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Factorial Validity of the Flight Risk Assessment Tool in General Aviation Operations

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Abstract

The Flight Risk Assessment Tool (FRAT) was developed and is recommended by the Federal Aviation Administration to provide a solution of proactively identifying and mitigating risk before each flight. General aviation (GA) operators are encouraged to adapt the FRAT based upon specific operational characteristics. Currently, most safety management systems-compliant GA operators have implemented various versions of FRATs with different operational purposes. However, the FRAT could be inappropriately implemented because of the dynamic operational features of GA operations. The purpose of this study is to explore insights into potential approaches to validate the FRAT that is used for flight risk assessment in routine GA operations. A FRAT from a flight school regulated under Title 14 Code of Federal Regulations Part 141 was used as a study case. In total, 1,832 sets of FRAT data were collected from flight operations between November 2016 and February 2017. Confirmatory factor analysis (CFA) was adopted in this research. The CFA results indicated that the studied FRAT model did not provide good fit with the root mean square error of approximation (RMSEA) = 0.13, standardized root mean square residual (SRMR) = 0.08, comparative fit index (CFI) = 0.98, and Tucker–Lewis index (TLI) = 0.98. Based on the modification indices, the studied FRAT model was restructured by removing 11 risk items from the original 33 risk items. The new model fitted the data acceptably (RMSEA = 0.07, SRMR = 0.05, TLI = 0.76, CFI = 0.69). In addition, implications and directions for further study are discussed.

Keywords: flight risk assessment, aviation safety, aviation risk management

Introduction

Air transportation plays a critical role in driving the growth of the global economy. To maintain healthy development of the air transport industry, adequate efforts must be invested in safety, security, efficiency, and sustainability of flight operations at the global, national, and regional levels (International Civil Aviation Organization [ICAO], 2016). With the continuous development of aviation technology and managerial strategies, the overall safety of commercial air transport

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services has been enhanced dramatically over the past few decades (National Transportation Safety Board [NTSB], 2014). As a major component of civil aviation, the general aviation (GA) accident rate has indicated a decreasing trend over the last few decades, but there were still 1,233 GA accidents which involved 331 fatalities within the United States in 2017 (NTSB, 2019).

Improvement of GA flight safety has been a challenge for many years due to a variety of limitations of GA operations, such as an aged GA fleet, large scope of operational purposes, and diverse pilot demographics. To enhance GA safety, the safety management system is recommended by ICAO, which should practically have the functions of identifying safety hazards, assessing the associated risk levels, developing and implementing remedial actions, and continuously monitoring and regularly assessing the appropriateness and effectiveness of safety management activities (ICAO, 2018). However, considering that GA accidents share fewer common accident causes presently, it becomes more difficult to further enhance flight safety by analyzing past aircraft accidents to develop preventive measures reactively (ICAO, 2018). Therefore, ICAO encourages aviation stakeholders to develop and implement more proactive approaches to supplement traditional reactive safety management (ICAO, 2018). A proactive safety management approach is accomplished by routinely collecting and analyzing safety-related data and identifying and mitigating the associated risk issues (ICAO, 2013; Maurino, Reason, Johnston, & Lee, 1995).

The Flight Risk Assessment Tool (FRAT) was developed and is recommended by the Federal Aviation Administration (FAA) as a proactive risk identification and mitigation strategy (FAA, 2016). As a proactive safety tool, the FRAT enables pre-flight hazard identification and risk assessment, and assists pilots to make better go/no-go decisions before each flight. Similar to other proactive safety management strategies, the FRAT was particularly developed for the GA community to improve flight safety. As per the FRAT instruction from the FAA, GA operators could flexibly modify the standard FRAT to better fit specific operational characteristics as needed (FAA, 2016). Currently, most safety management system-compliant GA operators have implemented various versions of FRATs for pre-flight risk assessment. However, there is no guideline or publication providing best practices of modifying the FRAT for GA operations. Therefore, the FRAT could be inappropriately modified and ineffectively used in flight risk assessment. The purpose of this study was to explore insights into potential approaches to validate the fitness of modified FRATs in routine GA flight risk assessment.

Literature Review

Hazards are intrinsic components of flight operations. Through appropriate risk management processes, the associated flight risk is expected to be identified and possibly reduced to an acceptable level. In general, the risk management process is comprised of three steps: hazard identification, risk assessment, and risk mitigation and monitoring. The hazard identification process allows relevant personnel to identify hazards in a proactive manner. Once hazards have been identified, associated risk level should be evaluated in the process of risk assessment. The risk assessment process involves analyses of the likelihood and severity of identified hazards. From the perspective of pilots, risk assessment is a key component of the aeronautical decision-making process (FAA, 2016). Risks evaluated as being unacceptable must be mitigated before a flight to reduce the severity and/or the likelihood of an undesired bad outcome. Pilots should suspend flight activities associated with intolerable flight risks. For the last step, appropriate mitigation measures should be developed and implemented based upon the assessed flight risk.

Hazard identification and risk assessment have been used as effective strategies to mitigate risk in many areas. In aviation, a variety of approaches are being used by aviation operators and organizations to identify and evaluate flight risk. One of the most popular approaches to study aviation risk is to analyze historical accident data to identify and estimate the likelihood and severity of risk events. For example, the European Space Agency's risk assessment strategy is based on the probabilistic evaluation of aircraft accidents or incidents as the basis of risk management (Preyssl, 1995). Janic (2000) and Lee (2006) presented probabilistic models for risk assessment by treating the pattern of accidents as a Poisson process. Shyur (2008) developed a specified proportional hazard model considering the baseline hazard function as a quadratic spline function to quantify human error-related risk. Those approaches provide insights into overall risk level and safety status of fleet operations relying on historical accident data analysis. This is usually regarded as post-flight risk assessment.

Pre-flight risk assessment is another type of strategy highly encouraged by ICAO to assist pilots in making the right decision by evaluating the risk for each flight (ICAO, 2013). One example of pre-flight risk assessment is use of the Pre-flight Risk Assessment Score (PRAS). The PRAS is a tool used to assess flight risk factors such as pilot experience, operational environment, and human factors. A pilot uses the go or no-go decision matrix to understand the flight risk and make the corresponding flight decision. The PRAS is recommended by the FAA for Helicopter Emergency Medical Service to help pilots assess flight risk. The use of the PRAS is also mandatory for Civil Air Patrol flight operations (Thomas, Groke, & Handrahan, 2011; U.S. Civil Air Patrol, 2018).

To promote pre-flight risk assessment in GA, the FAA facilitated the development of the FRAT through the General Aviation Joint Steering Committee for GA pilot

Table 1
A simplified example of FRAT, adapted from the FAA Information for Operators 07015 (FAA, 2007).

		Risk value	Assessed value
Pilot qualifications and experience			
1	Captain with less than 200 hours in type	5	
2	First Officer with less than 200 hours in type	5	
3	Single pilot flight	5	
Operating environment			
4	VOR/GPS/LOC/ADF (best approach available w/o vertical guidance)	3	
5	Circling approach (best available approach)	4	
6	No published approaches	4	
Equipment			
7	Special flight permit operation	3	
8	MEL/CDL items (items related to safety of flight)	2	
9	Special flight limitations based on AFM equipment limitations	2	
Total factor score			

pre-flight risk assessment (see Table 1) (FAA, 2016). As an outcome of the FAA Safety Enhancement Project 42, the FRAT is expected to enable proactive hazard identification and risk assessment, helping pilots make better go/no-go decisions before each flight (FAA, 2016).

As shown in Table 1, the FRAT lists a series of questions designed to identify and quantify risk level for each flight. The current version of FRAT proposed by the FAA Safety Team (FAAST) is based on the PAVE checklist, covering questions from the perspectives of pilot, aircraft, environment, and external pressure (FAA, 2016). The risk of each flight is evaluated by filling out of the FRAT by pilots. Pilots are expected to check all applicable items before each flight. A risk value is predetermined for each item and counts into the total factor score if the item is checked. The total factor score will be used to indicate the general risk level for a specific flight. Therefore, operators would have an overall view of the risk level and could call off a flight if necessary.

Problem Statement

It is critical for pilots to identify hazards and have knowledge of the associated risk level so that effective mitigation strategies and right decisions could be made for flight operations. The FAA recommends that operators and pilots familiarize themselves with the FAAST-proposed FRAT and the Advisory Circular 120-92B to decide to use either the FAAST's FRAT or a modified version based on specific operational characteristics (FAA, 2007). Currently, various versions of FRATs have been adopted and used by GA operators in routine operations. For instance, in comparison with the FAAST's FRAT which assesses the risk level from the perspectives of pilot, aircraft, environment, and external pressure, flight training schools may modify FRATs to incorporate additional risk items and different predefined risk values to better fit flight training operational features. However, there are no guidelines or literature to date regarding how to adapt the FRAT in routine flight operations. Given the current situation whereby the FRAT could be modified by operators with no instruction or official guideline, it is possible that the FRAT could be inappropriately modified and used in routine flight risk assessment. Therefore, it is crucial to investigate whether the FRAT is appropriately modified to fit operational characteristics as the operator wishes. The purpose of this study is to explore insights into potential approaches to validate the FRAT in GA operations by analyzing collected FRAT flight risk data from Purdue University from November 2016 to February 2017.

Methodology

This section introduces the methods used in this study to explore the use of confirmatory factor analysis (CFA) for validating the fitness of modified FRATs in daily hazard identification and flight risk assessment. A modified FRAT based on the FAA publication was implemented for hazard identification and flight risk assessment in daily flight operations at Purdue University. Available FRAT data from November 2016 to February 2017 were retrieved from the Purdue fleet operations center for analyses. CFA is a type of structural equation modeling specifically working with measurement models, which could be used to investigate the relationships between observed measures and latent variables (Brown, 2014). CFA is one of the most used statistical procedures to test whether a hypothesized model fits the measured data (Kline, 2010). Numerous studies can be found on the application of CFA to evaluate the fit of a hypothesized framework to collected data or to validate models. In this study, CFA was adopted to evaluate whether the modified FRAT legitimately assesses flight risk in daily flight operations. The studied FRAT model works as the pre-specified hypothesized model; CFA was applied to validate whether this FRAT fits the collected data from flight operations.

The FRAT of the Empirical Field

As described in the FAA Information for Operators 07015 and Advisory Circular 120-92B, it is up to an operator to adapt a specific version of FRAT in routine flight risk assessment. In this study, Purdue University professional flight training fleet operations were used as the empirical field. A modified FRAT (see Table 2) was developed and implemented by the Purdue fleet operation center for routine hazard identification and flight risk assessment. The specific risk items and values were determined by relevant flight safety personnel. This FRAT and collected flight risk assessment data were analyzed as a study case for factorial validity using CFA.

The studied FRAT, shown in Table 2, must be filled out by pilots before each flight, without knowing the risk value of each item. The value of each item adds up to the total factor score to indicate the overall risk level of the assessed flight. Purdue flight safety rules require pilots to call off a flight if the total factor score is higher than the threshold of 16 points.

Data Analysis

In this research project, CFA was explored to validate the studied FRAT. Items of the studied FRAT are observed measures. The upper level perspectives (pre-flight information, flight operations, weather, and training flights) of flight risk assessment could be regarded as latent variables (Figure 1).

In Figure 1, all ellipses represent unmeasured variables. The large ellipses are latent factors, whereas the smaller ellipses are errors of measurement. The rectangles stand for the measured variables, which are the items to be assessed

Table 2
The FRAT used at the empirical field.

		Risk Value	Flight Value
Pre-flight information			
1	Solo flight (pre-private)	1	
2	Student less than 50 flight hours	2	
3	Student 50–150 flight hours	1	
4	Instructor's first semester teaching	1	
5	Instructor has CFII or MEI	−1[a]	
6	Stress factor	2	
Flight operations			
7	Runway less than 4000 feet	2	
8	Night landing	1	
9	No precision approaches available at destination (IFR only)	2	
10	Non-towered airport	2	
11	Unfamiliar airport (departure)	2	
12	Unfamiliar airport (destination)	2	
13	Class C operations	1	
14	Student has not flown in the last 2 weeks	2	
15	Last sleep period (less than 4 hours)	3	
16	Last sleep period (4 to 6 hours)	2	
17	Last sleep period (6 to 8 hours)	1	
18	Show time (between 7 and 8 a.m.)	2	
19	Show time (after 6 p.m.)	3	
20	Maintenance test flight	3	
21	First flight after a Phase or 50hr inspection	3	
Weather			
22	Departure—MVFR	1	
23	Departure—IFR	2	
24	En route—turbulence forecasted along route	1	
25	En route—thunderstorm forecasted	2	
26	Arrival—MVFR	1	
27	Arrival—IFR	2	
28	Arrival—winds $>$ 15 knots	1	
Training flights			
29	Behind flight schedule	2	
30	Flying multiple approaches	2	
31	Pattern work	1	
32	Instructor or student back-to-back training	1	
33	Class immediately before/after flight	1	
Total factor score			

Note. This version of FRAT is for the use of piston-engine aircraft operations.
[a]Negative value indicates that the corresponding item contributes to mitigating the overall flight risk.

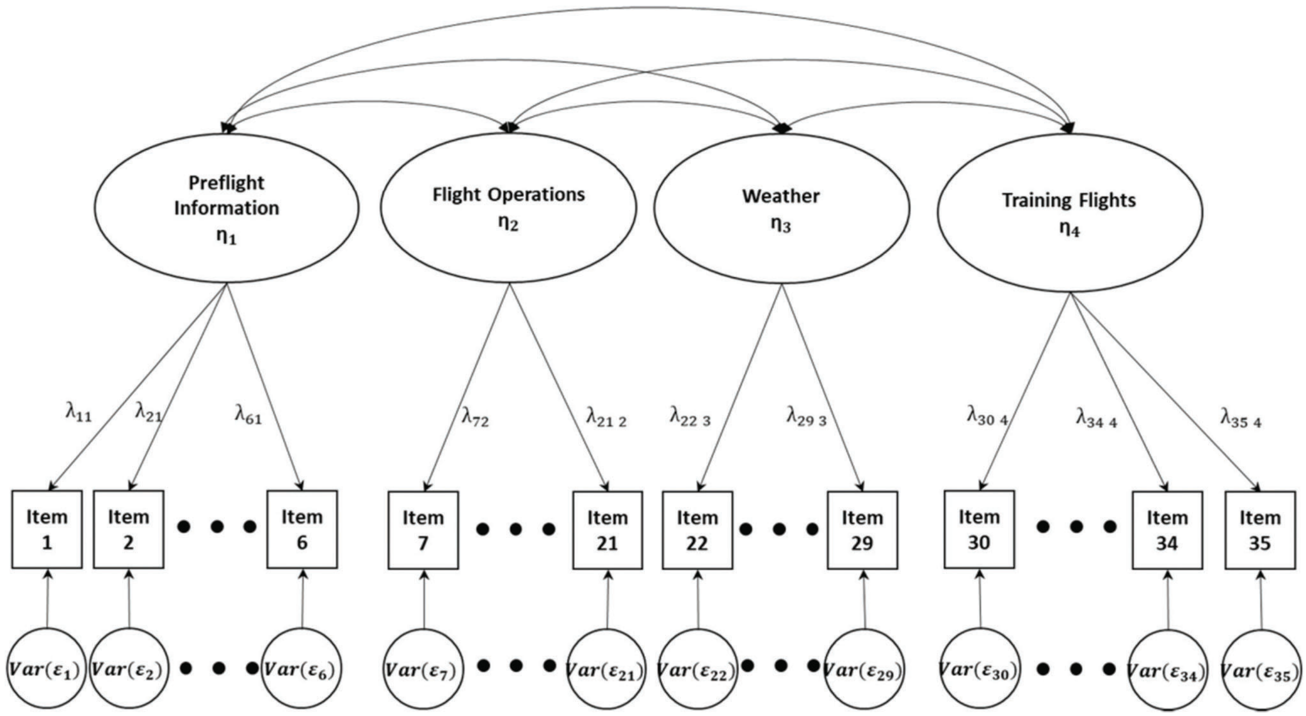

Figure 1. The path diagram of the selected FRAT using CFA.

in the FRAT. The single-headed arrows are causal influences. The two-headed arrows associated with the latent variables represent variances, while η_k ($k = 1, 2, 3, 4$) represents the latent factors. $\lambda_{i,j}$ represents the factor loading that item i loads on factor j and Var(ε_i) represents the error variance of item i (MacCallum, 1995; McArdle & Boker, 1990).

Like a factor in CFA, a construct is a theoretical concept. For instance, pilot qualification and experience is a construct manifested by eight items in the FAAST FRAT. Different from correlation, multiple regression assumes that variables are free of measurement error. The fundamental asset of CFA in construct validation is that the resulting estimates are adjusted for measurement error. Therefore, CFA is expected to provide a stronger analytic result compared to traditional methods that do not account for measurement error (Brown, 2014).

In order to test the fitness of the studied FRAT model, the assessment was conducted based upon the CFA method. However, variables in the FRAT are not continuous, and each item of the FRAT has a predetermined constant value and could be varied by operators. Only if the item is checked by pilot does the risk value of that item count into the total factor score. Therefore, the measurement of variables in the FRAT is a categorical value of yes or no. In this study, CFA is conducted with dichotomous data. To prepare data for analysis, the measurement of an item was first transformed into a binary value: 1 or 0. For example, if the item was checked by the pilot, the value of that item was assigned as 1; otherwise a 0 was assigned to the item. However, Pearson correlations tend to underestimate the relationship between underlying continuous variables that give rise to binary variables (Pearson, 1900; University of California at Los Angeles, 2020). In that case, the tetrachoric correlation coefficient is used to measure the relationship between dichotomous variables that represent categorized continuous variables. Therefore, CFA was conducted on tetrachoric correlations that reflect the associations among the FRAT items.

Results

Data Description

Historical flight risk assessment data were collected using a modified FRAT at Purdue University from November 2016 to February 2017. There had been no major change regarding the flight operating procedures and flight risk assessment methods across the period of the data collection process. Analyses of historical data across November 2016 to February 2017 were expected to reflect reliable information. In total, 1,832 sets of data were collected. The FRAT has been primarily used by pilots enrolled in the Purdue professional flight program. The collected data included the information of flight risk assessment for flight training using Cirrus SR20 aircraft. The frequencies of FRAT total factor scores are shown in Figure 2.

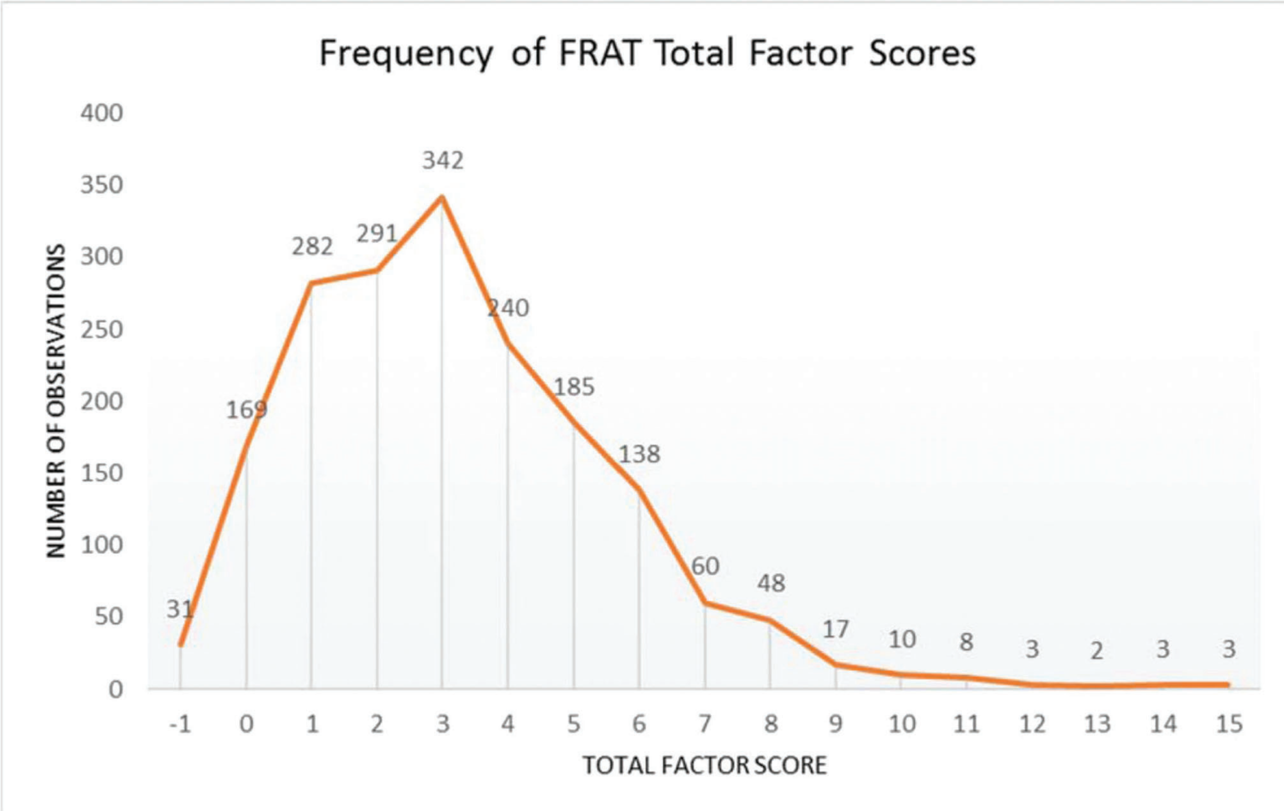

Figure 2. Frequency of FRAT total factor scores.

As mentioned previously, a flight will be grounded if the total factor score is above 16 points (including 16). In the empirical field, the collected FRAT data indicated that no flight was grounded during this period (from November 28, 2016 through February 21, 2017). To prepare data for CFA, collected data were converted into binary format. Table 3 describes the summary statistics of the transformed binary data.

Data in Table 3 show that two items have never been checked in flight risk assessment, namely *no precision approaches available at destination* and *arrival—IFR*. *No precision approaches available at destination* indicates that there is no available precision approach equipment at the destination airport; *arrival—IFR* describes that instrument flight rule (IFR) is required for arrival traffic. Therefore, these two items were eliminated in the confirmatory factor analysis since no data were observed. In addition to the two items that had never been checked as described above, *runway less than 4000 feet*, *maintenance test flight*, *first flight after a Phase or 50hr inspection*, *departure—IFR*, *en route—turbulence forecasted along route*, and *en route—thunderstorm forecasted* are risk items that were checked with low frequency (less than 1%). *Runway less than 4000 feet* describes a situation where either the takeoff or landing runway length is less than 4,000 feet; *maintenance test flight* indicates that the flight was for maintenance inspection rather than a training flight; *first flight after a Phase or 50hr inspection* shows the flight was the first flight after finishing either a phase maintenance inspection or 50hr maintenance inspection; *departure—IFR* shows that instrument flight rule was required at departure airport; *en route—turbulence forecasted* and *en route—thunderstorm forecasted* indicate an undesired weather situation was forecasted along the flight route.

Because the data came from a collegiate aviation flight training school, the majority of flights were flown by student pilots. In the collected FRAT data *student less than 50 flight hours*, *student 50–150 flight hours*, *last sleep period (6 to 8 hrs)*, and *instructor has CFII or MEI* were four of the most frequently (greater than 20%) checked risk items. The first three items describe the flight experience of student pilots by cumulative flight hours and the fatigue risk reflected by the last sleep period. *Instructor has CFII or MEI* indicates that the instructor on the flight is certified to teach instrument flying or multi-engine aircraft. This is the only item in the model that shows a negative risk value, which contributes to mitigating the total flight risk.

Parameter Estimation and Model Fit

Before conducting CFA, the tetrachoric correlation coefficients were calculated to measure the relationship

Table 3
Descriptive statistics of collected data.

Items	Frequency of being checked	%	Items	Frequency of being checked	%
Solo flight (pre-private)	105	5.73	Student has not flown in the last 2 weeks	153	8.35
Student less than 50 flight hours	403	22.00	Last sleep period (less than 4 hrs)	33	1.80
Student 50–150 flight hours	749	40.88	Last sleep period (4 to 6 hrs)	170	9.28
Instructor's first semester teaching	76	4.15	Last sleep period (6 to 8 hrs)	997	54.42
Instructor has CFII or MEI	466	25.44	Show time (between 7 and 8 a.m.)	159	8.68
Stress factor	124	6.77	Show time (after 6 p.m.)	32	1.75
Runway less than 4000 feet	8	0.44	Maintenance test flight	4	0.22
Night landing	72	3.93	First flight after a Phase or 50hr inspection	7	0.38
No precision approaches available at destination	0	0	Departure—MVFR	39	2.13
Non-towered airport	73	3.98	Departure—IFR	3	0.16
Unfamiliar origin airport	152	8.30	En route—turbulence forecasted along route	2	0.11
Unfamiliar destination airport	50	2.73	En route—thunderstorms forecasted	1	0.05
Class C operations	67	3.66	Arrival—MVFR	23	1.26
Arrival—IFR	0	0	Arrival—winds > 15 knots	65	3.55
Behind flight schedule	181	9.88	Flying multiple approaches	140	7.64
Pattern work	349	19.05	Instructor or student back-to-back training flights	123	6.71
Class immediately before/after flight	209	11.41			
	Minimum		Median		Maximum
Total factor score	−1[a]		3		15

[a]Negative value indicates that the corresponding item contributes to mitigating the overall flight risk.

Table 4
Tetrachoric correlations among the first six items.

	Solo flight (pre-private)	Student less than 50 flight hours	Student 50–150 flight hours	Instructor's first semester teaching	Instructor has CFII or MEI	Stress factor
Solo flight (pre-private)	1					
Student less than 50 flight hours	0.4982	1				
Student 50–150 flight hours	0.1908	−0.0000	1			
Instructor's first semester teaching	0.0330	0.3018	0.1151	1		
Instructor has CFII or MEI	0.2540	0.4168	0.2109	0.2045	1	
Stress factor	0.3574	0.2753	0.2466	0.0581	0.03120	1

between dichotomous variables. A set of tetrachoric correlations is shown in Table 4.

The studied FRAT framework is a four-factor model with preflight information, flight operations, weather, and training flight. The fitness of the model was evaluated using fit index levels identified by reviewing previous literature (Hu & Bentler, 1998, 1999). The indices include the root mean square error of approximation (RMSEA), comparative fit index (CFI), standardized root mean square residual (SRMR), and the Tucker–Lewis Index (TLI). The cutoff values for both RMSEA and SRMR were 0.05 as the ideal situation, while 0.08 was an acceptable value. In other words, the model fits well if both RMSEA and SRMR $\leq$ 0.05, and the model is acceptable if both RMSEA and SRMR $\leq$ 0.08. For CFI and TLI, the cutoff values were 0.95 as ideal, while 0.90 was an acceptable value. The model fits well if both CFI and TLI $\geqslant$ 0.95, and the model is acceptable if both CFI and TLI $\geqslant$ 0.90. The goodness-of-fit indices of CFA are shown in Table 5.

As shown in Table 5, the studied FRAT model does not provide a good fit. By reviewing the result of measurement loadings and the maximum likelihood estimation for the measurement in this model, this result suggests that the model might be improved by removing several items. In total, the following nine items were removed: *last sleep period (less than 4 hrs)*, *last sleep period (4 to 6 hrs)*, *show time (between 7 and 8 a.m.)*, *maintenance test flight*, *first flight after a Phase or 50hr inspection*, *en route—turbulence forecasted along route*, *en route—thunderstorms forecasted*, *pattern work*, and *class immediately before/after flight*. CFA was conducted after removing the above nine items; the model fit indices are shown in Table 6.

Table 5
Goodness-of-fit indices for original FRAT model.

Fit indices	Value	Interpretation
RMSEA (95%)	0.13	Ideal value ≤ 0.05, acceptable value ≤ 0.08
SRMR	0.08	Ideal value ≤ 0.05, acceptable value ≤ 0.08
TLI	0.99	Ideal value $\geqslant 0.95$, acceptable value $\geqslant 0.90$
CFI	0.98	Ideal value $\geqslant 0.95$, acceptable value $\geqslant 0.90$
χ^2 (df) (p)	1891.23 ($p < 0.01$)	To accept H_0, model fits data ($p > 0.01$)

Table 6
Goodness-of-fit indices for improved FRAT model.

Fit indices	Value	Interpretation
RMSEA (95%)	0.07	Ideal value ≤ 0.05, acceptable value ≤ 0.08
SRMR	0.05	Ideal value ≤ 0.05, acceptable value ≤ 0.08
TLI	0.76	Ideal value $\geqslant 0.95$, acceptable value $\geqslant 0.90$
CFI	0.69	Ideal value $\geqslant 0.95$, acceptable value $\geqslant 0.90$
χ^2 (df) (p)	918.17 ($p = 0.0113$)	To accept H_0, model fits data ($p > 0.01$)

Table 7
CFA model of FRAT.

			Loading	Standard error
Pre-flight information				
1	Solo flight (pre-private)		0.88	0.019
2	Student less than 50 flight hours		0.84	0.055
3	Student 50–150 flight hours		0.72	0.026
4	Instructor's first semester teaching		0.69	0.007
5	Instructor has CFII or MEI		0.78	0.013
6	Stress factor		0.71	0.007
Flight operations				
7	Runway less than 4000 feet		0.62	0.012
8	Night landing		0.75	0.019
9	Non-towered airport		0.77	0.023
10	Unfamiliar airport (departure)		0.72	0.033
11	Unfamiliar airport (destination)		0.83	0.023
12	Class C operations		0.91	0.032
13	Student has not flown in the last 2 weeks		0.87	0.004
14	Last sleep period (6 to 8 hours)		0.78	0.006
15	Show time (after 6 p.m.)		0.69	0.009
Weather				
16	Departure—MVFR		0.74	0.105
17	Departure—IFR		0.69	0.003
18	Arrival—MVFR		0.71	0.056
19	Arrival—winds > 15 knots		0.90	0.007
Training flights				
20	Behind flight schedule		0.88	0.089
21	Flying multiple approaches		0.91	0.025
22	Instructor or student back-to-back training		0.82	0.039
Factor correlation	**Pre-flight information**	**Flight operations**	**Weather**	**Training flights**
Pre-flight information	1			
Flight operations	0.24	1		
Weather	0.09	0.34	1	
Training flights	0.38	0.42	0.15	1

Considering the result for the goodness-of-fit indices, the improved FRAT model, as shown in Table 7, is acceptable to fit the data. However, the correlations between four factors, especially the higher correlation between training flight, pre-flight information, and flight operations, suggest that flight risk items might be overlapped across pre-flight information, flight operations, weather, and training flights.

Discussion and Conclusion

Pre-flight risk assessment is a critical component of flight operations, which helps prevent aviation operations with unacceptable risks. Although GA operators can hardly anticipate all possible hazards, pre-flight risk assessment enables pilots to identify hazards and assess risk level before takeoff. The FRAT, as a pre-flight risk assessment tool, is highly encouraged by the FAA (2016). It is important to note that diverse versions of FRAT are being used by a variety of GA operators. However, the lack of guidelines and instructions for appropriate implementation of the FRAT leaves its effectiveness uncertain. This study, from a statistical perspective, explored CFA as a possible validation approach for the use of FRATs in GA operations.

In this study, CFA was used to test whether flight operational data fitted a hypothesized FRAT measurement model. A FRAT implemented at Purdue University was investigated with historical FRAT data collected from the empirical field. Descriptive statistics of the transformed binary data were presented. Based on the CFA results, the studied FRAT model does not show an ideal fit of collected data (RMSEA = 0.13; SRMR = 0.08). The CFA result suggests that an improvement of the studied FRAT might lead to a better fit of the data. An improved FRAT model was constructed by removing eleven items from the studied FRAT model based on the fit indices. The improved FRAT model shows an acceptable fit (RMSEA = 0.07; SRMR = 0.05). However, the improved FRAT model should be further examined from the perspective of flight safety management personnel. CFA was studied as an option for aviation operators to validate whether the implemented FRAT model fitted the actual flight operations, as well as to help further develop a more effective FRAT. In general, this study is expected to provide references for GA operators in validating and improving their implementation of the FRAT. However, limitations were observed in this study, and further studies are necessary to include the consideration of both the FRAT framework and the weight of FRAT items into validation.

Limitations

A few limitations were observed in this study.

1. CFA only considered validation by examining whether the model framework fitted the data. The value of each item (equivalence of weight) was not considered in this study.
2. The analytic results suggested removal of a few items from the studied FRAT to better fit the data. However, most of removed items were rarely checked by pilots as unusual events. A simple removal of those items might exclude important unusual risk factors.
3. The flight operations in the empirical field are primarily flight training activities. Education of proper use of the FRAT for students was unknown. The collected data might only reflect the characteristics of student pilots and might have resulted in biased study results.

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