Investigating subjective comfort with aircraft seat via ordinal regression

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Abstract In the scientific literature, the debate about how define and evaluate seat comfort is still open, but three points are not in question [1]: 1. comfort is a construct of a subjective nature; 2. comfort is affected by factors of various nature (physical, physiological, psychological); 3.comfort is a reaction to the environment. The subjective nature of the comfort experience is universally recognized; any comfort analysis cannot disregard subjective methods ('directly asking people about how comfortable they are'), which can be regarded as the most direct way to detect subjective feelings of comfort and/or discomfort. This paper focuses on the assessment of aircraft seating comfort based on subjective comfort responses collected during laboratory experiments. During each experimental session, participants were asked to express their overall seat comfort perception and to evaluate specific seat design features. Comfort responses were analyzed with the aim to relate the perceived overall seat comfort to some design features, as well as to the user anthropometrical characteristics and feelings. The adopted statistical modeling approach is based on generalized linear mixed models. Differently from the traditional strategies used for the analysis of subjective sitting comfort data (e.g. correlation analysis, non-parametric hypothesis tests), the model-based approach allows to investigate and quantify the relationship between overall seat comfort and specific seat/user characteristics. The results show that the overall comfort perception is significantly influenced by age, lumbar support, height of seat pan and reclining.

Keywords: seat comfort, repeated evaluations, laboratory experiments, ordinal regression

1 Introduction

Over the years, commercial air traffic and number of passengers have been constantly increasing and airlines are facing a fiercer competition in the international context. Being strictly related to passenger's satisfaction and willingness to pay, comfort improvement has become a major strategic goal for the airline management [1]. A variety of definitions of passenger comfort have been provided in literature and the scientific debate about the main factors impacting on it and the relationship with discomfort is still open [2-9].
Despite the variety of positions, it is undoubted that comfort perceptions are the outcomes of subjective experiences resulting from a reaction to the environment, influenced by psychological, physiological and physical factors. It is thus evident that any comfort analysis cannot disregard subjective methods ('directly asking people about how comfortable they are'), which can be regarded as the most direct way to detect subjective feelings of comfort. Large survey studies have been proposed in literature to investigate factors impacting on passenger perceptions of comfort/discomfort. Vink et al. [10] analyzed the online trip questionnaires of more than 10000 passengers in order to identify the critical factors influencing comfort experience during a flight; Amadhpour et al. [11] investigated whether the factors underlying the passenger experience of comfort differ from those of

discomfort; Bowens et al. [12] surveyed a sample of students about their aircraft sensory experiences and relate them to a feeling of comfort or discomfort. Most of the available studies evidence that seat comfort is one of the most important factors impacting on passenger on-board experience and a main driver for flight selection [13]. In order to attract and retain more passengers, airlines need to distinguish their offer from the competitors by providing a better seat comfort experience. However improve the design of aircraft seat for economic class is maybe one of the most difficult challenge for manufacturers since many necessary yet conflicting expectations and requirements have to be fulfilled (*e.g.* increase aircraft capacity, improve comfort and living space, lighten aircraft and meet safety requirements).

An effective strategy to collect and process comfort data is crucial to detect the seat design features which mostly impact on passenger perceived comfort and thus provide a *diagnostic* assessment of seat comfort.

Laboratory experiments allow to collect aircraft seat comfort data by involving potential passengers in simulated flight experiences [*e.g.* 14-16]. During these experiments, participants reveal information about their "real time" comfort feelings (e.g. thermal comfort, noise, cabin comfort, seat comfort, legroom); indeed, they are focused on the undertaken experiment rather than recall retrospective flight experiences like it happens for surveys. The main advantages of laboratory experiments are that: 1) researchers can control the environment under which potential passengers make their evaluations and also can compare different seats and/or aircraft environments; 2) a small sample representative of the passenger target population can be considered; 3) it is possible to learn more about aircraft seat experience with a significant reduction in costs and time for data collection and analysis [17-18]. Besides these advantages, experimenters are well aware that human responses in experimental research can be difficult to measure: 1) personal characteristics (*e.g.* demographic like age, nationality, income; physical like body size; physiological like blood pressure, state of health and general well-being; psychological linked to memory of previous flights, expectations about future experiences and personal preferences) make people experience different levels of comfort (or discomfort) in identical environments [*e.g.* 17-22]; 2) different personal experiences can cause people to react to the same situation in different ways and makes it difficult to measure the human responses to different stimuli (*i.e.* experimental treatments); 3) individual differences in rating scale usage cannot be neglected; 4) the same participants generally test several items (e.g. physical products or concepts) and, of course, these evaluations cannot be assumed independent; 5) subjective comfort data are collected via ordered categorical scales, in which scores are meaningful for comparison only.

All these factors and their interdependencies cannot be neglected in order to end up with reliable and robust comfort analysis [23]. Specifically, the first three criticisms may impact on the reproducibility and replicability of the study and they can be addressed by detailed experimental protocols and appropriate experimental design; the last two criticisms, instead, impact on the interpretation of comfort data and can be addressed by a suitable statistical modeling.

The approach adopted in this paper is model-based and accounts for both subjective (user anthropometrical characteristics and perceptions) and objective (seat features) covariates.

Comfort evaluations were modeled through a cumulative link mixed models (CLMMs), an extension of linear mixed models for ordinal data whose model specification and interpretation are more complex due to the discrete nature of the data and the nonlinearity in its parameters [24, 26]. The higher computational complexity of CLMMs is counterbalanced by the higher flexibility. Indeed the adopted CLMM accounts for the ordinal nature of the overall comfort response as well as the potential correlations among repeated comfort evaluations collected in laboratory experiments using a panel of aircraft passengers.

The paper is organized as follows: an overview of the experiment is provided in Section 2; the adopted data analysis strategy is illustrated in Sections 3; the experimental results are reported in Section 4; conclusions are drawn in Sections 5.

2 Overview of the experiment

The experiment involved 17 participants who tested 5 aircraft seat conditions. The participants were frequent flyers of working age with no health problems. The main anthropometric characteristics of participants are reported in Table 1.

During each test session, lasting about 40 minutes, each participant was asked to adopt a fixed posture and perform the task of reading/playing a game with the smartphone. At the end of each test session a trained interviewer asked the participant to evaluate the comfort of some seat features using a scale with three ordered categories (i.e. 1: low comfort, 2: medium comfort and 3: high comfort) and score the overall seating experience using an ordinal scale ranging from 0 (i.e. no comfort) to 8 (i.e. extreme comfort).

Table 1. Main anthropometric characteristics of participants.

	Num.	Age [year] [min-max]	Weight [kg] [min-max]	Height [m] [min-max]	BMI [kg/m^2] [min-max]
Males	9	[27-41]	[73-101.8]	[1.60-1.90]	[22.8-34.7]
Mean (SD)		35 (4.4)	88(8.53)	1.77 (0.08)	28.03 (3.46)
Females	8	[26-44]	[55-75]	[1.55-1.73]	[21.15-27.55]
Mean (SD)		34 (5.9)	66 (5.4)	1.66 (0.05)	24.1 (2.08)

3 Methods

Comfort ratings have been analyzed in a regression setting using a set of covariates representing: 1) objective seat features (*viz*. height of seat, height of seat pan, width of seat pan, backrest configuration, height of backrest, thick of backrest, reclining); 2) user anthropometrical characteristics (*viz*. gender, age, BMI); 3) comfort feelings with specific seat features (*viz*. seat pan, backrest, seat pan padding, backrest padding, lumbar support, lumbo-sacral support).

The cumulative logit model (CLM) is probably the most popular model for ordinal data; it relies on the idea that a subjective evaluation expressed on an ordinal scale (e.g. comfort rating) is actually a categorized version of an unobservable (latent) continuous variable. The CLM uses the cumulative logits to measure how likely the response is to be in a given category or below versus in a category higher than it.

Let Y_i the outcome category selected by subject i for the response variable. Given a set of p covariates, $x_1,..,x_k,...x_p$, the model is defined as follows:

$$\text{logit}\left[P(Y_i \le j)\right] = \alpha_j + \beta_1 x_1 + \ldots + \beta_k x_k + \ldots + \beta_p x_p \quad j = 1,\ldots,J-1 \tag{1}$$

The model in (1) is characterized by (J−1) intercepts and p slopes. Intercepts may differ across the ordinal categories, whereas the coefficients β_k are the same across the categories, meaning that the effect of x_k is assumed to be the same for all the categories of the response Y. The parameter β_k measures the impact of x_k on Y, indeed it can be interpreted as the increase in the log-odd of falling into or below any category associated with a one-unit increase in x_k holding all the other covariates constant. The parameters α_j are the category cut-points on a standardized version of the latent variable and satisfy the condition

$$-\infty = \alpha_0 < \alpha_1 < \alpha_2 < \cdots < \alpha_J = +\infty \tag{2}$$

An extension of this model that includes random effects as well as fixed effects is the cumulative logit mixed model (CLMM). The CLMM allows taking into account both the ordinal nature of the rating scale and the potential correlation between ratings provided by the same subject under different conditions (*e.g.* the same subject testing different seats).

Let Y_{it} denote the overall comfort response over J ordered categories provided by subject i (i = 1, …, 17) for the seat t (t = 1, 2, 3, 4, 5); let $x_{1it}, x_{2it} ,.., x_{kit}$ denote a set of k covariates; let u_i denote the random effect due to subject i for response categories $j=1, 2, ..., J-1$. The cumulative logit mixed model can be formulated as follows [25]:

$$logit\left[P(Y_{it} \le j)\right] = u_i + \alpha_j + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_p x_{pit} \tag{3}$$

The random effect u_i is assumed normally distributed and centered at zero (u_i ~ N (0, σ_u^2)).

When a random effect is included in the model, it is important to look at the intra-class correlation (ICC). ICC is defined as the correlation of observations within a group and it is a way to look at how similar these within cluster observations are to one another. The ICC is calculated as follow:

$$ICC = \frac{\hat{\sigma}_u^2}{\hat{\sigma}_u^2 + \sigma^2} \tag{4}$$

where $\hat{s}_u^2$ represents the estimated variance of the random effect, whereas s^2 is the residual variance and assuming the hypothesis of an underlying standard logistic latent variable it can be calculated as $s^2 = p^2/3$. Values of ICC near one indicate that observations within a cluster are very similar to one another, while values close to zero indicate that the random effect can be neglected since observations within a group are nearly independent [25].

4 Results

In the adopted CLMM, the participant effect was assumed to be random and fixed effects included anthropometrical characteristics (*viz*. gender, age, BMI), objective seat features (*viz*. height of seat, height of seat pan, width of seat pan, backrest configuration, height of backrest, thick of backrest, reclining) and comfort feelings with specific seat features (*viz*. seat pan, backrest, seat pan padding, backrest padding, lumbar support, lumbo-sacral support).

A forward selection algorithm was applied in order to obtain the optimal model which includes 4 significant covariates: age (*age;* 1: ≤ 35 year; 2:≥ 35 year); lumbar support (*lumbsu;* 1:low, 2:medium; 3:high); height of seat pan (*heightsp*; 1:low, 2:medium; 3:high) and reclining (*rec;* 0:yes, 1: no).
Table 2 reports the estimated parameters β_k, $k = 1, 2, 3, 4$; the cut-points α_j, $j = 1, 2, 3, 4, 5, 6, 7$ with asymptotic standard error (in parentheses) and AIC index.

Table 2. CLMM fitted on comfort data.

Parameters	β_{age}	β_{lumbsu}	$\beta_{heightsp}$	β_{rec}	α_1	α_2	α_3	α_4	α_5	α_6	α_7
Estimates (Std Error)	0.824 (0.412)	1.478 (0.356)	-0.832 (0.288)	-2.01 (0.474)	-4.001 (1.21)	-3.971 (1.17)	-2.623 (1.15)	-1.262 (1.13)	0.198 (1.11)	1.549 (1.11)	3.257 (1.18)
AIC					292.42						

The coefficient values highlight that overall comfort ratings falling in higher categories are more likely as the values for age and comfort of lumbar support increase; instead overall comfort ratings falling in lower categories are more likely for seat in reclined position and higher seat pans.

The $\hat{\sigma}_u^2 = 0.003$ for the random effects model implies a low effect due to repeated evaluations provided by the same participant (Fig. **1**). Moreover, ICC equals to 0.0009 confirms the substantial independency of observations provided by the same participants for different seat conditions.

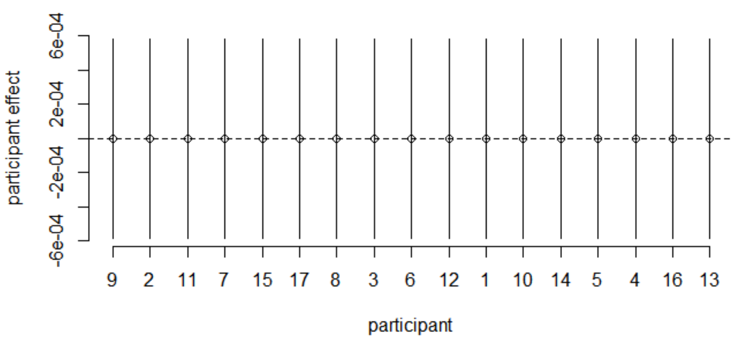

Fig. 1. Participant effect.

5 Conclusions

The adopted model based approach allows to investigate the strength and direction of association in subjective comfort data taking into account their ordinal nature as well as the potential grouping structure of replicated observations, overcoming the hypothesis of independency that is often unrealistic in experimental settings.

The findings highlight that the probability of low overall comfort perceptions is higher for seats in reclined position and seat with a higher seat pan; instead the lumbar support has a significant positive impact on the overall comfort perception. It is worthwhile to note that in our study, participant effect resulted negligible; this finding could be related to the involvement of a group of expert assessors (*i.e.* frequent flyers) who may show less individual psychological biases in the evaluation task. However, since psychological and physiological biases generally affect the subjective assessment in a sample set, assessor's effect cannot be disregarded.
Further investigations are necessary in order to check the generalizability of findings outside laboratory setting.

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