Exploring the Mathematical Predictability of the Advanced Aircraft Training Climate

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EXPLORING THE MATHEMATICAL PREDICTABILITY OF THE ADVANCED AIRCRAFT TRAINING CLIMATE

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Effective pilot training on advanced aircraft is vital in ensuring flight safety, and positive perceptions of the training climate can contribute to the success of the training. Hypothetically, characteristics of the trainee can predict the training climate. Thus far, predictive models have provided little information about the mental viscosity or psychological comfort of the processes of pilot training. The purpose of this study was to develop a mathematical model to predict the psychological comfort of the organisational environment for advanced aircraft pilot transition training using a dichotomous categorical criterion. A predictive model of the phenomena was contemplated from a non-parametric regression process. Original data were captured using a previously validated instrument, namely the Advanced Aircraft Training Climate Questionnaire (AATC-Q) from a cohort of 229 respondents. The final regression model containing four independent variables correctly predicted 63.8% of overall cases. The developed model may assist in implementing training interventions.

Pilot selection, recruitment and training are some of the more important measurable antecedents available, to detrmine the suitability of a pilot to operate an advanced aircraft (Machin & Fogarty, 2003; Pasztor, 2009). Anecdotally, for example, the final report into a well-publicised air crash involving an Air France Airbus A330 in 2009, suggested that human action, stemming from specific training issues, was a significant contributor. This paper attempts to statistically analyse some of the possible behavioural variables which may impact advanced aircraft pilot recruitment and training.

The ‘advanced aircraft training climate’ construct

Two separate climatic constructs are generally differentiated in the literature, namely a ‘psychological climate’ and an ‘organisational climate’ (Denison, 1996, p. 619). The psychological climate refers to making sense cognitively of the organisational environment. An organisational climate refers to the subjective summated (average) sense that individuals make of interpersonal constructs. An extension to this is their understanding of policies, procedures and structure in an organisation. The organisational culture can be defined as a set of group assumptions created after learning from a number of internal and external difficulties or problems. Climate researchers are therefore ‘generally less concerned with [social] evolution but more concerned with the impact that organisational systems have on groups and individuals’ (Denison, 1996, p. 621). The advanced aircraft training climate is (for the purposes of this paper) defined as all factors in the person, learning and organisation that influence [the] transfer of knowledge to the job function. According to Fishbein and Ajzen (2001), the study of behaviour is defined as an analysis of the functional relationship between events in the environment and human action, or inaction. The theory supports a link between an individual’s attitude and subsequent behaviour (Fishbein & Ajzen, 2001). Thus, it follows that a training perception may directly impact trainees’ learning attitudes. Prior research in this topic tend to adopt a linear regression method in order to formulate relationships between perceptions, attitude, beliefs and intention with behaviour. These variables are then interconnected within relationships with specific mediating demographic variables. Analyses of these linear linkages provided the foundational hypothesising in this study to predict both flight performance success and inter-crew behaviour. Due to space constraints this is not elaborated here.

Briefly, airline pilot training in general, consists of a theoretical or learning part, flight simulation training and route (or practical flying) training. The airline uses route training for the final assessment of a candidate's ability to safely operate an advanced aircraft. Based on this background, specific demographic variables were selected and analysed when regressing a predictive mathematical model of the problem.

Research design

Participants

The target population consisted of around 1200 South African airline pilots who were experienced in advanced commercial aircraft. A final cohort of 229 participants was used for the analyses. A convenience sample was derived from the six large, medium and small airline organisations based in South Africa. Although 10.9% of the total sample held a South African pilot's licence, they were not affiliated to any particular carrier. Nonetheless, in general the sample frame was well represented. The majority of the participants (48.7%) were affiliated with the state carrier. In terms of the general flight experience levels of the group, the sample was fairly well distributed, and most of the respondents had more than 5 000 hours flying experience (Mean=9753.29; SD=6116.719). However, the dispersion of the participants in terms of flight experience was large – the majority of the sample had between 3 000 and 16 000 flight hours. The high standard deviation of this descriptor simply reflects the heterogeneity of pilots found in the South African airline industry (Vermeulen, 2009). This is also a testament to the high levels of industry experience in the South African aviation market. A fair proportion of the respondents (41.5%) were experienced in some of the most advanced commercial airline aircraft currently in operation globally, namely Airbus A319/A320/A330/A340 (41.5%) and Boeing 747-400/737-400/800 (24.9%). These demographics further articulate the skewed proportions regarding aircraft type and manufacturer category within this airline environment.

Measuring instrument

The Advanced Aircraft Training Climate Questionnaire (AATC-Q) was used as a data collection instrument (Naidoo, Schaap & Vermeulen, 2014). The instrument is a valid and reliable ($\alpha >$ 0.70) measure of South African airline pilots' perceptions of the training climate associated with the advanced aircraft mentioned earlier. The main scales of the instrument measured three latent factors. Factor 1 (Organisational Professionalism) consists of statements that measure both the macro domain (the airline) and the intermediate (instructor-trainee) domain. The component expresses the theoretical construct in terms of the efficiency, effectiveness and professionalism of both the company and its flight instructors. Factor 2 (Intrinsic Motivation) consists of items representing the micro level of analysis (the individual or person). The subscale predominantly reflects individual trainees' ability and eagerness to learn. Factor 3 (Individual Control of Training Outcomes) expresses the micro level of analysis (the person) relating to an individual trainee's own perceived level of control in terms of stress levels and learning decision-making. The essence of this third behavioural subscale relates to the levels of perceived personal control experienced by trainee pilots during training, their belief in their ability to effect the outcome of a training session, their capacity to maintain appropriate levels of stress (eustress or anxiety) in order to perform well, and ultimately their grasp of the amount of information required to cope with their training (intelligent decision-making).

Results

A backward stepwise logistic regression, was the process of choice, because '[r]egression methods have become an integral component of any data analysis concerned with describing the relationship between a response variable and one or more explanatory variables' (Hosmer & Lemeshow, 2000, p. 1). The probability of a binary outcome on a discrete variable was modeled from the most likely relationship between specific demographic covariates. The logistic equation began with all the selected independent variables first entered and then deleted after evaluation (Table 1). A dichotomous dependent variable was constructed, based on the level of favourability perceived by the respondents. As in discriminant analysis, a dummy variable (1 or 0) was allocated to the dichotomy of perceiving a favourable or unfavourable training climate, assuming that a positive perception of the favourability of climate exceeds 5.0 (on the AATC-Q behavioural scale), which is an average perception on the aforementioned three-factor model. This provided a dichotomous measure (labeled 'Favourability') of a categorical outcome that indicated the level of airline pilots' comfort (psychological viscosity) in the advanced aircraft training climate, in terms of their overall perception.

Table 1.
Values for demographic predictors used in the logistic model (independent variables)

Categorical variable	Value	Meaning
Interaction effect between flight experience*perceived level of computer literacy	1	Low Experience*Low Computer Literacy
	2	Low Experience*High Computer Literacy
	3	High Experience*Low Computer Literacy
	4	High Experience*High Computer Literacy
Age	0	40 years old or younger
	1	41 years old or older
Actual flight experience in advanced aircraft	1	Low experience (< 2000 hours)
	2	High experience (> 2001 hours)
Preference for route training	1	Never enjoy
	2	Sometimes enjoy
	3	Always enjoy
Preference for simulator training	1	Never enjoy
	2	Sometimes enjoy
	3	Always enjoy
Size of carrier employed at	1	Large
	2	Medium
	3	Small
Pilot unionisation	1	Unionised
	2	Non-unionised
Perceived level of computer literacy	1	Low
	2	High
Position at company	0	Co-pilot
	1	Captain

Final regression model

The data were regressed on an S-curve, which begins exponentially and thereafter tapers off. The plotted logistic regression model (not reproduced here) describes an initial exponential change in the probability of a favourable climate and thereafter, at some critical point, a slowing down or tapering off of probability. The logit formula, or curve, logit (p) = ln (p/1-p), also referred to as the log odds, described the final mathematical probability model. It was also noted that there were some distinct, yet acceptable disadvantages associated with using this particular logistic regression technique. For instance, the method required the researcher to use a high number of data points to produce meaningful and stable results. To determine how powerful the developed regression equation was in predicting the proportion of variance in the criterion variable associated with the predictor variable, a pseudo R^2 was computed, based on the methods of Cox and Snell's R^2, Nagelkerke's R^2, and McFadden's (adjusted) R^2 (Table 2). Therefore a pseudo R^2 was computed to evaluate the goodness-of-fit of the logistic model. The value of R^2 computed in this paper ranged from 0 to 1 (because squaring the correlation between the predicted values and the actual values of the regression model would produce a positive value). This value is referred to as the pseudo R^2. Generally, a high pseudo R^2 value indicates that there is a high magnitude of correlation between the predicted values and the actual values. A cut-off value of $R^2\Delta = 0.02$ was used because the pseudo R^2 is not technically a goodness-of-fit index, and cannot explain the proportion of the variance *per se*. Nagelkerke's $R^2\Delta$ was computed by first calculating the value of the pseudo R^2 at the initial step and thereafter finding the difference at each subsequent step (Table 2). The Wald test was used to test the statistical significance of each of the coefficients in the regression model. A Z-score (Z = coefficient [B]/SE) was also calculated. The hypothesis of inclusion or exclusion of the coefficients was thus based on the subsequent chi-square fit. Because of the relatively small sample size in this study, a decision was made to use the likelihood-ratio test, comparing the maximised value of the likelihood function for the full model (L_1) to that of the likelihood function for the simpler or null model (L_0) associated with a chi-square goodness-of-fit. In addition, the Hosmer-Lemeshow goodness-of-fit test was applied to determine whether or not the model prediction differed significantly from the observed number of subjects in each group.

Discussion of results

A backward stepwise regression analysis was completed after five steps (Table 2). The final model containing four predictors subsequently emerged. Analyses revealed that the variables were, [1] an interaction effect between a pilot's level of flight experience in advanced aircraft and their perceived level of computer literacy (a unit change in this variable correctly predicted climate favourability by 65%); [2] practical flight experience in advanced aircraft; [3] preference regarding training in the flight simulator (a unit change in the pilot's enjoyment of simulator training improves the predictability of a positive climate by 69%); and [4] preference regarding route training in the actual aircraft. Additionally, five other exploratory predictor variables (Table 1) were not significant and were removed iteratively. It should be noted at this stage that McFadden's (1996) model contrasts the present results by finding that the independent variables; age, flying experience (total flying hours) and employer (major airline or non-major) as significant in pilots' perceptions of training in general. However, the difference in results between the two models may stem from the fact that the present model assesses the flight deck behaviour in terms of the training climate, whilst the McFadden model examined flight deck behaviour from an indepth analysis of aviation incidents. The overall percentage of cases for which the dependent variable was correctly predicted by the present study's mathematical model was 63.8%. The model is regarded as robust becuase it correctly predicts perceptions of a favourable climate 100% of the time (high positive predictive validity), however, disappointingly does not successfully predict respondents' perceptions of an unfavourable training climate. This result may be due to the design of the data collection instrument, which consisted of only positively worded statements, or items. A computation of Nagelkerke's $R^2\Delta$ suggested that the effect size of the model at each subsequent step was less than 0.02 and should therefore be regarded as not practically significant in terms of this criterion. Nonetheless, the findings in this study provide sufficient evidence to suggest that the final model is a highly efficient perception predictor. The efficiency of the resulting model is endorsed by the non-significance in the result of the Hosmer and Lemeshow test chi-square statistic in the final step ($\chi 2$ [7, N=229] = 2.365, p = 0.937). Because the dependent variable in this regression model is dichotomous or categorical in nature, only approximations of R^2 is possible. Hence Nagelkerke's pseudo R^2 was selected to gauge an alternative effect. Both Cox and Snell's R^2, together with Nagelkerke's R^2 values, were used in the study to conclude that the final model could reasonably account for approximately 12% to 17% of the variability in whether trainee pilots' perceived the training climate as either favourable or unfavourable. The researcher discovered moderate changes occurring in the -2 log-likelihood values between the constant only model, and the first and last step, which was a good indication that the modeling in the final step had an improved predictive power. A nominal regression of the final four predictor variables then produced a comparison in which the -2 log-likelihood values of the intercept only (95.338) and final model (65.456) indicated that the change in the amount of predictive power provided in the final solution was statistically significant [$\chi 2$ (4)

= 29.883, $p < 0.0001$]. McFadden's p^2 [1-log likelihood (final)/log likelihood (constant)] = 0.313 was computed as an indication of a measure of the strength of association between the predictor variables and the model. McFadden's p^2 is expected to be 'lower' than the traditional R^2 as a measure of effect size, and values between 0.20 and 0.40 are considered highly satisfactory. In terms of McFadden's p^2 (as opposed to Nagelkerke's $R^2\Delta$), the study concluded that the size of the final logistic model is large and of practical significance. Finally, the aforementioned logistic regression analyses show that the probability that a respondent would perceive the advanced aircraft training climate as favourable can be modelled using the following two logistic regression equations:

Equation 1
Logit = ln (p/1-p) = -2.603 + 0.63 * (interaction effect) – 1.064 * (advanced aircraft experience) + 0.485 * (route training) + 0.806 * (simulator training)

Equation 2
$$\text{Prob (Favourable perception)} = (e^{-2.603 + 0.63 X_1 - 1.064 X_2 + 0.485 X_3 + 0.806 X_4})/(1+ e^{-2.603 + 0.63 X_1 - 1.064 X_2 + 0.485 X_3 + 0.806 X_4})$$

Table 2
Final logistic regression prediction model

Predictors in the equation (X_J)	B	S.E.	Wald Chi-Square ($B^2/S.E.^2$)	Df	Sig.	Odds Ratio (E^b)	95% C.I. For Odds Ratio	
							Lower	Upper
Interaction effect	0.630	0.310	4.126	1	0.042	1.878	1.022	3.448
Advanced aircraft experience	-1.064	0.613	3.011	1	0.083	0.345	0.104	1.148
Enjoy route training	0.485	0.289	2.814	1	0.093	1.624	0.922	2.861
Enjoy simulator training	0.806	0.267	9.138	1	0.003	2.238	1.327	3.773
Constant	-2.603	0.912	8.142	1	0.004	0.074		

Practical implications and conclusion

The present study showed that predicting the psychological viscosity (ease and comfort of learning within the training climate) could be quantified within two mathematical formulae. This provides a more practical understanding of airline training success or failure. Airline recruitment specialists would therefore find that knowledge of these predictors might be of value when determining the success rates of potential new-hire pilots. The logistic equations show that perceived computer literacy (pilots' attraction or averseness to technology) plays a significant predictive role in the model only when it is combined with flight experience. Counter-intuitively, high flight experience did not necessarily imply a high probability of flight training success. The model predicts that when high flight time was coupled to technological averseness, the result was low psychological viscosity at the training level (that is, low climate favourability). In addition, pilots' preference for simulator training was by far the most statistically dominant predictor. The study provides evidence to suggest that pilots tend to associate overall advanced aircraft flight training with their experiences in the flight simulator. Advanced aircraft incident and accidents have attracted, and will continue to attract international attention and scrutiny of pilot training. Selection, recruitment and training therefore play a critical role in flight safety and public opinion of organisations. However, determining precisely whether the organisation itself is actually capable of producing the competency in its pilots plays an increasingly important role in what eventually occurs on the flight deck. An implication predicted by the derived model in this paper, is that airlines should ensure that simulator-training devices are used to its full potential and are of a world-class standard. Advanced aircraft pilots should be given more opportunities to practice non-jeapordy exercises in flight simulator training devices. Additionally, the model also suggests that organisations that focus solely on a pilot's flight time (hours of experience), whilst neglecting perceived levels of computer literacy, create a myopic view of individual ability, and can hamper the overall training effort. Conversely, selecting pilots for advanced aircraft training with an experience level below a minimum threshold can also have an adverse impact on the training climate, due to the S-curve nature of this regression model. The logistic model produced here can provide predictions of what the ideal candidate experience and perception levels should be, implying greater training success for the individual, and effective and safer overall flight deck beahviour for the company.

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References

Caretta, T.R., & Ree, M.J. (1995). Air Force Officer Qualifying Test validity for predicting pilot training performance. *Journal of Business and Psychology*, *9*, 379–388.

Denison, D.R. (1996). What is the difference between organizational culture and organizational climate? A native's point of view on a decade of paradigm wars. *Academy of Management Review*, *21*(3), 619–654.

Fishbein, M. & Ajzen, I. (2001). *Belief, attitude, intention and behaviour: an introduction to theory and research*. Reading, MA: Addison-Wesley.

Hosmer, D.W., & Lemeshow, S. (2000). *Applied logistic regression*. (2nd edn.). New York, NY: Wiley.

Machin, M.A., & Fogarty, G.J. (2003). Perceptions of training-related factors and personal variables as predictors of transfer implementation intentions. *Journal of Business and Psychology*, *18*(1), 51–71.

Naidoo, P., Schaap, P., & Vermeulen, L. P. (2014). The development of a measure to assess perceptions of the advanced aircraft training climate, *The International Journal of Aviation Psychology*, *24:3*, 228-245. doi: 10.1080/10508414.2014.918441

Parasuraman, R., & Byrne, E.A. (2002). Automation and human performance in aviation. In P.S. Tsang, & M.A. Vidulich (Eds.), *Principles and practices of aviation psychology* (pp. 311–356). Washington, DC: Erlbaum.