifest (X) Variables and Delta Term (D)

Similarly, the LX matrix shown below represents the factor loading for the independent variable between latent (K) and manifest (X). LX (1,1) is the factor loading of COMM on ADS, and LX (2,1) is COMM on PLAN.

$$COMM \textit{ consist of } LX\ (1,1)\ ADS \textit{ and } LX\ (2,1)\ PLAN$$

$$COMM \textit{ consist of } 1.05(ADS) \textit{ and } 0.63(PLAN)$$

3.4.3. Relationship Between Independent (K) and Dependent (E) Latent Variables and Theta Term (Z)

The GA matrix below represents the influence of external latent variables (K) on internal latent variables (E). For instance, GA (1,1) indicates the influence of COMM on SUR, GA (2,1), which represents the influence of COMM on NAV, and so forth,

$$\begin{matrix} \\ \text{SUR(E1)} \\ \text{NAV(E2)} \\ \text{ATM(E3)} \\ \text{ASM(E4)} \end{matrix} \begin{bmatrix} \text{COMM(K1)} \\ \text{GA}(1,1) \\ \text{GA}(2,1) \\ \text{GA}(3,1) \\ \text{GA}(4,1) \end{bmatrix} = \begin{bmatrix} \text{COMM(K1)} \\ 0.30 \\ 0.17 \\ 0.39 \\ 0.46 \end{bmatrix}$$

which could mathematically be written as a set of equations shown below.

$$\begin{aligned} \text{COMM} = \text{GA}(1,1)\text{SUR} + \text{Z}_1 \rightarrow \text{COMM} = 0.30(\text{SUR}) \\ \text{COMM} = \text{GA}(2,1)\text{NAV} + \text{Z}_2 \rightarrow \text{COMM} = 0.17(\text{NAV}) \\ \text{COMM} = \text{GA}(3,1)\text{ATM} + \text{Z}_3 \rightarrow \text{COMM} = 0.39(\text{ATM}) \\ \text{COMM} = \text{GA}(4,1)\text{ASM} + \text{Z}_4 \rightarrow \text{COMM} = 0.46(\text{ASM}) \end{aligned} \quad (7)$$

3.4.4. Relationship Between Dependent Latent Variable (E)

The BE matrix illustrated below represents the influences between the variables (E). In other words, BE (1,3) represents the influence of ATM on SUR, and BE (2,3) represents ATM on NAV, and so on for all four latent variables.

$$\begin{matrix} \\ SUR(E1) \\ NAV(E2) \\ ATM(E3) \\ ASM(E4) \end{matrix} \begin{bmatrix} SUR(E1) & NAV(E2) & ATM(E3) & ASM(E4) \\ BE(1,1) & BE(1,2) & BE(1,3) & BE(1,4) \\ BE(2,1) & BE(2,2) & BE(2,3) & BE(2,4) \\ BE(3,1) & BE(3,2) & BE(3,3) & BE(3,4) \\ BE(4,1) & BE(4,2) & BE(4,3) & BE(4,4) \end{bmatrix} = \begin{bmatrix} SUR(E1) & NAV(E2) & ATM(E3) & ASM(E4) \\ & & 0.25 & 0.175 \\ & & 0.14 & \\ & & & 0.17 \\ & & & \end{bmatrix}$$

From the matrix, it could be mathematically written as shown below. These equations indicate that:

1. The main variable SUR influences both ATM and ASM.
2. NAV influences ATM.
3. ATM influences ASM.

$$\begin{aligned} \text{SUR} = \text{BE}(1,3)\text{ATM} + \text{BE}(1,4)\text{ASM} + \text{Z}_1 \rightarrow \text{SUR} = 0.25(\text{ATM}) + 0.175(\text{ASM}) \\ \text{NAV} = \text{BE}(2,3)\text{ATM} + \text{Z}_2 \rightarrow \text{NAV} = 0.14(\text{ATM}) \\ \text{ATM} = \text{BE}(3,4)\text{ASM} + \text{Z}_3 \rightarrow \text{ATM} = 0.17(\text{ASM}) \end{aligned} \quad (8)$$

4. Discussion

This study analyzed the direct and indirect influences of the key components, namely COMM, ASM, ATM, SUR, and NAV, in airspace optimization using SEM. This method has been widely applied by other researchers related to safety, operations, and optimization [29,30], as it enables the simultaneous analysis of relationships between latent and observed variables.

One of the key findings of this application highlights the interconnected nature of these systems, including both direct and indirect effects, which is consistent with ICAO standards [17] and SESAR initiatives [31]. In particular, COMM emerged as the most influential factor for safe and efficient airspace optimization, aligning with NASA's aviation safety reporting, which also identified it as a leading factor in aviation safety incidents [32].

Furthermore, COMM was found to have both direct and indirect effects on ASM and ATM, which are considered backbone systems for ensuring safe and efficient operations [33].

These results suggest that future efforts should focus on structuring and aligning airspace systems to better support capacity, enhancing ATS's ability to provide separation and sequencing, and expanding the use of PBN for flight planning and route optimization. The findings also emphasize that SUR and NAV systems remain critical, particularly through continuous monitoring and the use of GNSS for precise positioning.

Based on these results and existing research on European airspace [34], to effectively manage the increased volumes of aircraft, arrival and departure procedures, airspace design, and COMM systems must be optimized. The results of this study indicate that COMM has the strongest and statistically significant influence on ASM, SUR, ATM, and NAV, respectively. Based on these findings, the reliance on voice-based aeronautical communication can be minimized by promoting alternative communication methods. In particular, ASM can be adapted to support Trajectory-Based Operations, enabling more flexible and efficient flight operations. Furthermore, the current three-dimensional operational framework can be upgraded to a four-dimensional system through ASM management by incorporating time-based aircraft tracking and scheduling. The implementation of the PBN concept for arrival and departure operations, along with increasingly automated continuous climb and descent procedures, can further enhance operational efficiency. In addition, improving system interoperability and enabling automated data exchange between aviation systems will further reduce reliance on voice communication. This, in turn, is expected to decrease the occurrence of aircraft proximity events, thereby enhancing both flight safety and overall operational efficiency.

However, the study is limited by its cross-sectional design and potential variability in measuring complex constructs across regions. Future research should use longitudinal data, real-time operational inputs, and machine learning, as well as cross-country comparisons, to better understand dynamic and context-dependent effects in aviation safety systems.

5. Conclusions

In conclusion, this study investigates the theoretical foundation and causal influences that enhance the effectiveness of ASM, with a particular focus on COMM, SUR, NAV, and ATM. It employs both experimental and quantitative approaches during data collection and utilizes linear regression analysis, CFA, and SEM. These mathematical tools help analyze the key components with direct and indirect effects relating to safe and efficient airspace optimization.

From linear regression analysis, the component that strongly influences ASM is COMM, followed by ATM, NAV, and SUR. Subsequently, SEM was employed to identify the direct and indirect determinants of COMM. The results indicate that ASM exerts the strongest influence, followed by ATM, SUR, and NAV. Both direct and indirect relationships between COMM and all other variables were observed. These findings highlight the interconnected nature of aviation systems in which each individual subsystem depends on other, and failure in one area can lead to cascading effects.

As a result, future efforts should prioritize strengthening the COMM system, particularly in terms of digitalizing real-time data exchange and planning capabilities, as these offer the greatest leverage for improving the overall performance of Thailand's airspace. Furthermore, given the strong influence of COMM on ASM and ATM, modernization initiatives should adopt an integrated approach, in which communication enhancements are implemented alongside improvements in conflict detection and resolution, aircraft separation and sequencing, and forecasting flight planning and route optimization. For the SUR and NAV systems, priority should be given to continuous monitoring and alerting

aircraft along enroute corridors, particularly in congested zones. This includes the use of GNSS for precise position, as well as the integration of meteorological data to enhance situational awareness and operational efficiency. Lastly, these findings can be adapted and applied worldwide.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/aerospace13050457/s1, File S1: Questionnaire for "Structural Equation Modeling for Airspace Optimization: The Analysis of Causal Factors Influencing Aviation Safety" research.

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

Abbreviations

The following abbreviations are used in this manuscript:

AFGI	Adjusted Goodness of Fit Index
ASM	Airspace Management
ATM	Air Traffic Management
ATS	Air Traffic Services
AVE	Average Variance Extracted
CFA	Confirmation Factor Analysis
CNS	Communication Navigation Surveillance
CR	Composite Reliability
GFI	Goodness of Fit Index
GNSS	Global Navigation Satellite Systems
ICAO	International Civil Aviation Organization
NM	Nautical Miles
KU	Kurtosis
LISREL	Linear Structural Relation
PBN	Performance Based Navigation
RMR	Root Means square Residual
RMSEA	Root Means Square Error of Approximation
SEM	Structural Equation Modeling
SK	Skewness
SRMR	Standard Root Mean Square Residual
SUR	Surveillance
TMA	Terminal Control Area
USOAP	Universal Safety Oversight Audit Program
VIF	Variance Inflation Factor

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