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ORIGINAL PAPER

Analyzing the moderating effects of respondent type and experience on the fuel efficiency improvement in air transport using structural equation modeling

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Abstract
Introduction The limited nature of oil, and hence aviation fuel is increasingly becoming a restraining factor for the air transport industry. Also, fuel efficiency is crucial for commercial air transport as fuel is one of the most costly operating parameters for an airline.
Methodology This study employs structural equation modelling (SEM) approach to identify key dimensions influencing fuel efficiency in air transport (FEAT) and to explore the correlational relationships among constructs from the perspectives of fuel efficiency improvement. Self-administered questionnaires were used to collect data from 375 aviation experts. Correlation, multi-group moderation analysis, and interaction using structural equation model were used to analyses these data.
Results The results and applications of SEM evolve a variety of findings; aircraft technology & design, aviation operations infrastructure, socioeconomic & political measures, and alternative fuels & fuel properties, and aviation infrastructure are proved to be the five key influential dimensions affecting the fuel efficiency and have a positive effect on the FEAT. In addition, the moderating effect of industry type and experience were established. The results also showed that no significant interaction effect between dimensions of FEAT.
Conclusions The findings of this research can provide air transport valuable information for designing appropriate strategy for fuel efficiency improvement.

Keywords Fuel efficiency in air transport (FEAT) · Multi-group moderation, Structural equation modelling (SEM) · Environmental impact

1 Introduction

The limited nature of oil, and hence aviation fuel is increasingly becoming a restraining factor for the air transport industry. Now, airlines are more attentive than ever to raise fuel efficiency due to rising fuel prices and competition among them [20, 36]. According to the projections of Penner [63] the global passenger air traffic, as measured in revenue passenger km, is estimated to grow by about 5 % per year between 1990 and 2015, whereas total aviation fuel consumption, including passenger, freight, and military is projected to increase by 3 % per year. In addition, the fuel consumption of air transport industry has increased at a rate of more than 6 % over the previous 10 years, although, fuel production has developed slowly, increasing at less than 6 % over the same period [20, 53]. Also, the mean price of jet fuel has increased over the previous 10 years, which was above $120 a barrel [36, 53]. The growing demand of jet fuel and high price will force air transport to improve fuel efficiency. Therefore, airlines are adopting fuel efficient aircrafts, modifying operating practices, and implementing the socioeconomic & policy measures to improve the fuel efficiency of airlines [13, 83]. The International Air Transport Association (IATA) seeks to raise fuel efficiency across the air transport industry by 1.5 % per annum up to 2020 [37], while the International Civil Aviation Organization (ICAO) is attempting for a 2 % per

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annum improvement up to 2050 [38]. An improved fuel efficiency of airliners, and the consequent lower carbon emission, will reduce the operating cost of an airline along with environmental impact [62].

Fuel efficiency in air transport (FEAT) can be defined as ratio of fuel consumed in liters to revenue tonne kilometer (RTK) [4, 13, 51]. Fuel efficiency of transport aircrafts mainly depends upon two main factors i.e., technology & design, and aircrafts operations [4, 51]. Further, aircraft technology & design depends upon the engine efficiency, aerodynamic efficiency, and structural efficiency, while the aircraft operations relies on ground efficiencies, and airborne efficiencies [4, 73, 74]. In case of aircraft technology & design, aerodynamic features such as blended wing body (BWB), flying wing, higher aspect ratios, and engines with higher bypass ratios are installed on modern jets to improve the fuel efficiency [1]. Aviation operations contain air traffic management procedures such as performance-based navigation, continuous descent approaches, reduced vertical separation minimum (RVSM) and various air traffic flow management systems, beside improved aircraft operating techniques [13, 26].

For the previous few years, existing literature related to estimating air transport fuel efficiency have been limited. Inside the range of air transport fuel efficiency literature, Lee et al. [51] analyzed the relationship between aircraft fuel efficiency and cost, and estimated the aviation emissions reduction potential based on analytical and statistical models. Babikian et al. [4] compared the fuel efficiency of different aircraft types, and emphasized that differences in fuel efficiency could be described largely by differences in aircraft operations. Peeters et al. [62] analyzed the fuel efficiency of commercial aircraft since their initiation in the 1930s, and results showed that the last piston-powered aircrafts were at least twice as fuel-efficient as the first jet-powered aircraft. Williams (2007) highlighted the engineering options for the improvement in aircraft fuel efficiency, and these options had included the changes to airframes, engines, avionics, air traffic control systems, airspace design, and improved market based measures. Morrell [56] investigated the potential for greater fuel efficiency by utilizing larger aircraft and different operational practices. Lee [50]; Lee and Mo [52] have presented the key technologies and policy issues for the induction of energy efficient, environmentally friendly innovations in aircraft systems. Zou et al. [83] used ratio based, deterministic and stochastic frontier approaches to investigate fuel efficiency of transport aircrafts, and the results showed that potential cost savings of airlines. Singh and Sharma [74] explored the aircraft technology, operations, alternative fuels, socio-economic measures, and infrastructural factors for fuel efficiency improvement. Chandra et al. [13] compared fuel efficiencies of selected airlines around the globe, and results found that, the average fuel efficiency of the airlines reported was is 0.4 L/RTK (revenue tonne kilometer), respectively. Also, this study has investigated the variances in fuel efficiency among airlines from different regions. Li et al. [53] employed the virtual frontier dynamic range adjusted measure to estimate the energy efficiency of 22 airlines during the period of 2008–2012, and the results showed that the aggregate airline energy efficiency consistently increased from 2008 to 2012. Baklacioglu [5] employed a genetic algorithm-optimized neural network topology to predict the fuel flow-rate of a transport aircraft using real flight data, and results showed that the saving in fuel energy, and reducing flight costs.

While all these studies have evaluated the fuel efficiency of different airlines or aircrafts, a comprehensive examination of the relationship between fuel efficiency and its factors, has not been seen in the literature. Only the study of Singh and Sharma [73] analyzed the relationship between fuel efficiency and its factors using structural equation modelling (SEM). However, this study has not analyzed relationships between depend and independent factors of fuel efficiency. Also, moderating effect of industry type respondents and experience, and interaction effect were not discussed in the study of Singh and Sharma [73]. In this study, SEM approach using moderating and interaction effect is proposed to evaluate the relationships between the factors of fuel efficiency. Moreover, SEM has drawn the attention of many researchers as a commonly adopted technique used to examine data about many airline disciplines including passenger loyalty [3], passenger's overall satisfaction with an airport [6], a comprehensive relationship marketing model [15], low cost carrier travelers [18], airline performance [42], airline service quality [48, 75], fuel consumption optimization [73], cabin safety [14, 34], customer loyalty [22, 54], job satisfaction [17, 57, 81] and carbon offset scheme [16].

Therefore, the aims of this study are to explore the holistic relationships among the factors of FEAT, and to examine their effects using multigroup moderation and interaction. To achieve these goals, the critical factors related to fuel efficiency were extracted based on literature reviews, and a questionnaire was constructed for the assessment of FEAT. Self administrated surveys of 375 experts of aviation were performed using the questionnaires to evaluate fuel efficiency perceptions in air transport. Based on the survey results, the conceptual fuel efficiency model was tested using structural equation modeling. In the time of rising fuel prices and mounting environmental concerns, the FEAT model could help us to frame future strategies to improve fuel efficiency of air transport industry.

Following this introduction, Section 2 presents the hypothesized relationships, leading to the development of the research model. Then, Section 3 provides the instrument development, measuring instrument, and techniques of data analysis adopted in this study. Section 4 presents the results of the research study and discuss findings of factor analysis and SEM. Finally, the conclusions and implications are provided in Section 5.

2 Hypotheses and research model

2.1 Hypotheses

Based on a review of existing literature on FEAT, five key factors that have direct effects on fuel efficiency improvement are identified as aircraft technology & design (ATD), aviation operations (AO), socioeconomic & policy measures (SEP), alternative fuels & their properties (AFP), and aviation infrastructure (AI) [4, 26, 50–52, 62, 73, 74]. Our hypotheses include five dimensions namely: ATD, AO, SEP, AFP, and AI. The detailed theoretical basis of the hypotheses, and observed variables will be analyzed in the following section.

2.1.1 Aircraft technology & design

ATD is an important dependent factor related to the fuel efficiency. According Williams (2007); Parker [61]; Graham et al. [24] and Miyoshi and Ibáñez [55] the technological advancement has resulted in a positive trend of fuel efficiency. ATD was measured from engine efficiencies, aerodynamic efficiencies, and structural efficiencies [4, 51]. Engine efficiencies were expressed in term of engine thrust specific fuel consumption (TSFC), lower value of TSFC result in better fuel efficiency [4, 25]. Aerodynamic efficiencies were evaluated in term of lift/drag (L/D) ratio [74]; higher value of lift/drag ratio can result in improved fuel efficiency. Structural efficiencies were assessed in term of ratio of operating empty weight (OEW) to maximum takeoff weight (MTOW) [4, 73]. The use of advanced composite material has reduced the structural weight of aircrafts [76]. Therefore, our construct include the TSFC, L/D ratio, OEW, and MTOW for the measurement of ATD dimension.

2.1.2 Aviation operations

AO is another important dependent factor related to the fuel efficiency. According to Peeters et al. [62] and Hileman et al. [32] improved aviation operations have resulted in better value of fuel efficiency. The relationships between operational efficiency and efficiency are expressed by payload fuel efficiency equation [21, 32]. Therefore, aircraft operational efficiency were measured in terms of parameters such as aircraft range [4, 51], fuel weight, reserve fuel weight, payload, aircraft speed, crew weight, takeoff filed length, and landing filed length ([2, 4, 5, 27, 29, 65]). Aircraft range is the total distance that an aircraft can fly with full fuel tank. We can improve the aircraft fuel consumption by optimizing the aircraft range. Optimized fuel weight, reserve fuel weight, and crew weight have also contributed toward the improved fuel efficiency [2, 27]. The payload rate is another operational performance indicator that is commonly used to assess fuel burn. Air transport emission can be reduced with increased payload (reduce the number of empty seats flown) while optimizing the flight frequencies. Also, optimized aircraft speed [5], has also improved the fuel efficiency of airliners [4, 65]. Optimum values of takeoff filed length, and landing filed length also affects positively the fuel efficiency. So, therefore we have included the aircraft range, fuel weight, reserve fuel weight, payload, aircraft speed, crew weight, takeoff filed length, and landing filed length to measure AO construct.

H2 (AOI) –The effective aviation operation & infrastructure contribute positively towards the ERP.

2.1.3 Alternate fuels & their properties

AFP is another important independent factor related to the fuel efficiency. A viable alternative aviation fuel can stabilize fuel price fluctuation and reduce the reliance from the crude oil. Due to the high growth rate of aviation sector, supply security of fuel, and environmental impact of fuel has caused the aviation industry to investigate the potential use of alternative fuels [8]. Presently, it appears that a blend of kerosene and synthetic fuel will be possible for use in existing and near-term aircraft [7]. While, future mid-term aircraft may use a blend of bio-fuels and synthetic fuels in ultra-efficient airplane designs, and future long term engines and aircraft in the 50-plus year horizon may be specifically designed to use alternative fuels with low to zero carbon content, such as liquid hydrogen or liquid methane [82]. Hence, based on past studies, we tried to balance several factors when selecting AFP measures. The AFP parameters including fuel availability, net calorific value, energy density, aromatic content, carbon content, thermal stability, and flash point [7, 8, 33, 41, 73, 74] were shown to influence fuel efficiency, and hence were incorporated in the current study.

Net calorific value and density are important parameters in determining the performance of any aviation fuel [58]. Net calorific value of a fuel portion is the amount of heat evolved when a unit weight of the fuel is completely burnt and water vapor leaves with the combustion products without being condensed. One of the most important requirements of aviation fuel is high net calorific value for maximum range or payload [8]. Energy density is the amount of energy stored in a given system or region of space per unit volume. High energy density per unit volume or mass, provides long-range flight, and decreases takeoff weight and improves fuel efficiency [40]. Also, aromatic content is another indicator affecting the FEAT. One of the biggest concerns of alternative fuels has come from their low aromatic content. In addition, the carbon content is another most essential indicator affecting the FEAT. Carbon particles that are not completely consumed are responsible for the higher specific fuel consumption of the engine [33]. Similarly, the parameters such as thermal stability and flash point [8] have shown the positive relation with the FEAT. Therefore, best alternative fuel amongst the alternative fuels can be selected on the basis of compatibility with aircraft operations, fuel production technology, chemical, and physical properties of fuel. Therefore, we hypothesized that:

H1: The AFP is positively related to ATD.
H2: The AFP is positively related to AO.

2.1.4 Socioeconomic & policy measures

SEP is another important independent factor related to the fuel efficiency. The SEP was analyzed from several dimensions. Based on past studies, we tried to balance several factors when selecting SEP measures. The SEP parameters including social demand, fuel cost, voluntary measures, demand shift, passenger load factor, charging carbon emission, and taxing aviation fuel [12, 46, 52, 68, 69, 72, 74] were shown to influence fuel efficiency, and hence were incorporated in the current study.

Currently, the social demand for fuel efficient and low-emission aircraft is not strong enough because the general public is not well aware of the effects of aviation emissions on the global climate [52]. Also, the fuel cost is the main driver for improvements to aircraft fuel efficiency [4, 74]. When fuel cost soar, airlines actively adopt advanced aircraft with greatly improved fuel efficiency. Another potential fuel efficiency measure is voluntary agreement [80] to meet environmental targets and funding of research to better understand the impact of aircraft higher fuel consumption. Demand shift [68] relates to another set of parameters affecting the FEAT, which account for changes in travelers' mode choice behavior (such as high speed trains, urban rail transit) or reduction of demand due to non-travel alternatives (such as video-conferencing, virtual meetings) [31] etc. In addition, the charging carbon emission is another most essential indicator affecting FEAT [9]. Finally, fuel tax [46] was also included in the study, which affects the fuel efficiency. Furthermore, high fuel prices may inspire manufacturers to focus on ATD which reduce fuel burn, rather than maximizing passenger comfort. These parameters could influence the success of SEP measures aimed at reducing aviation's fuel burn through technological intervention. Also, the study of Singh and Sharma [73] had shown that the positive correlation exist between SEP and AO. Therefore, we hypothesized that:

H3: The SEP is positively related to ATD.
H4: The SEP is positively related to AO.

2.1.5 Aviation infrastructure

AI also another important independent factor related with the fuel efficiency. Infrastructure improvements present a major opportunity for fuel efficiency improvement. Congestion at the airport and inappropriate air traffic management raised the fuel burn of an aircraft [4]. We have included the independent variables- origin airport, destination airport, flight profile, runway design, taxiway, apron, and weather conditions, as suggested by Senzig et al. [67]; Upham et al. [77]; Kazda and Caves [45]; IATA [37]; Salah [66]; Simaiakis et al. [71]; Singh and Sharma [74] for AI construct. There are a number of ways that airports, airlines and air traffic management providers can improve the air transportation system to minimize fuel burn. These include improving the use of the airspace, air traffic control, and operations. Further, improving the use of airspace and air traffic control includes the flexible use of airspace, route redesign, using the new tools and programmes to find most effective route, and reduced separation between the aircraft [26, 32]. Also, developed AI has contributed to the ATD and AO for fuel improvement [26, 74].

Finally, the study of Singh and Sharma [73] had analyzed the positive correlation between AI-AFP, AFP-SEP, and AI-SEP. Therefore, we hypothesized that:

H5: The AI is positively related to ATD.
H6: The AI is positively related to AO.
H7: The AI is positively correlated to AFP.
H8: The AFP is positively correlated to SEP.
H9: The AI is positively correlated to SEP.

2.1.6 Respondents' type as a moderating effect on SEP and ATD

Respondents type have different understandings of outcomes they expect to get from FEAT because of the different nature of their functioning industry; also they are exposed to different organization environment i.e. aviation or academic, which may influence them in answering the survey questionnaires. Kim [47] examined the moderating effects of job relevance and experience on mobile wireless technology acceptance; the results found that significant moderating effect of job relevance. Therefore, we insisted that individuals' understanding about the importance of FEAT to their industry type would strengthen the relationship between SEP and ATD toward the FEAT. Thus, we hypothesized:

H3a: Industry type moderates the positive effect of SEP on ATD such the effect is stronger for aviation industry respondents than for academic respondents.

2.1.7 Experience as a moderating effect on SEP and AO

The effect of SEP might change with prior experience. Experience has been considered as a key in relating individual differences. Ismail and Jenatabadi [39] analyzed the moderating effect of firm age on the relationships of airline performance, economic situation and internal operation. The results analyzed that significant moderating effect of lower age group and higher age group. It was, however, vital to examine closely at the influence of prior experience. Thus, to examine a user's beliefs concerning BI on MWT, prior experience was considered by adding.

Therefore, we observed that there was a moderating effect of user experience (lower experience group, higher experience group) on the importance of SEP and AO as determinants of FEAT. Thus, we hypothesized:

> **H4a:** Experience moderates the positive effect of SEP on AO such that the effect is stronger for higher experienced respondents than for lower experienced respondents.

2.1.8 Interplay between SEP, ATD, and AFP

We argue that when SEP measures are low, then there will be positive relationship between ATD and AFP for FEAT. Low or optimum SEP measures do not put pressure on airline to raise the ticket prices, to improve the technologies, and to adopt the suitable alternative fuel for fuel efficiency improvement [32, 52]. In contrast, high SEP measures do not maintain a focus on travel demand rather than ATD and AFP. Thus, we hypothesized:

> **H1b:** An increase in SEP will strengthen the negative relationship between ATD and AFP.

2.1.9 Interplay between SEP, AO, and AI

Finally, we argue that when SEP measures are low, then there will be positive relationship between AO and AI for FEAT. Low or optimum SEP measures create the opportunities for AI improvements, and implementation of successful measures AO for better fuel efficiency [26, 50]. In contrast, high SEP measures put pressure on airlines. Thus, we hypothesized:

> **H6b:** An increase in SEP will strengthen the negative relationship between AO and AI.

2.2 Research model

The conceptual research model of FEAT is shown in Fig. 1. Because ATD, AO, AFP, SEP, and AI are represented by more than one measure, and these measures are related, each of the measurements can be represented by a latent variable. The above hypotheses reveals that AFP, SEP, and AI have a positive and direct effect on ATD and AO. Therefore, hypotheses H1, H2, H3, H4, H5, and H6 have a positive and direct effect on FEAT. Also, as shown in Fig. 1 hypotheses H3a, industry type respondents (1=Academic, 2=Aviation) is a full mediator of the impact of SEP on ATD. In addition, as depicted in Fig. 1 hypotheses H4a, respondent's experience (1=Low, 2=High) is a full mediator of the impact of SEP on AO. Finally, hypotheses H1b and H6b shows the interplay between AFP X SEP →ATD, and AI X SEP→AO.

The current study includes age and education level into the research model as control variables. This is important, because these variables may be significantly related to study constructs and may have confounding effects on the hypothesized relationships. Further description of the decision variables is given in the appendix A.

3 Methodology

3.1 Instrument development

A survey instrument was developed in order to test the research model. Initially, the measurement items were reviewed by five aviation experts who were asked to comment on the appropriateness of the research constructs. Based on the assessment from the experts, redundant and ambiguous items were either changed or eliminated. New items were finally accepted and included in the questionnaire. Hence, the content validity of the survey instrument was considered as appropriate. The questionnaires along with a covering letter mentioning objectives of the study were sent to various persons of government and private organizations dealing with the aviation. The specific sampling strategy was stratified random sampling. The main reasons for using a specific sampling strategy were to increase the precision in FEAT research and to reduce the sample variation and error.

This empirical study was carried out in the time period from January, 2014 to December, 2015. It took approximately 1 year of span for data gathering. The study was conducted in two parts the first part was provided with demographic information's such as; gender, working experience in organization, category of organization, title of the post and in the second part responses to the questions were based on a five-point Likert scale ranging from "1= strongly disagrees" to "5= strongly agree". The questionnaires were distributed to the 1200 participants and finally 421 the questionnaires were completed. The response rate was 35 % and out of 421 respondents 46 questionnaires were excluded due to missing data. So numbers of valid samples were 375. The majority of the respondents were male. Specifically, 288 (77 %) respondents were male and 87 (23 %) were female. One hundred twenty six (34 %) respondents were aged between 24 and 34 years, 97 (26 %) were aged between 35 and 44 years, and 65 (17 %) were

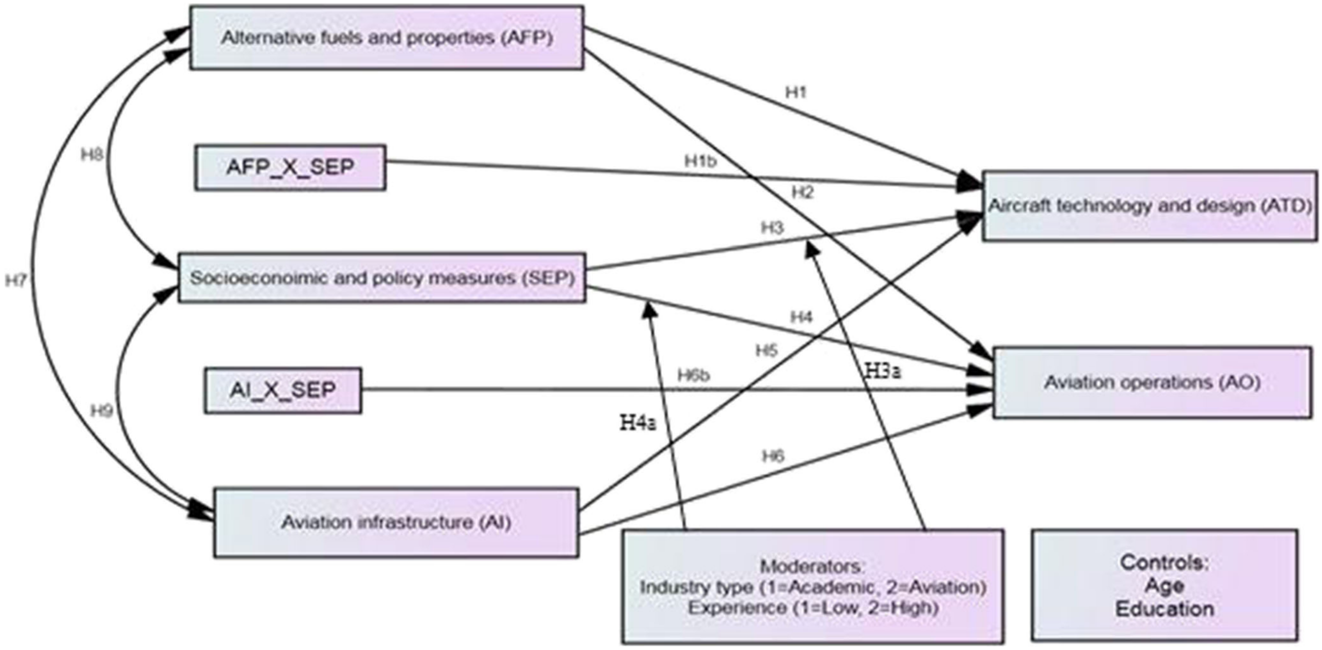


Fig. 1 Research model of FEAT

aged between 45 and 54 years. The rest were older than 55. With respect to educational level, One hundred two (27 %) respondents had the graduation degree, while 129 (34 %) had the masters degree. The rest had PhD degrees. One hundred and sixty-six (44 %) respondents were from academic organization and 209 (56 %) respondents were from aviation organization. One hundred and fifty-nine (42 %) respondents had the experience between 3 and 15 years, and 131 (26 %) had the experience between 16 and 30 years. The rest had the experience more than 31 years. In addition, the participants are divided into two major experience group i.e. low experience (between 3 and 15 years) and high experience (16 years and above). Furthermore, sample have included the occupation detail of respondents i.e. 39 directors (10 %), 63 managers (17 %), 96 research scientists (26 %), 11 aircraft pilots (3 %), 37 (10 %) professors, 48 (13 %) assoc. professors, 55 (15 %), asst. professors, 14 (4 %) lecturers, and 12 (3 %) senior lecturers. Table 1 shows the demographic characteristics of the sample.

3.2 The measuring instruments

The proposed model incorporates five constructs related to ATD, AOI, AFP, SEP, and AI. In total, 33 questions were used to measure the five constructs. Since the five constructs in the proposed model of FEAT are unobserved variables, observed variables are designed as survey instrument to measure the five constructs. The questionnaire composed of two parts. The first part was provided with demographic characteristics of the sample as shown in Table 1 and in the second part responses to the questions were based on a five-point Likert scale ranging from "1= strongly disagrees" to "5= strongly agree". The second part covers with the measurement of ATD with 4 items, AO with 8 items, SEP with 7 items, AFP with 7 items, and finally, the fifth construct with 7 items.

3.3 Techniques of data analysis

Structural equation modelling (SEM) is a multivariate technique that allows the simultaneous estimation of multiple equations comprising factor analysis, multiple regression analysis, and path model analysis [28]. SEM is a handy statistical tool for evaluating the whole set of relationships among the latent constructs that are indicated by multiple measures defining a research model and for differentiating between the indirect and direct relationships between the latent constructs [24, 73, 79].

SEM includes two types of factor: exploratory and confirmatory factor analysis. Exploratory factor analysis (EFA) is employed to obtain the structure of a set of measured data [28]. EFA assesses the construct validity during the initial development of an instrument [73]. While in confirmatory factor analysis (CFA) is used to validate the hypotheses unobserved variables and latent variables [28]. In conducting SEM analysis, EFA was used to extract the principal factors, and CFA was then employed to validate the factor structure of the FEAT elements. SEM for FEAT perception was proposed using the factor structure from the CFA results. The AMOS 20.0 software package was employed to examine CFA and SEM.

Table 1 Demographic characteristics of the sample

Demographic categories	Frequency	Percentage (%)
Gender		
Male	288	77
Female	87	23
Age (years)		
24–34	126	34
35–44	97	26
45–54	65	17
55 and above	87	23
Education level		
Graduation	102	27
Masters	129	34
Ph.D or Doctorate	144	38
Industry type		
Academics	166	44
Aviation	209	56
Experience level		
3–15	159	42
16–30	131	35
31 and above	85	23
Occupation		
Directors	39	10
Managers	63	17
Research scientists	96	26
Aircrafts pilots	11	3
Professor	37	10
Associate professors	48	13
Assistant professors	55	15
Lecturer	14	4
Senior lecturer	12	3

4 Data analysis

4.1 Data screening

Data screening is the procedure of checking the data for errors and fixing or removing these errors. We have conducted the data screening in order to ensure the data is useable, reliable, and valid for testing causal theory.

Missing data: ATD2 and AFP3 had one missing value, which we imputed with the median. Missing values, occur when no data value is stored for the variable in an observation. The missing values can arise due to carelessness in observation, errors made during data entry, data loss due to misplacement etc. We have used median imputation because ATD2 and AFP3 are an ordinal variables (were measured using a Likert scale). In addition, controlling for outliers and maintaining the normal distribution help in controlling the diversity of the data.

Normality: The normality testing used in SEM is based on the value of skewness and kurtosis [10, 28]. If the absolute kurtosis value of skewness and kurtosis is between +2 and −2, the endogenous variables normality is acceptable [10, 59]. As Table 2 displays, skewness ranges between −.047 and −1.000 and kurtosis values range between 1.967 and −.182; the absolute value of kurtosis and skewness are less than ±2. Hence, the normality of the endogenous variables is acceptable. Additionally, the standard deviation of all the items was above 0.5 on five point scale. Therefore, their responses exhibit enough variance for better analysis.

Table 2 Normality test of FEA decision variables

Decision variables	Skewness	Kurtosis	Std. Deviation
AFP1	.316	−.364	.831
AFP2	.122	−.782	.893
AFP3	.318	−.445	.885
AFP4	−.265	−.725	.927
AFP5	−.058	−.879	.946
AFP6	−.093	−.923	.955
AFP7	.069	−.637	.897
SEP1	−.699	1.019	.704
SEP2	−.724	1.374	.703
SEP3	−.590	.978	.705
SEP4	−.597	1.232	.682
SEP5	−.592	.963	.701
SEP6	−.605	1.097	.662
SEP7	−.374	−.006	.687
AI1	−.406	−.215	.927
AI2	−.456	−.182	.930
AI3	−.630	.267	.909
AI4	−1.000	1.331	.829
AI5	−.283	−.441	.956
AI6	−.665	.336	.859
AI7	−.773	.698	.861
ATD1	−.893	1.901	.670
ATD2	−.660	1.243	.650
ATD3	−.325	1.946	.549
ATD4	−.567	1.328	.631
AO1	−.739	1.048	.761
AO2	−.897	1.967	.723
AO3	−.614	1.028	.733
AO4	−.729	1.021	.762
AO5	−.690	1.124	.713
AO6	−.748	.711	.811
AO7	−.511	.728	.740
AO8	−.047	−.465	.901

4.2 Exploratory factor analysis

We conducted an EFA using maximum likelihood with promax rotation to see if the observed variables loaded together as expected, were adequately correlated, and met criteria of reliability and validity. Maximum likelihood estimation was chosen in order to determine unique variance among items and the correlation between factors, and also to remain consistent with our subsequent CFA. Maximum Likelihood also provides a goodness of fit test for the factor solution. Promax was chosen because the dataset is quite large ($n = 375$) and promax can account for the correlated factors. We have addressed each of these below for the final five-factor model depicted in the pattern matrix below.

4.2.1 Adequacy

Before conducting the exploratory factor analysis (EFA), the Bartlett's test of sphericity and Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy were used to assess the suitability of the questionnaire. The results reveal that KMO=0.937 and Bartlet's test is significant at $\alpha = 0.000$ with a Chi-square of 9779.544, indicating the suitability of conducting exploratory factor analysis, according to Kaiser [44]. After EFA, the individual items AFP1, AO6, and AO8 had the low communalities less than 0.400. Therefore, they were removed from the study.

In this study, factor loadings of 0.50 and higher will be considered practically significant [28, 30]; Lai and Chen [49]. Also, the AO1, and AO7 were not sufficiently loaded to their factor, so were also neglected. Finally, after removing these items, the communality for each item were sufficiently high (all above 0.500), thus indicating the chosen variables were adequately correlated for a factor analysis. Additionally, the reproduced matrix had only 4 % non-redundant residuals greater than 0.05, further confirming the adequacy of the variables and 5-factor model.

4.2.2 Reliability

Reliability for each of the factor was calculated using Cronbach's α coefficient. The Cronbach's α coefficient ranged from 0.849 to 0.938, as shown in Table 3. All the factors' reliability values were above the cut-off criterion of 0.7 recommended by Nunnally [60]; Hair et al. [28]; Cortina [19].

Table 3 Relibility of FEAT factors

Factor Label	Cronbach's alpha
ATD	0.892
AO	0.849
AFP	0.915
SEP	0.912
AI	0.938

4.2.3 Validity

The Table 4 below illustrates a very clean factor structure in which convergent and discriminant validity are evident by the high loadings within factors, and no cross-loadings between factors. The factors demonstrate sufficient convergent validity, as their loadings were all above the 0.600 for a samples size of 375. Table 4 shows the factor loadings for each of the factor.

Also, the factors demonstrate sufficient discriminant validity, as the correlation matrix Table 5 shows no correlations above 0.700. Finally, this five-factor model had a

Table 4 Pattern matrix

Parameters	Factor				
	1	2	3	4	5
AFP2			.802		
AFP3			.707		
AFP4			.677		
AFP5			.924		
AFP6			.929		
AFP7			.696		
SEP1	.808				
SEP2	.807				
SEP3	.946				
SEP4	.972				
SEP5	.852				
SEP6	.692				
SEP7	.668				
AI1		.662			
AI2		.866			
AI3		.823			
AI4		.868			
AI5		.842			
AI6		.788			
AI7		.886			
ATD1					.715
ATD2					.705
ATD3					.674
ATD4					.778
AO2				.825	
AO3				.902	
AO4				.754	
AO5				.716	

Extraction Method: Maximum Likelihood

Rotation Method: Promax with Kaiser Normalization

Rotation converged in 6 iterations

Table 5 Factor correlation matrix

Factor	1	2	3	4	5
1	1.000	.487	.358	.526	.550
2	.487	1.000	.528	.369	.509
3	.358	.528	1.000	.265	.408
4	.526	.369	.265	1.000	.613
5	.550	.509	.408	.613	1.000

Extraction Method: Maximum Likelihood

Rotation Method: Promax with Kaiser Normalization

total variance explained of 67.105 %, with all five extracted factors having eigenvalues above 1.0. The five factors in terms of FEAT perceptions derived from EFA were similar to those in previous studies [73, 74]. This confirmed that fuel efficiency perception can be summarized as ATD, AO, AFP, SEP, and AI.

4.3 Confirmatory factor analysis

4.3.1 Model fit

All the constructs have items with significant loadings ≥ 0.70. Modification indices were consulted to determine if there was opportunity to improve the model. Accordingly, we covaried the error terms between e2-e5, e3-4, e6-e7, e12-e13, e12-e14, e13-e14, e18-19, and e23-24. Figure 2 shows the measurement model of FEA. The Table 6 below indicates that the goodness of fit for our measurement model is sufficient.

4.3.2 Validity and reliability

- To test for convergent validity (CV) we estimated the average variance extracted (AVE). Table 7 shows that the AVE are ranging from 0.588 to 0.687, so all values are above the recommended 0.50 levels [23], indicating that the convergent validity of the measurement model is confirmed.
- To test for discriminant validity we compared the square root of the AVE (on the diagonal in the Table 7 below) to all inter-factor correlations. Table 7 shows that the mean shared variance (MSVs) < AVEs. This was significantly lower than their individual AVEs. The results have demonstrated evidence of discriminate validity for the study constructs (Table 7).
- We also computed the composite reliability (CR) for each construct. In all cases the CR was above the minimum threshold of 0.70 [28], indicating we have reliability in our constructs.

4.3.3 Common method bias

Because the data for both independent variables and dependent variables was collected using a single instrument (a survey), we conducted a common method bias test to determine if a method bias was affecting the results of our measurement model. Figure 3 shows the Common Latent Factor (CLF) based model. The test we used was the "unmeasured latent factor" method recommended by Podsakoff et al. [64] and Siemsen et al. [70] for studies that do not explicitly measure a common factor (as in this work). Comparing the standardized regression weights before and after adding the CLF shows that none of the regression weights are dramatically affected by the CLF—i.e., the deltas are less than 0.200 and the CR and AVE for each construct still meet minimum thresholds. Nevertheless, to err on the conservative side, we have opted to retain the CLF for our structural model (by imputing composites in AMOS while the CLF is present), and thus we have CMB-adjusted values.

4.3.4 Invariance tests

Since we are planning on moderating the structural model with two categorical variables, we conducted configurable and metric invariance tests.

- **Industry type:** The model fit of the unconstrained measurement models (with groups loaded separately) had adequate fit (χ^2/DF = 1.587; CFI =0.964), indicating that the model is configurally invariant. After constraining the models to be equal, we found the chi-square difference test to be significant ($p = 0.000$). Thus, our measurement model meets criteria for metric invariance across industry type as well.
- **Experience:** The model fit for experience was equally good (χ^2/DF = 1.605; CFI =0.964). The chi-square difference test was again significant ($p = 0.000$).

4.4 SEM analysis

4.4.1 Multivariate assumptions

Linearity: We tested linearity by performing curve estimation regression for all direct effects in our model. The results show that the relationships between variables are sufficiently linear (i.e., all p-values were less than 0.05).
Multicollinearity: We tested the Variable Inflation Factor (VIF) for all of the exogenous variables simultaneously. The VIFs were all less than 2.0, indicating that the exogenous variables are all distinct.

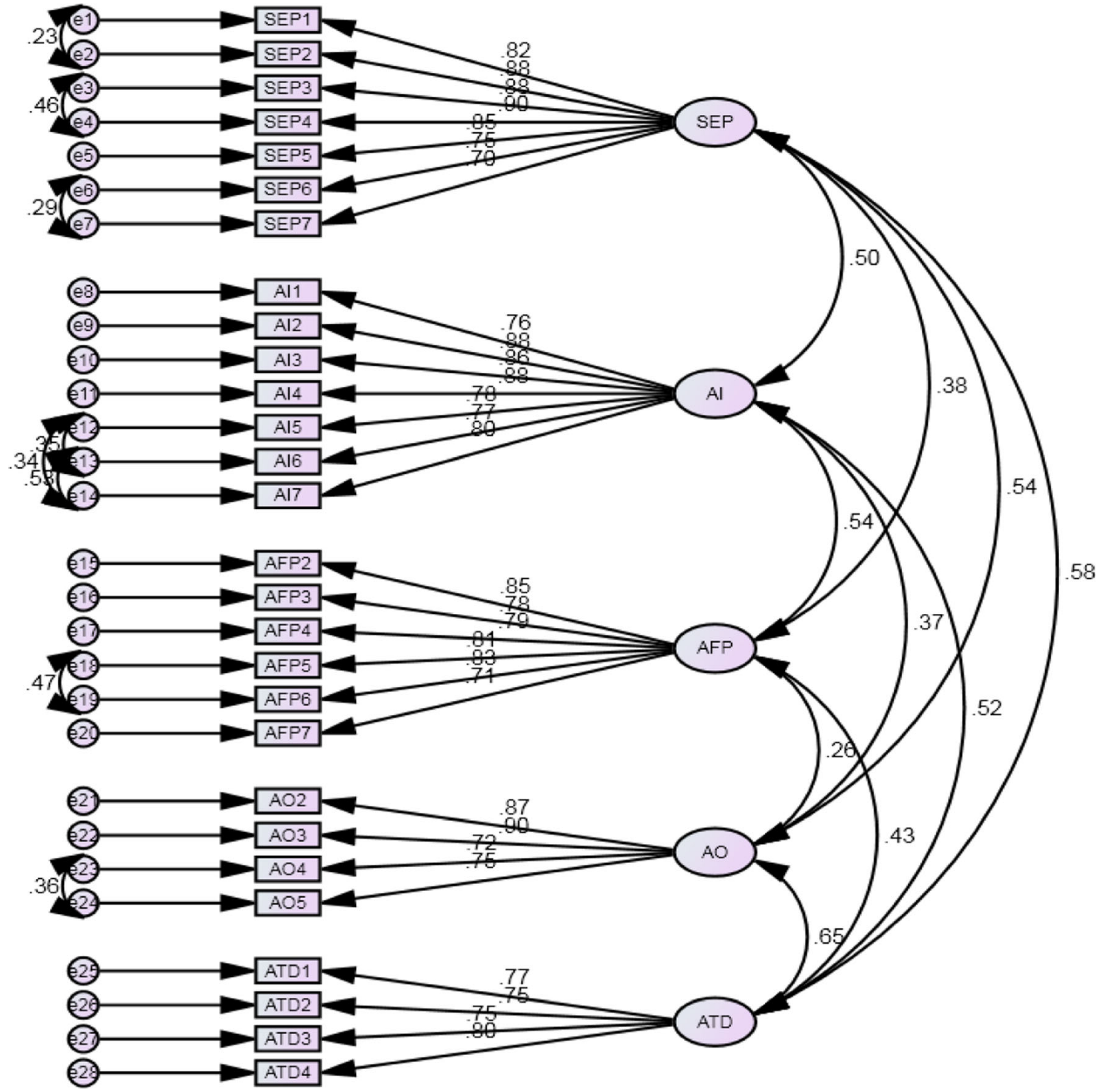


Fig. 2 Measurement model of FEAT

Table 6 Goodness of fit statistics in CFA

Indices	Abbreviation	Observed values	Recommended criteria	References
Chi square	χ^2	578.677	pval>0.05	Hair et al. [28];
Normed chi square	χ^2/DF	1.743	$1<\chi^2/df<3$	Byrne [10];
Goodness-of-fit index	GFI	0.904	>0.90	Hu and Bentler [35];
Adjusted GFI	AGFI	0.883	>0.80	Jöreskog and Sörbom [43]
Normed fit index	NFI	0.933	>0.90	
Comparative fit index	CFI	0.970	>0.95	
Root mean square error of approximation	RMESA	0.045	<0.05 good fit <0.08 acceptable fit	
Tucker-Lewis index	TLI	0.966	0<TLI<1	

Table 7 Reliability and validity in CFA

	CR	AVE	MSV	ASV	AO	SEP	AI	AFP	ATD
AO	0.884	0.658	0.423	0.230	0.811				
SEP	0.938	0.687	0.339	0.256	0.541	0.829			
AI	0.934	0.669	0.296	0.240	0.369	0.502	0.818		
AFP	0.912	0.634	0.296	0.174	0.262	0.377	0.544	0.796	
ATD	0.851	0.588	0.423	0.306	0.650	0.582	0.524	0.434	0.767

Note; For Composite reliability (CR>.70); Convergent validity (CR>AVE>.50); Discriminate validity (MSV<AVE); *MSV* Maximum shared variance, *ASV* Average shared variance [28]

4.4.2 Model fit of structural model

Figure 4 displays the outcomes of the initial structured model with standardized parameters while controlling for age, and education for DVs. The fitted structural model demonstrates adequate fit. In order to achieve good fit, we additionally covaried the error terms of the DVs and controls, as we wanted to account for their correlation without adding theoretical complexity to our model. While there may exist causal relationships between these variables, this is not the focus of this model. Table 8 shows the Goodness of fit statistics of structural model. Additionally, the controls did not have a significant impact on either dependent variable, except the respondents age had a slight negative effect on ATD and AO (standardized beta for ATD and AO = −0.018*, −0.003*).

4.4.3 Hypotheses testing of the research model

All hypotheses were tested while controlling for age, and education. Controlling for variables that may influence the relationship between ATD, AO, AFP, SEP, and AI helps to minimize unrelated effects. Furthermore, it helps to improve the robustness and validity of the results.

The relationship between two DVs, i.e., ATD, AO and three IVs, i.e., AFP, SEP, AI is determined by the proposed model. The proposed model hypotheses that the ATD, AO, and AFP, SEP, and AI are directly and indirectly interrelated. The standardized path loadings and their statistical significance are shown in Table 8. It was found that nine paths out of fourteen specific hypotheses were statistically significant except for H2, H5, H9, H1b, and H6b.

The path coefficients in the SEM are shown in Fig. 5 and the results of the hypothesis testing are summarized in Table 9. Table 9 show that hypothesis H1 is supported, because AFP has a positive impact on ATD ($\beta = 0.101$, $p < 0.01$). This implies that selection of suitable AFP depends upon the development of ATD, which contributes to the improvement of air transport fuel efficiency. Hence, this confirms that H1 is supported. Also, the path coefficient between AFP and AO is

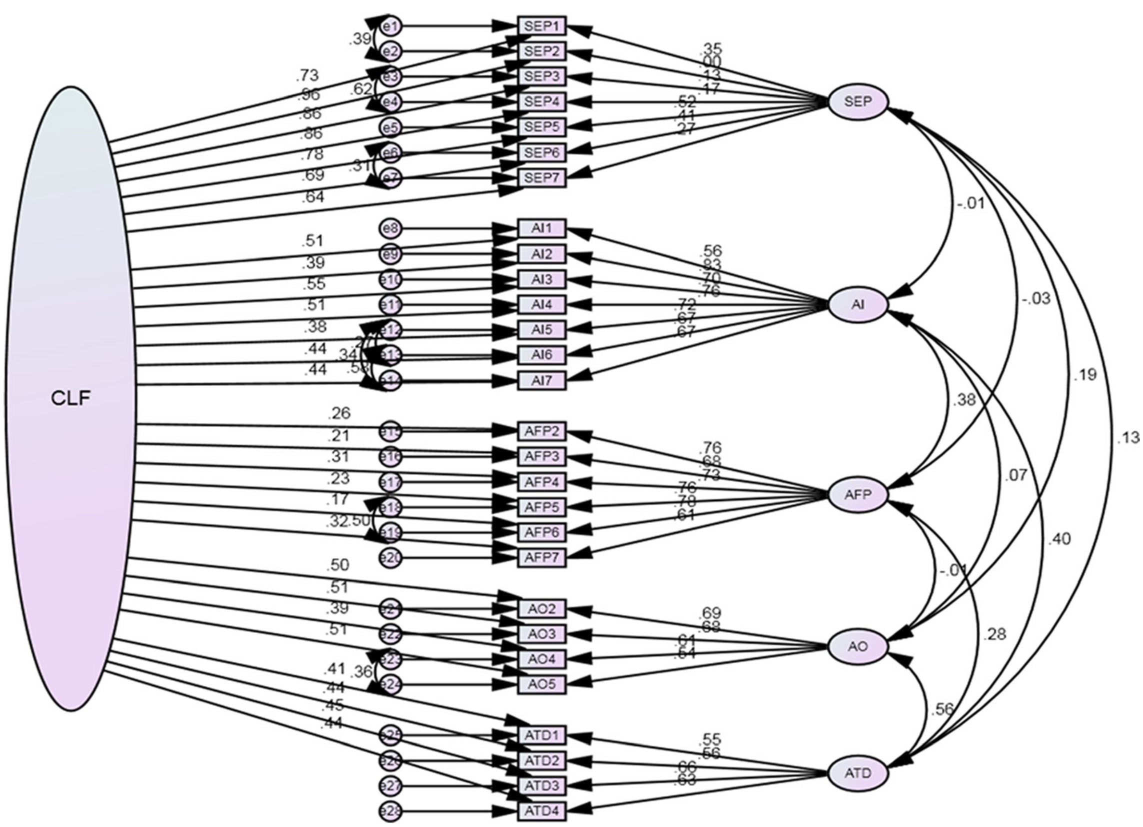


Fig. 3 The Common Latent Factor (CLF) based model of FEA

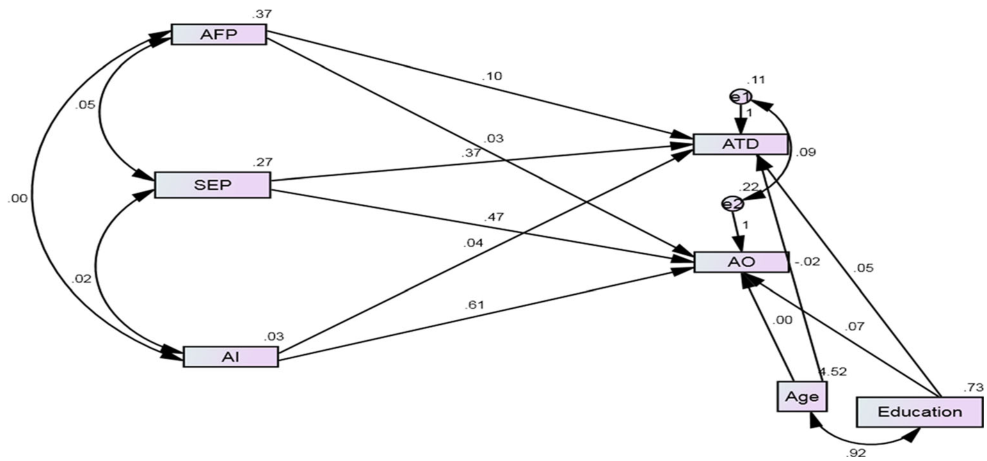


Fig. 4 Initial structural model of FEAT

0.035 ($p > 0.05$), which is a positive but not significant relation, indicating that AFP has no significant positive impact on AO. This confirms that H2 is not supported. The path coefficient between SEP and ATD is 0.368 ($p < 0.01$), which is a significant positive correlation, indicating that when air transport adopt and implement the SEP measures for ATD, their adoption and implementation increases fuel efficiency of airlines, which supports hypothesis H3.

The path coefficient between SEP and AO is 0.0467 ($p < 0.01$), which is a significant positive correlation, indicating that when air transport regulate and implement the SEP measures for optimal AO, their regulation and implementation increases fuel efficiency of airlines, which supports hypothesis H4. The path coefficient between AI and ATD is 0.042 ($p > 0.05$), which is a positive but not significant correlation, indicating that AI has no significant positive impact on ATD. This confirms that H5 is not supported. The path coefficient between AI and AO is 0.609 ($p < 0.01$), which is a significant positive correlation, indicating that proper planned AI increases the productivity of AO, which contributes to the improved fuel efficiency. Hence, this confirms that H6 is supported.

Also, the correlation between SEP and AFP, and SEP and AI were found to be positive ($\beta = 0.053$; 0.025) and significant ($p < 0.01$), and this confirms the results of previous study [73]. This indicates that the suitable amounts of SEP measures are necessary for AFP adoption and for the development of AI, which contribute to the improved fuel efficiency. Therefore, the hypothesis H7 and H8 are supported. Finally, AFP had no significant ($\beta = 0.003$, $p > 0.1$) effects on the AI. This is somewhat at odds with previous study [73] showing that AFP had a correlation with the AI. This difference occurs because the AFP in this study was dominantly produced from near term synthetic fuels. So, there is no need to change the existing AI. This confirms that hypotheses H9 is not supported.

Multi-group moderation Multi-group moderation tests were conducted using the full model, but prior to adding the interaction variables. To test the categorical moderation hypotheses, we produced the critical ratios for the differences in regression weights between groups of industry type (academic, aviation) and experience (low, high). From these critical ratios we calculated p-values to determine the significance of the difference. The results are summarized in the hypotheses summary Table 9 below. The results in Table 8 indicated that SEP significantly and positively affected ATD for the both academic ($\beta = 0.268$, $p < 0.01$) and aviation ($\beta = 0.515$, $p < 0.01$) group respondents. This has also showed that the effect of SEP on ATD were stronger for aviation group than the academic group. Therefore, the hypothesis H3a is supported.

Table 8 Goodness of fit statistics of structural model

Indices	Abbreviation	Observed values	Recommended criteria	References
Normed chi square	χ^2/DF	1.624	$1<\chi^2/df<3$	Hair et al. [28];
Goodness-of-fit index	GFI	0.993	>0.90	Byrne (2013);
Adjusted GFI	AGFI	0.966	>0.80	Hu and Bentler [35];
Normed fit index	NFI	0.983	>0.90	Jöreskog and Sörbom [43]
Comparative fit index	CFI	0.993	>0.95	
Root mean square error of approximation	RMESA	0.041	<0.05 good fit <0.08 acceptable fit	
Tucker-Lewis index	TLI	0.976	0<TLI<1	

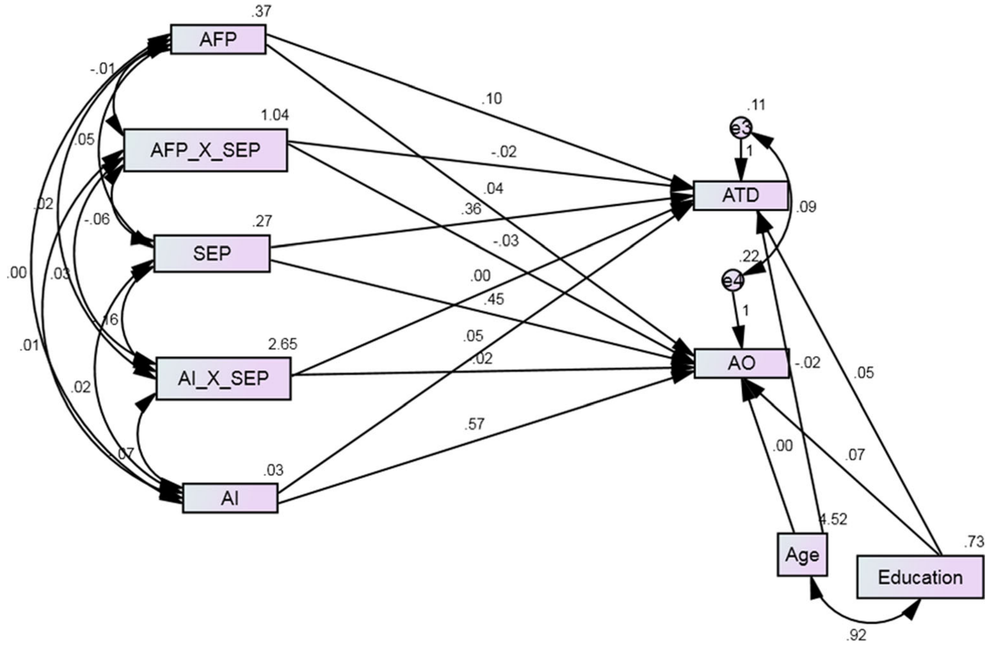


Fig. 5 Structural model test results

Furthermore, the results showed that SEP significantly and positively affected AO for both low ($\beta = 0.380$, $p < 0.01$) and high ($\beta = 0.618$, $p < 0.01$) experienced respondents. This has also showed that the effect of SEP on AO were stronger for highly experienced group than the low experienced group. Therefore, the hypothesis H4a is supported.

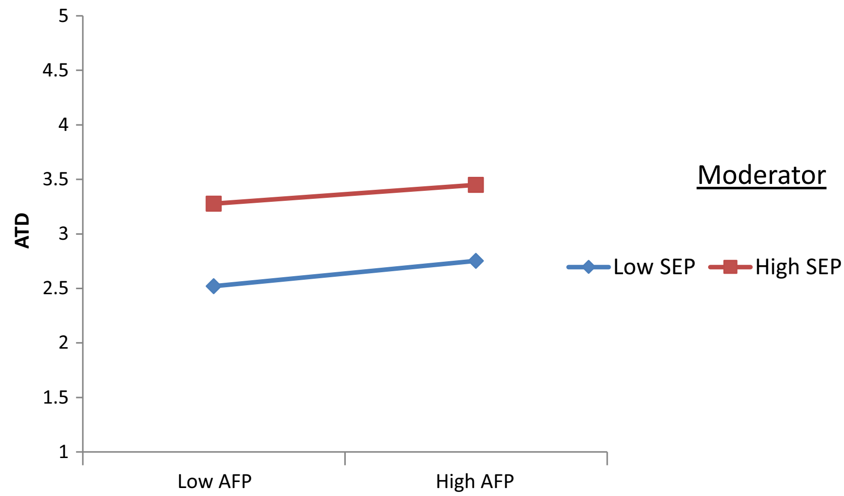
Table 9 Hypotheses summary table

Hypotheses	Evidence	Supported?
H1: AFP → ATD	0.101***	Yes
H2: AFP → AO	0.035 (ns)	Not
H3: SEP → ATD	0.368***	Yes
H4: SEP → AO	0.0467***	Yes
H5: AI → ATD	0.042 (ns)	Not
H6: AI → AO	0.609***	Yes
H7: SEP → AFP	0.053***	Yes
H8: SEP → AI	0.025***	Yes
H9: AFP → AI	0.003 (ns)	Not
Multi-group moderation		
H3a: Industry type moderates the positive effect of SEP on ATD that such the effect is stronger for aviation industry respondents.	Academic:0.268*** Aviation:0.515*** ΔZscore:3.57***	Yes: Stronger for aviation respondents
H4a: Experience moderates the positive effect of SEP on AO such that the effect is stronger for higher experience.	Experience low: 0.380*** Experience high:0.618*** ΔZscore:2.437***	Yes: Stronger for more experienced respondents
Interaction		
H1b: An increase in SEP will strengthen the negative relationship between ATD and AFP.	Interaction effect: −0.015	Not
H6b: An increase in SEP will strengthen the negative relationship between AO and AI.	Interaction effect: −0.022	Not

ns Not significant

*** p-value < 0.01; ** p-value < 0.05

Fig. 6 Interaction between the AFP and SEP



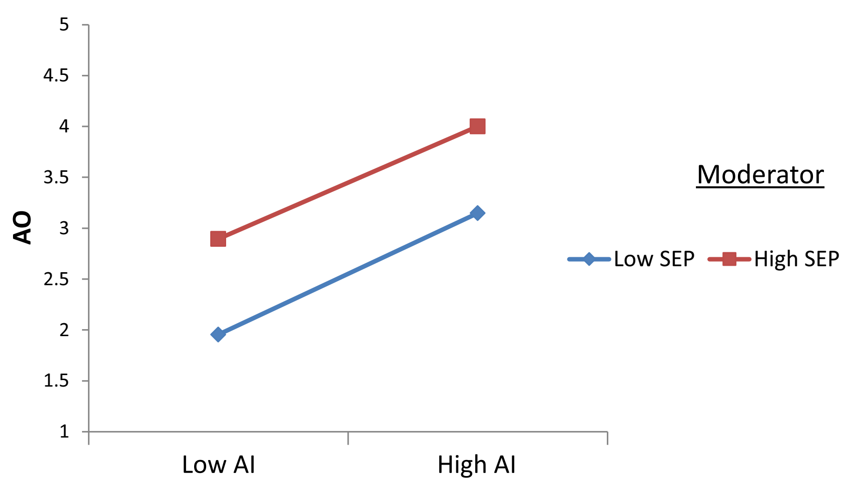
Two way interactions Interaction effects were tested using the full dataset, rather than the moderated dataset. To test the interaction hypotheses we first standardized the IVs and then created product variables. In this case, none of the interactions were significant. We plotted these interactions as shown in Figs. 6 and 7. When effect of SEP is low, then there is positive relationship between ATD and AFP as shown in Fig. 6. But, when the effect of SEP is high, then there is negative relationship between ATD and AFP. So, SEP dampens the positive relationship between ATD and AFP. Thus, the hypothesis H1b is not supported. Furthermore, when effect of SEP is low, then there is positive relationship between AO and AI as shown in Fig. 7. But, when the effect of SEP is high, then there is negative relationship between AO and AI. So, SEP dampens the positive relationship between AO and AI. Thus, the hypothesis H6b is not supported. Also, the results of the interaction tests are summarized in the Hypothesis Summary table below. Additionally, we observed that model fit was very good (χ^2/DF = 1.078; CFI = 0.999; GFI = 994; RMSEA = 0.014) for the final moderated model.

5 Conclusions and implications

The study contributes to the extant literature as the instrument employed was effective in evaluating fuel efficiency in air transport and can therefore be confidently used again in FEAT related studies. This study attempts to identify the key FEAT-related factors. The results show that the key fuel efficiency improvement related factors in the air transport can be represented by five constructs (measured by 28 items), and this confirms the results of previous studies [73, 74], although, some of measured items were different. The results of this study supported the new inclusions and casual relations in the FEAT model. The effect of new inclusions and casual relations has not been examined in previous studies.

The SEM analysis showed that AFP had a significant and positive ($\beta = 0.101$, $p < 0.01$) effect on ATD. This indicates that when we adopt new alternative fuel, air transport need to strengthen ATD for fuel efficiency improvement. The contributions of AFP and AO on fuel efficiency improvements were positive but not significant ($\beta = 0.035$, $p > 0.05$). This means

Fig. 7 Interaction between the AI and SEP



that there is no need to change the aviation operations on the adoption of new alternative fuel. The selection of new aviation alternative will on near term synthetic fuels. SEP had a significant positive effect ($\beta = 0.368$, $p < 0.01$) on ATD. This means that SEP strategies are very important in determining the technological potentials for fuel efficiency improvement. Also, SEP had a significant positive effect ($\beta = 0.0467$, $p < 0.01$) on AO. This implies that regulation and implementation of suitable SEP measures are necessary for optimal AO. AI had a positive but not significant ($\beta = 0.042$, $p = 0.675$) relation with the ATD. This implies that AI are necessary for improved ATD, hence, for fuel efficiency. In addition, AI had a significant positive ($\beta = 0.609$, $p > 0.01$) effect on AO. This means that AI developments are very important for fuel efficient aircraft operations.

The moderating effect of industry type (academic, aviation) on SEP and ATD was also found to be positive and significant (academic = 0.268, aviation = 0.515, ΔZscore = 3.57, $p < 0.01$). The effect of SEP on ATD was stronger for aviation respondents than the academic respondents. This implies that the aviation respondents are well aware of the fuel efficiency aspects than the academics respondents. Also, this supports the validity of our FEAT model. Therefore, different levels of working environment will produce markedly different results in different modelling perspectives. In addition, The moderating effect of experience (low, high) on SEP and AO was also found to be positive and significant (low experienced = 0.380, high experienced = 0.618, ΔZscore = 2.437, $p < 0.01$). The effect of SEP on AO was stronger for more experienced respondents than the low experienced respondents. Nonetheless, it is important to consider both experience levels since this makes it possible to identify the difference between the moderation effects on the direct relationship between SEP and AO. After grouping the users according to their level of experience, in each group there should be respondents with both high and low experience. Nevertheless, when users are divided according to their level of aviation research experience, it is necessary to consider a source of bias—those users with high aviation research experience will have a more clear, and enduring attitude towards FEAT improvement.

We did not find clear support for the hypothesis on the two-way interaction between SEP and AFP on ATD. We also did not find evidence for our hypothesis on the two-way interaction of SEP and AI on AO. This implies that high SEP measures put pressure on airlines for fuel efficiency improvement; so optimum SEP measures are necessary. Since fuel efficiency is primarily evaluated by factors such as ATD and AO, policy makers and transportation researchers need to focus on changing the built environment in a way that does not promote extreme SEP measures.

This study, however, had one major limitation which must be noted. One is common to all survey research: a possible self reporting bias: some of the variables were self-reported. Future studies can also include some of the variables which were not included in this study, such as aircraft size, wing span, tail areas, engine fan pressure ratio, engine turbine inlet temperature, initial cruise altitude, final cruise altitude, community awareness, viscosity, and storage stability. Furthermore, around 56 % of samples have drawn from aviation firms, in the future, the sample size of airline industry insiders can be improved for more aviation industry specific model of ERP. The finding of the study will help aircraft manufacturer & airlines to frame their criteria regarding fuel efficiency improvement in air transport. The air transport sector can also prioritize the criteria on which they should focus in order to improve their performance. Finally, for improving the fuel efficiency from aviation the policy makers should focus on five dimensions & their relationship. Also, they should encourage for continued investment in airframe and engine technology. Furthermore, the policy makers should introduce appropriate policies and incentives for sustainable alternative fuels, improved air traffic management and airport infrastructure, and more efficient operations of aircraft.

Appendix

Table 10 Description of FEAT decision variables

Decision variables	Description of decision variables
ATD1	Thrust specific fuel consumption
ATD2	Lift/drag ratio
ATD3	Operating empty weight
ATD4	Maximum takeoff weight
AO1	Takeoff filed length
AO2	Aircraft range
AO3	Fuel weight
AO4	Payload,
AO5	Aircraft speed
AO6	Crew weight
AO7	Reserve fuel weight
AO8	Landing filed length
AFP1	Fuel availability
AFP2	Net calorific value
AFP3	Energy density
AFP4	Aromatic content,
AFP5	Carbon content,
AFP6	Thermal stability
AFP7	Flash point
SEP1	Social demand
SEP2	Fuel cost
SEP3	Voluntary measures
SEP4	Demand shift
SEP5	Passenger load factor
SEP6	Charging carbon emission, and
SEP7	Taxing aviation fuel
AI1	Origin airport
AI2	Destination airport
AI3	Flight profile
AI4	Runway design
AI5	Taxiway
AI6	Apron
AI7	Weather conditions

Survey instrument of FEAT study

Part 1: Respondents demographic information

1.	Gender	Male- ☐	Female- ☐	
2.	Age (Years)	24-34 -☐ 35-44 - ☐	45-54 - ☐	55 and Above - ☐
3.	Education level	Graduation - ☐	Post-graduation-☐	Doctorate- ☐
4.	Industry type	Academics - ☐	Aviation- ☐	
5.	Experience level	3-15 -☐	16-30 - ☐	31and Above - ☐
6.	Occupation	Director- ☐ Manager- ☐ Research Scientist-☐	Aircraft Pilot-☐ Professor-☐ Associate Professor-☐	Assistant Professor-☐ Lecturer-☐ Senior Lecturer -☐

Part 2: Survey questionnaire

You are requested to kindly weight these variables on five point likert scale for exploring importance rating in fuel consumption optimization in air transport sector.
Key: (1) Strongly Disagree (2) Disagree (3) Undecided (4) Agree (5) Strongly Agree

Decision Variable	Unimportant ⟷ Very important
Aircraft technology & design	
1. Thrust specific fuel consumption	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
2. Lift/drag ratio	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
3. Operating empty weight	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
4. Maximum takeoff weight	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
Aviation operations	
5. Takeoff filed length	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
6. Aircraft range	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
7. Fuel weight	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
8. Payload,	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
9. Aircraft speed	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
10. Crew weight	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
11. Reserve fuel weight	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
12. Landing filed length	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
Aviation alternative fuels & properties	
13. Fuel availability	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
14. Net calorific value	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
15. Energy density	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
16. Aromatic content,	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
17. Carbon content,	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
18. Thermal stability	
19. Flash point	
Socioeconomic & policy measures	
20. Social demand	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
21. Fuel cost	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
22. Voluntary measures	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
23. Demand shift	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
24. Passenger load factor	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
25. Charging carbon emission, and	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
26. Taxing aviation fuel	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
Aviation infrastructure	
27. Origin airport	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
28. Destination airport	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
29. Flight profile	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
30. Runway design	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
31. Taxiway	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
32. Apron	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐
33. Weather conditions	(1) ☐ (2) ☐ (3) ☐ (4) ☐ (5) ☐

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