MEASURING THE ACCEPTANCE FROM COMMERCIAL PILOTS TOWARDS THE USAGE OF FLIGHT DATA FOR PREDICTIVE MAINTENANCE

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Abstract

Further development of digitalization and technology increases the amount of usable data and the possibilities of using it. With increasing competition in aviation around the world and decreasing profits, the value of this flight data is rising. Therefore, it is not surprising, that ways of misusing the data are growing likewise, which in some cases has led to compromised safety [1]. Hence storing and using data in a suitable way is one of the major challenges these days. One of the many stakeholders in this difficult process of finding an appropriate way of handling this kind of data are the pilots. They are the ones, who are producing the flight data and who can primarily face consequences by the misuse of such data. In the LuFo project OBSERVATOR predictive maintenance technologies are examined.

Therefore, the acceptance from commercial pilots to use flight data for predictive maintenance is measured through structural equation modelling. Especially the influence of facilitating conditions and the pilots' perceived risk are considered.

The findings of this paper reveal that while the facilitating conditions have a positive impact on the perceived usefulness, which positively affects the intention to allow such usage of flight data, they also have a negative impact on the perceived risk, which negatively influences said intention.

Furthermore, we asked the pilots what would help them feel more comfortable with the flight data being used for predictive maintenance and whom they trust the most with handling their flight data. The results of this give some advice on what future systems should consider.

1. INTRODUCTION

Flight Data already has an essential value in aviation. Therefore, Flight Data Monitoring (FDM), also known as Operational Flight Data Monitoring (OFDM) or Flight Operations Quality Assurance (FOQA), and Flight Data Analysis (FDA) are very common among the airlines to improve safety and maintenance actions. For commercial air transport with aeroplanes in excess of 27000kg it is even mandatory "to establish and maintain a flight data analysis program as part of its safety management system" [2]. With further development of digitalization and technology the amount and quality of usable data increases, as do the possibilities to use this data. [3] For example, combining different datasets adds even more value to the data. Thus, it is not surprising, that airlines want to analyse more and more data to find inefficient processes and reduce their costs.

However, it becomes critical when the analysed data gets evaluated. In the year 2012 three aircrafts of a low-cost-carrier, which was accused of ranking their pilots by their fuel usage, had to declare 'Mayday' due to low fuel on board. [1] An investigation found no concerns regarding compliance issues with existing law. [4] Nevertheless, this case raises doubts about the safety culture resulting in such data analysis. If lots of parameters of the aircraft are examined by analysts for damage, this could become like monitoring work performance for the pilots. While current discussions about predictive maintenance mainly focus on the legal and technical enforcement of such systems, this paper aims to measure the acceptance of the pilots towards the increasing data usage for predictive maintenance. In addition, past studies have shown that user acceptance is decisive for success and is often underestimated. [5] Thus understanding and improving the system from the pilots' point of view is important.

Instead of just measuring the acceptance, this paper aims to find out how to improve such a system in the pilots' point of view. One thing is the system itself, meaning what features would make pilots feel more comfortable. In the end the pilots are the ones who produce the data, which means that they are more likely to experience consequences from it. Even if it only means that some pilots have concerns in such data usage, it could lead to a change in their behaviour. Since safety should be number one priority in aviation, a change of behaviour into a solely economically driven direction could end badly and should be avoided. The second point we approached is whom pilots' trust the most with handling flight data.

This study was carried out in the context of the LuFo project OBSERVATOR in which predictive maintenance for aircrafts is examined and improved.

2. MEASURING ACCEPTANCE

Since there is no single or standardized definition of ‘acceptance’ in general, there are many different approaches to measure it. [6] In this study the acceptance was measured with the Structural Equation Modeling method.

2.1. Theoretical Framework

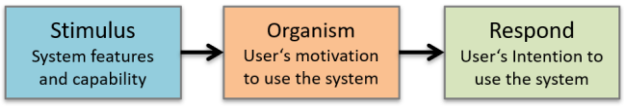

BILD 1 Stimulus Theoretical Framework developed by Lai [7]

The basic structure of this study is based on the Stimulus Theoretical Framework from Lai, which is shown in BILD 1. [7] Like a lot of different acceptance models this framework suggests system features and capabilities as a background construct influencing the user’s motivation to use the system, which then has direct impact on the user’s intention to use the system.

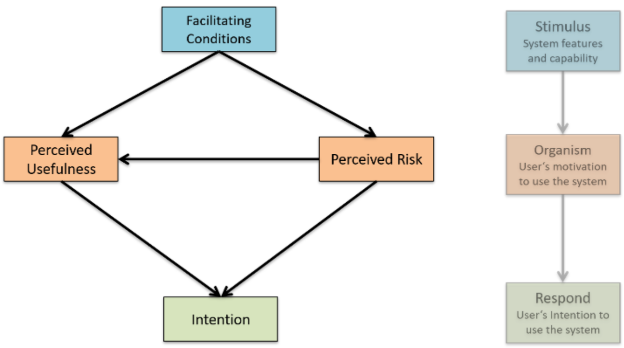

BILD 2 Research Model

Therefore, we measure the user’s intention (“ITN”) to use the system as the respond construct. Based on the Technology Acceptance Model 2 (TAM2) the construct ‘perceived usefulness’ (“PU”) is adopted as an organism factor. This construct was found to be a strongly influencing factor for new technology systems in past studies [5]. The perceived ease of use turned out to be another influencing factor in past studies, but cannot be adopted for this research, since pilots have no direct interaction with the system. A construct, that emerged more interest when dealing with personalized data is the perceived risk (“RSK”). Previous studies, which were also dealing with personalized data, found a direct influence from perceived risk to the intention to use a system. [8] [9] Furthermore the effect from perceived risk to the perceived usefulness is measured, as this was seen in technology systems handling personal data. [10] The system’s features and capabilities in this case are represented by the construct “facilitating conditions” (“FAC”), which includes the technical infrastructure and safety culture of the respective airline. Although the Unified Theory of Acceptance and Use of Technology (UTAUT) suggests a direct influence from facilitating conditions to the intention [11], we follow the approach by Lai and assume it to be part of the background construct as Lai described the ‘stimulus’. The resulting theoretical research model is presented in BILD 2.

2.2. Data Collection

The data was collected by means of a technology acceptance questionnaire consisting of 16 questions from previous studies as well as some new questions. Participants rated each statement on a 6-point-Likert scale. In the second part of the survey, they had to answer the question of whom they trust the most (single choice) and the question of what would make them feel more comfortable regarding this data usage (multiple choice). The last part collected descriptive statistics including type of airline they fly for, age and experience. The online survey was open from 17th of January until 17th of March 2021 and was mainly distributed via social media. Overall, 100 people completed the survey completely. The minimum recommended sample size to do a structural equation modelling is 100 participants or the number of items multiplied with factor 5. [12] [13] Therefore, the minimum of 80 or 100 participants was reached.

3. METHODS

The majority of the participants are based in Europe (70 out of 100), the remaining pilots are distributed in North America (9), Middle East (7), Asia (7), Africa (4), Oceania (2) and South America (1).

Likewise, most of the participants were flying for a major/legacy/flag carrier (42). The remaining can be separated into three groups: the low-cost carrier (19), student pilots (18) and ‘others’ (21), which includes Charter (7), Fractional (5), Cargo (5), Regional (2) and other business models (2).

3.1. Structural Equation Modelling

To carry out the structural equation modelling the statistical program SPSS is used following the general process according to Weiber and Mühlhaus. [14]

First the data is screened for outliers by checking the continuous decrease of the Mahalanobis Distance. Next the normality is tested by checking the skewness and kurtosis. The highest absolute value is reached with 1.66 for skewness and 3.53 for kurtosis, which are in the recommended limits by Hair et al. of < 2 for skewness and < 7 for kurtosis. [15]

As part of the exploratory factor analysis the dataset is checked for adequacy. Therefore, the Kaiser-Meyer-Olkin criterion is determined. With a value of 0.847 it indicates that the data may be grouped into a smaller set of underlying factors. [16] In addition the Bartlett’s test is significant and therefore confirmed the assumption of having a correlated population. The factor analysis is done by SPSS and the resulting factor loadings are shown in TAB 1. Values below 0.3 are blanked out. For the extraction method we choose the Maximum-Likelihood and for rotation method Promax (kappa=4) is used. The factors are forced into four groups.

The items are loading as expected on the different factors and have a sufficient loading and show no critical cross-loadings. Thus, convergent and discriminant validity can be assumed. Furthermore, the correlation matrix shows no absolute value above 0.616 between the factors. The reliability of the factors was checked by determining Cronbach's alpha, which is sufficient (>0.7) for each factor and shown in the first row of TAB 1. [17]

TAB 1. Factor loadings Exploratory Factor Analysis

	1	2	3	4
Cronbachs Alpha	0.890	0.787	0.727	0,855
PU1	,739	-,311		
PU2	,477			
PU3	,672			
PU4	,813			
PU5	,865			
PU6	,868			
FAC1		,805		
FAC2		,898		
FAC3		,513		
FAC4		,580		
RSK1			-,538	
RSK2			-,509	
RSK3			-,832	
RSK4			-,596	
ITN1		,303		,531
ITN2				,838

The confirmatory factor analysis was done with the program IBM SPSS AMOS. To check for reliability and convergent and discriminant validity the 'Master Validity Tool' developed by Gaskin [18] was used to calculate the corresponding composite reliability (CR), Average Variance Extracted (AVE), Maximum Shared Variance (MSV) and McDonald Construct Reliability (MaxR(H)), which are shown in TAB 2 and TAB 3.

TAB 2. Validity Analysis [18]

Construct	CR	AVE	MSV	MaxR(H)
PU	0,904	0,614	0,577	0,934
FAC	0,794	0,499	0,340	0,834
RSK	0,723	0,405	0,466	0,764
ITN	0,863	0,761	0,577	0,906

Reliability is assumed if CR > 0.7, which is fullfilled for the four constructs. [15] Furthermore, Convergent Validity can be checked by CR alone, as suggested by Malhotra and Dash. [19]

TAB 3. Validity Analysis Continuation

Construct	PU	FAC	RSK	ITN
PU	0,784			
FAC	0,583***	0,706		
RSK	-0,493***	-0,472***	0,637	
ITN	0,759***	0,548***	-0,683***	0,872
*** = Significance of Correlation p<0,001				

For Discriminant Validity the heterotrait-monotrait ratio of correlations (HTMT) analysis shows no issues as every value is clearly below the threshold of 0.850 as can be seen in TAB 4. [20]

TAB 4. HTMT Analysis [21]

Construct	PU	FAC	RSK	ITN
PU				
FAC	0,595			
RSK	0,445	0,394		
ITN	0,794	0,524	0,610	

Finally, the model fit of the research model was tested. Again, a Plugin developed by Gaskin and Lim was used to calculate the recommended criteria by Weiber and Mühlhaus and can be seen in TAB 5. [14] [22] The corresponding thresholds vary in literature, so that a single value below/above this threshold is not a cut-off criterion. The thresholds are more of a guideline rather than a cut-off criterion. As TAB 5 shows, the actual values are overall in limits. The only exception is the Comparative Fit Index (CFI), which has a value of 0,892 and is therefore below the recommended value of 0,9. Nevertheless the deviation is minor and Hu and Bentler see a value above 0,8 sometimes as permissible. [23] Thus, the overall model can be assumed to be acceptable.

TAB 5: Model fit

Criteria	Recommended Threshold	Actual Value
CMIN	-	190,745
DF	-	99
CMIN/ DF	< 3 [24]	1,927
CFI	> 0,9 [25]	0,892
SRMR	< 0,1 [26]	0,081
RMSEA	< 0,1 [27]	0,097

The causal model was then tested in AMOS and the parameters are presented in BILD 3. In TAB 6 the corresponding statistical key figures and regression weights are shown.

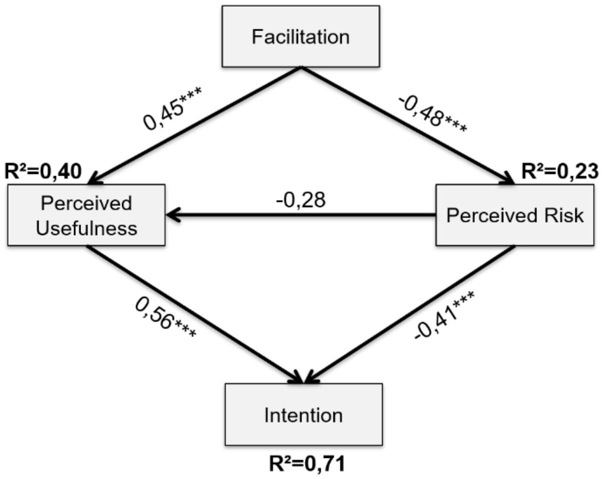

BILD 3: Results of the research model

The plausibility of the model is mainly checked by the Standard Error (S.E.). TAB 6 only shows the numbers for the different paths. Including the different items, the S.E. has values between 0,08 and 0,147, which is slightly high and shows some scatter of the parameter estimate. The values of the C.R. (critical ratio) are all between 2,205 and 9,583 and therefore above 1,96, which is an indication, that the parameters make a significant contribution to the formation of the model structure [14]. In addition all p-values, with the exception of the path coefficient between "Risk" and "Usefulness", show a significant correlation with a error probability of <0,1% (marked in BILD 3 and TAB 6 with ***). Moreover, the strength of the correlation can be determined by looking at the standardized regression weights of the corresponding path. These values should be above 0,2 or even better above 0,3 to be considered as meaningful. [28]

TAB 6. Regression weights and statistical figures

Path			Estimate unstandardized	Estimate standardized	S.E.	C.R.	PLabel
RSK	<-	FAC	-,552	-,479	,147	-3,762	***
PU	<-	RSK	-,256	-,276	,116	-2,205	,027
PU	<-	FAC	,484	,452	,137	3,525	***
ITN	<-	PU	,675	,562	,127	5,301	***
ITN	<-	RSK	-,456	-,409	,117	-3,905	***

The Squared multiple Correlations (SMC), also known as the Coefficients of determination (R^2), were calculated by AMOS as well and are shown in BILD 3. Huber et al. recommend values above 0,3 for good predictions. [29] In this research model seventy percent of the variance in the intention to use the new system can be explained by perceived risk and perceived usefulness. Whereas only a minor part of the variance of perceived risk can be explained. However, the only influencing variable is facilitation, which seems not to be sufficient.

4. RESULTS

The results of this paper point out some key elements that should be at least considered before and while implementing this kind of data usage.

TAB 7. Results of the Questionnaire

Item	Mean	Std.-Deviation	Variance
PU1	4,6300	1,06035	1,124
PU2	4,5300	1,19304	1,423
PU3	3,5100	1,46677	2,151
PU4	4,6300	1,11604	1,246
PU5	4,9100	,97540	,951
PU6	4,6800	1,00383	1,008
FAC1	4,5000	1,13262	1,283
FAC2	4,7700	1,11785	1,250
FAC3	4,5100	1,18488	1,404
FAC4	4,8200	1,05773	1,119
RSK1	2,4700	1,18454	1,403
RSK2	3,7000	1,30655	1,707
RSK3	3,1900	1,44736	2,095
RSK4	2,5600	1,17482	1,380
ITN1	4,2800	1,30330	1,699
ITN2	4,4100	1,17288	1,376

The actual mean values of the different employers are shown in BILD 4. As one can see there is no significant difference between the groups, which is confirmed by the Kruskal-Wallis-Test. The corresponding statements for the items can be found in TAB 8 (Appendix).

Mean values, Standard deviation and variance of all participants are shown in TAB 7. Apart from the construct 'perceived risk', all values are above 3,5 and thus agree with the statements. The highest value of 4,91 is reached by PU5 and shows that pilots especially see a benefit for their company. The highest variance is reached by PU3, which shows some disagreements about this statement. Furthermore, this statement is also significantly lower than the other values in the construct of perceived usefulness. Therefore, the pilots rather see benefits for their company than for their own daily operation. The lowest value is RSK1 with 2,47. Since lower values in this construct mean lower risk perception, it indicates that pilots fear no interference with their work. Overall, the risk perception is low. The only concern that this questionnaire shows is RSK2, which reached a value greater 3,5 and therefore shows a slight agreement with the statement. However, it rather states concerns about the technical implementation than the risk of data misuse. The intention to voluntarily share the flight data for the purposes of predictive maintenance (ITN1 and ITN2) achieve an averaged value of 4.35 and thus clearly shows acceptance of the pilots for such a system.

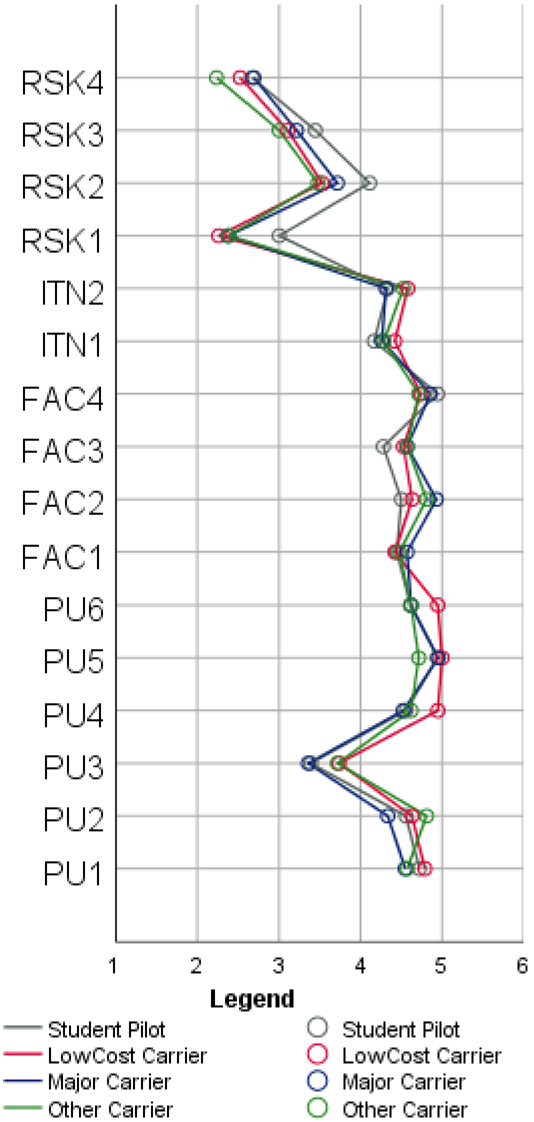

BILD 4. Mean values grouped by airline business model

However, this intention is often bound by conditions, which became more obvious analysing the answers of the open question regarding a potential change in landing behaviour. Since this was a voluntary question, only 81 of the 100 people answered it. Though 51 people answered with no, they often bounded conditions like “as long as the just culture in the company is fine”, “as long as data is used in a non-punitive way” or “as long as data is anonymized”. This topic was addressed in a further question, in which the pilots were asked about their preferences when dealing with personalized data for predictive maintenance. The results can be seen in BILD 5. Since multiple choice was possible, every choice is scaled for every colour to 100%. The guarantee for no negative consequences, transparency of the system and anonymization can be summarized as the main factors, that pilots would prefer.

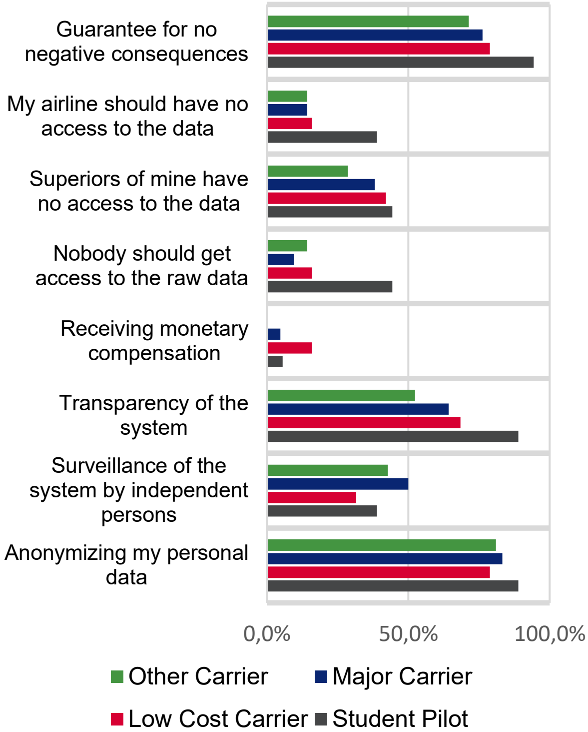

BILD 5. "What would make you feel more comfortable to allow the use of your data for predictive maintenance?" (multiple choice)

Furthermore, in terms of the open question regarding possible change in behaviour one pilot stated “my airline has a very punitive culture when it comes to QAR data and FOQA. I find most of my colleagues feeling negative about the QAR data analysis” and another one mentioned “[name of airline] is not conform with FODA data and uses this tool to make pressure on pilots”. Therefore, we asked the pilots whom they would trust the most handling flight data. The results can be seen in BILD 6. As can be seen, the majority answered with their current airline.

Last but not least 16 of the 81 pilots answering the open question do have some concerns regarding a possible change in their landing behaviour. Among those the most addressed issues are “It may lead to focusing more on gaining favorable data than prioritizing a safe landing” or “I believe the landing behavior will shift in the direction that fits the perfect parameters”.

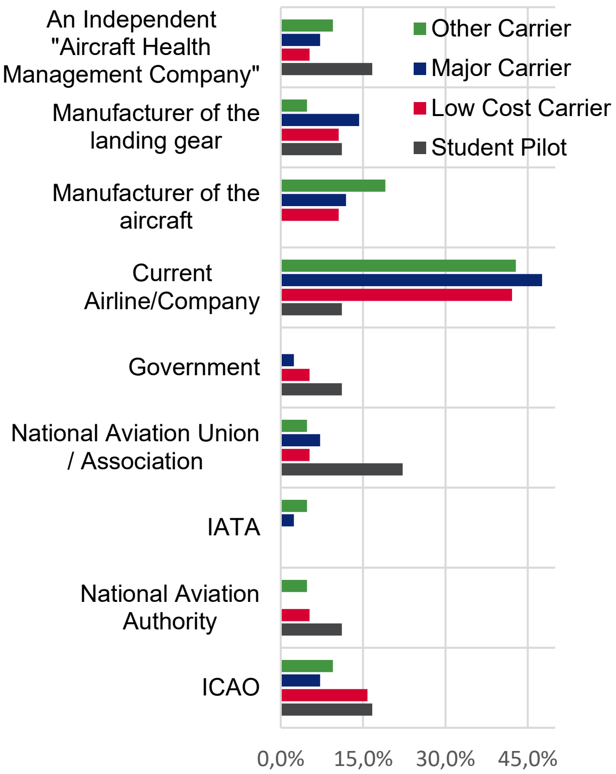

BILD 6. “Which of the following Organizations/Companies do you trust the most with handling your flight data for predictive maintenance of the landing gear?“ (single choice)

5. LIMITATIONS

The results of this paper are only based on 100 pilots, from which the majority is from Europe and flying for a major carrier. Therefore, this survey is not representative for all pilots, but still gives some insights into the pilots’ opinion regarding data usage for predictive maintenance. Next to the small sample size, the number of items for the different constructs with three or four items is at the lower end as well. Thus, the overall model fit is not perfect and could be improved. Nevertheless, as mentioned the model fit is acceptable and the results are consistent for this sample. Although this survey did not show significant differences between different airline models, it should be kept in mind, that the different business models are represented by few people. For further studies it would be interesting to see, if a larger sample size with more pilots from different cultures and regions show no significant difference as well. Since Merrit already identified cultural differences for pilots we expect to find at least some effect. [30]

6. CONCLUSION

The pilots of this sample overall have a positive intention towards allowing flight data to be used for predictive maintenance. The key factors influencing this intention are the perceived usefulness and the perceived risk. These two are again influenced by the system features and capability. Furthermore, the impact of data misuse was confirmed by a minority of pilots and some even have concerns regarding a potential change in behaviour. Even if this number is small, it should be kept in mind, that one pilot alone bears responsibility for many more passengers. Thus, this paper recommends transparency, anonymization and a guarantee for no negative consequences when handling personal data.

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] European Cockpit Association AISBL, “www.eurocockpit.be,” 14 November 2016. [Online]. Available: https://www.eurocockpit.be/news/ryanair-metamorphosis-hardly-possible. [Accessed 5 July 2021].

[2] International Civil Aviation Organization, Annex 6, Operation of Aircraft Part I, International Commercial Air Transport - Aeroplanes, 9 ed., 2010.

[3] H. Meyer, J. Zimdahl, A. Kamtsiuris, R. Meissner, F. Raddatz, S. Haufe and M. Bäßler, *Development of a Digital Twin for Aviation Research,* Deutsche Gesellschaft für Luft- und Raumfahrt - Lilienthal-Oberth e.V.., 2020.

[4] Comisión de investigación de accidentes e incidentes de aviación civil, “mitma.gob.es,” October 2014. [Online]. Available: https://www.mitma.gob.es/recursos_mfom/2010_010_in_final_eng_0.pdf. [Accessed 5 July 2021].

[5] F. Davis, “User acceptance of information technology: system characteristics, user perceptions and behavioral impacts,” *International Journal of Man-Machine Studies,* vol. 38, pp. 475-487, 1993.

[6] E. Adell, *Driver experience and acceptance of driver support systems - a case of speed adaption,* L. University, Ed., Institutionen för Teknik och samhälle, 2009.

[7] P. C. Lai, “Design and Security impact on consumers’ intention To Use Single Platform E-Payment,” *Interdisciplinary Information Sciences,* vol. 22, no. 1, pp. 111-122, 2016.

[8] A. Kesharwani and S. Singh Bisht, “The Impact of trust and perceived risk on internet banking adoption in India: an extension of technology acceptance model,” vol. 30, no. 4, pp. 303-322, June 2012.

[9] X. Yong, X. Jianbin and B. Yu, “A Study on the Factors about Customers' Acceptability to Airline Ancillary Products,” vol. 107, pp. 39-46, 2017.

[10] C. Hampshire, “A mixed methods empiricalexploration of UK consumerperceptions of trust, risk andusefulness of mobile payments,” *International Journal of Bank Marketing,* pp. 354-369, 2017.

[11] V. Venkatesh, M. Morris, G. Davis and F. Davis, “User acceptance of information technology: Toward a unified view,” *MIS Quarterly,* vol. 27, no. 3, pp. 425-478, 2003.

[12] P. Bentler and C. Chou, *Practical Issues in Structural Modeling,* vol. 16, Socilogical Methods & Research, 1987, pp. 78-117.

[13] A. Boomsma, The Robustness of LISREL against small sample sizes in factor analysis models, vol.

149, K. G. Jöreskog and H. Wold, Eds., Amsterdam, The Netherlands: North Holland, 1982, pp. 149-173.

[14] R. Weiber and D. Mühlhaus, Strukturgleichungsmodellierung. Eine andwendungsorientierte Einführung in die Kausalanalyse mit Hilfe von AMOS, SmartPLS und SPSS, 2 ed., Berlin, Heidelberg: Springer Gabler, 2014.

[15] J. Hair, W. Black, B. Babin and R. Anderson, Multivariate data analysis, vol. 7, New Jersey : Pearson Educational International: Upper Saddle River, 2010.

[16] H. Kaiser and J. Rice, “Little Jiffy, Mark IV,” *Educational and Psychological Measurement,* vol. 34, pp. 111-117, 1974.

[17] C. Lance, M. Butts and L. Michels, “What did they really say?,” *Organizational Research Methods,* vol. 9, no. 2, pp. 202-220, 2006.

[18] J. J. M. a. L. J. Gaskin, *Master Validity Tool,* Gaskination's Statistics. http://statwiki.gaskination.com, 2019.

[19] N. Malhotra and S. Dash, Marketing Research an Applied Orientation, London: Pearson Publishing, 2011.

[20] J. Henseler, C. M. Ringle and M. Sarstedt, “A New Criterion for Assessing Discriminant Validity in Variance-based Structural Equation Modeling,” *Journal of the Academy of Marketing Science,* vol. 43, no. 1, pp. 115-135, 2015.

[21] J. Gaskin, M. James and J. Lim, *HTMT Analysis Tool, AMOS Plugin,* Gaskination's Statistics. http://statwiki.gaskination.com, 2019.

[22] J. Gaskin and J. Lim, *Model Fit Measures,* Gaskination's Statistics. http://statwiki.gaskination.com, 2016.

[23] L.-T. Hu and P. M. Bentler, “Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives,” *Structural Equation Modeling: A Multidisciplinary Journal,* pp. 1-55, 1999.

[24] C. Homburg and A. Giering, “Konzeptualisierung und Operationalisierung komplexer Konstrukte – Ein Leitfaden für die Marketingforschung,” *Marketing ZFP,* pp. 3-24, 1996.

[25] C. Homburg and H. Baumgartner, “Beurteilung von Kausalmodellen,” *Marketing ZFP,* pp. 162-176, 1995.

[26] C. Homburg, M. Klarmann and C. Pflesser, “Konfirmatorische Faktorenanalyse,” *Handbuch Marktforschung: Methoden, Anwendungen, Praxisbeispiele,* pp. 271-303, 2008.

[27] D. Kenny, B. Kaniskan and D. McCoach, “The Performance of RMSEA in Models withSmall Degrees of Freedom,” *Sociological Methods & Research,* vol. 44, no. 3, pp. 486-507, 2015.

[28] W. Chin, “Commentary: Issues and opinion on structural equation modeling,” *Management InformationSystems Quarterly,* vol. 22, pp. Vii-Xvi, März 1998.

[29] F. Huber, A. Herrmann, F. Meyer, J. Vogel and K. Vollhardt, Kausalmodellierung mit Partial Least Squares: Eine anwendungsorientierte Einführung, Wiesbaden: Gabler Verlag, 2007.

[30] A. Merritt, “Culture in the Cockpit: Do Hofstede's Dimensions Replicate?,” *Journal of Cross-Cultural Psychology,* vol. 31, no. 3, pp. 283-301, Mai 2000.

9. APPENDIX

TAB 8. Statements

PU1	Using flight data for predictive maintenance of the landing gear would enhance effectiveness.
PU2	I would find the usage of flight data for predictive maintenance of the landing gear useful in my job.
PU3	The use of flight data for predictive maintenance of the landing gear may improve my overall daily operation.
PU4	Using flight data for predictive maintenance of the landing gear for aircraft maintenance is a good idea.
PU5	The use of flight data for predictive maintenance of the landing gear is beneficial for my company..
PU6	In my opinion, the use of flight data for predictive maintenance of the landing gear will have a positive impact.
FAC1	I think that my airline has the necessary technical infrastructure to support the adequate protection of the data.
FAC2	I think that my airline has the necessary safety culture to support the usage of flight data for predictive maintenance of the landing gear.
FAC3	I think my airline would support the adequate usage of the data.
FAC4	Management would welcome the fact that I allow the usage of flight data for predictive maintenance of the landing gear.
INT1	I have the intention to allow the usage of flight data for predictive maintenance of the landing gear, when it becomes available for voluntary use in my airline.
INT2	Given that I could allow the usage of flight data for predictive maintenance of the landing gear, I predict that I would allow it.
RSK1	I think using flight data for predictive maintenance of the landing gear will interfere with my work.
RSK2	I think using flight data for predictive maintenance of the landing gear instead of mechanics in assessing the aircrafts condition has a potential risk.
RSK3	I think using flight data for predictive maintenance of the landing gear puts my privacy at risk..
RSK4	I think using flight data for predictive maintenance of the landing gear will have negative consequences for me.