# A Cognitive-Computational Model of Comfort Categorization in Civil Aviation Propeller Aircraft

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## Abstract

The present work is dedicated to modeling and analyzing processes of vibro-acoustic comfort perception among passengers in a civil aviation propeller aircraft. The experimental data analyzed in this study were collected as part of the European project IDEA PACI (IDEntification of an Aircraft PAssenger Comfort Index) and encompass both vibro-acoustic and psychometric characteristics.

We introduce a computational model of the perceptual processes of passenger comfort for this vehicle class based on an automatic classification system with cognitive plausibility. This system incorporates both prototype theory and exemplar theory of categorization. The study has two primary objectives: first, to develop an artificial classification system with high performance, serving as a valuable support tool for designing more comfortable aircraft; second, to investigate which of the considered cognitive theories most accurately represents the categorization process of human comfort.

The experimental results, including other instance-based systems, demonstrate that the computational model used (the Prototype Exemplar Learning - Classifier) effectively predicts human passenger comfort, and the type of representative instances inferred by the system indicates a clear predominance of exemplar theory over prototype theory in modeling the perception of comfort.

**Keywords:** Comfort; Categorization; Cognitive model; Prototype theory; Exemplar theory; Design; Human factors; Propeller; Aircraft.

## Introduction

The study and understanding of passengers' comfort perception aboard commercial aircraft encompass both traditional disciplines—such as psychophysics, vibro-acoustics, and psychoacoustics (Jacobson *et al.*, 1978; Vecchio *et al.*, 1999)—and interdisciplinary fields. These include aviation psychology (e.g., Tsang & Vidulich, 2002), cognitive science, and concepts like hot-thought (FAA, 2023, Chapter 14; Thagard, 2006).

In the field of aeronautical engineering, these aspects closely linked to cognitive science, while originating from a common foundation in aviation psychology, have now evolved into more distinct and specialized areas. These are widely recognized under the umbrella term "human factors" (FAA, 2023, Chap. 14) which can be defined as *"the discovery and application of information about human abilities, limitations, and other characteristics to the design of tools, machines, systems, tasks, jobs, and environments for safe, comfortable, and effective human use"* (Chapanis 1983).

In this work, we address the problem of vibro-acoustic comfort (Ahmadpour, 2014; Brindisi & Concilio, 2008; Brindisi & Gagliardi, 2016; D'Ischia & Brindisi, 2005; Vink, 2011; Mansfield *et al.*, 2021) for passengers of regional commercial aircraft. Specifically, we analyze one of the datasets comprising vibro-acoustic and psychometric experimental data collected within the framework of the European project IDEA PACI (IDEntification of an Aircraft PAssenger Comfort Index, 1998-2000). Our focus is particularly on the dataset related to passengers of high-speed propeller-driven aircraft.

The original objective of this project was the development of a *"Virtual Passenger"*, using an artificial neural network (ANN) to simulate the *"Transfer function"* between external stimuli and the subjective impressions of a generic passenger. Instead, in this approach, we use a different machine learning system that overcomes the well-known opacity issues of ANNs by employing a cognitively plausible machine learning system.

Therefore, we aim to create an explainable model (cf. Angelov *et al.*, 2021; Freitas, 2013; Gagliardi, 2007; Linardatos, Papastefanopoulos, & Kotsiantis, 2021; Rudin, 2019) of the perceptive processes involved in passengers' comfort, which is of assistance in the aeronautical design phases of new civil aircraft (Paonessa, d'Ischia, Repole, Brindisi, 2005; Sorrentino, Concilio, Cenedese, 1999) and is also valuable for exploring the nature of categorization processes underlying human comfort perception.

Below, we introduce the problem of comfort evaluation and describe the experimental procedure followed for its



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measurement. Then, we present the computational models of categorization, based on prototypes and exemplars, that have been applied to the considered dataset. Finally, we outline the results of the simulations performed and draw the related conclusions.

## The problem of comfort evaluation

Comfort is a condition of ease and convenience that an individual experiences when placed in a certain environment or subjected to certain stimuli. Comfort is determined by the environment, but being a perception of the individual, it is conditioned by countless personal factors that act on the subject at that moment, such as the state of health, psychological attitude, expectations, stress, etc. (Ahmadpour, 2014; Vink, 2011). The comfort of a given environment, characterized for example by a given temperature, humidity, a given noise, or sufficient space to sit or move around comfortably, is ultimately a subjective experience since it refers to a personal evaluation of the individual who is in that specific condition at that moment.

Comfort evaluation studies are of interest in the industrial field, such as in the aeronautical field, where aircraft design that takes into consideration the well-being of the traveler or crew has a competitive advantage in the safety of flight.

The internal comfort of an aircraft is currently evaluated both for passengers and for onboard personnel, such as pilots and flight attendants, for whom it has an additional value: the human factor (mental, emotional, and physical state) that influences safety, (FAA, 2023). Multidisciplinary studies that start from aeronautical psychology (Tsang, Vidulich, 2002) and that include contributions from cognitive science, engineering, industrial design, statistics, anthropometry, medicine, and physiology, deal with interaction between the on-board personnel and the aircraft environment.

The first studies on comfort inside aircraft and dedicated to passengers were carried out in the 1980s and essentially focused on what was believed to be the first source of "inconvenience", noise, and on trying to eliminate its main cause, that is, the vibrations generated by the engines and transmitted inside the aircraft through the structure (Jacobson *et al.*, 1978). Subsequently, they tried to understand how the internal acoustic field influenced comfort: the characteristic parameters of the noise and the subjective responses of the passengers were evaluated (Vecchio *et al.*, 1999). The European Union has financed, through its framework programmes, various projects intending to improve knowledge on the psychological and subjective aspects of the internal comfort of civil transport aircraft, both for passengers and for the crew.

One of the objectives is to define environmental comfort that includes, in addition to noise and vibration, other parameters such as temperature, relative humidity, pressure, or pollutants, with the aim of more accurately modeling the comfort evaluation processes and their causes (Brindisi, Concilio, 2008; Brindisi, Gagliardi, 2016; d'Ischia, Brindisi, 2005; Sorrentino *et al.*, 1999) also dealt with the physiological effects of the acoustic environment on on-board personnel.

## Experimental procedure for comfort evaluation

One of the preliminary requirements within the scope of this work and more generally of the entire IDEA PACI project is the definition of an appropriate numerical index that synthetically represents the sensation of comfort perceived by a passenger. This scalar index (CI - *Comfort Index*) was obtained from statistical processing of opinions expressed by 117 ordinary people (i.e., non-expert listeners) responding to questionnaires regarding the personal condition and the comfort perceived inside a regional aircraft in the presence of its vibro-acoustic field (Quehl, 2001, p. 57 and onward; Sorrentino, 2003). The Comfort Index represents, in a synthetic manner, the perception of passenger comfort when subjected to the main environmental stressors typically present in the aircraft interior, such as noise and vibration.

The experimental activities were conducted in dedicated cabin simulators, which were created using real fuselage segments, to obtain an adequate database of environmental stressors and relative passenger responses. At first glance, the CI appears to depend on several factors such as the position inside the cabin, the flight conditions, which influence both the noise and the vibrations inside the aircraft, as well as on all those other factors that can influence the vibro-acoustic field inside the aircraft, from flight maneuvers to the operation of the air conditioning.

During each measurement session for a given flight condition, several tests were repeated, changing the position of the passengers inside the cabin so that the obtained CI would depend as much as possible on the specific vibro-acoustic conditions rather than on the status of the individual passenger; the CI value is, therefore, a measure of the comfort perceived by an average passenger subjected to particular vibro-acoustic conditions.

## Computational models of categorization based on typicality

Categorization is a fundamental cognitive function in the thought processes of the human mind. Categorizing means assigning a percept or stimulus to a class. In the field of cognitive science, various theories have been proposed on how the human mind categorizes physical and social reality (Medin, 1989; Houde, 1998; Medin, Aguilar, 1999; Murphy, 2002; Thagard, 2005). The theories that we take into consideration in this work are the prototype theory and the exemplar theory.

According to Prototype Theory (Rosch, 1975; Rosch, Mervis, 1975), concepts are prototypes that represent the typical characteristics of the objects of a category, rather than the necessary and sufficient conditions foreseen by classical theory. According to prototype theory, human beings tend to identify a category of objects and reason about their members by referring to a specific object typical of the family.

A different point of view on concepts is to consider them as a collection of memorized examples. This theory, known as exemplar theory, was first proposed by Medin and Schaffer (1978). It rejects the idea, common to classical and prototype theory, that people have some type of representation capable of describing the entire category.

We can consider prototype theory and exemplar theory, if taken individually, as incomplete and unsatisfactory. G. Murphy (2002, 4) highlighted how it is necessary to look for new ways of thinking about the problem of categorization, rather than pursuing the prototypes versus exemplars debate, thus suggesting the need for a more *"comprehensive"* approach. This approach can consist of developing new theories that subsume existing ones, or contain them as limit cases or particular cases. What, beyond the individual theories, does not lend itself to criticism is the existence of typicality seen as a phenomenon present in categorization processes (see *"Typicality as phenomenon"* in Murphy, 2002, 28). This "phenomenon" cannot be fully explained with any of the theories developed to date.

A common aspect between the theory of prototypes and that of exemplars is the belief that the category is represented by instances of the class, which in one case are abstracted from observation (prototypes) and in the other are previously observed instances (exemplars).

In the field of machine learning (Duda, Hart, Stork, 2000; Witten, *et al.*, 2016), and in particular in the problem of automatic classification, one of the learning methodologies known in the literature is learning based on instances (instance-based learning)[1] (Aha, *et al.*, 1991; Cover, Hart 1967; Gagliardi, 2011; Nieddu, Patrizi, 2000) in which the classes, learned by the automatic classification system, are represented by more or less abstract instances of the class.

In this field, there are classifiers based on prototypes, such as the Nearest Prototype Classifier (NPC) (Bezdek, *et al.*, 1998), those based on exemplars such as the Nearest Neighbor Classifier (NNC) (Aha, *et al.*, 1991; Cover, Hart, 1967) and hybrid classifiers (Nieddu, Patrizi, 2000) such as PEL-C (Prototype Exemplar Learning - Classifier) (Gagliardi, 2008; 2012) which creates a cognitively plausible model of categorization based on typicality.

The learning algorithm of the PEL-C is iterative; the starting condition is that of a single representative instance per category (the prototype) and, at each iteration, another representative instance is added to increase the predictive accuracy of the model.

To avoid the occurrence of overfitting, the PEL-C uses the *tuning by cross-validation curve* technique (Henery, 1994; p. 108) to estimate the best number of representative instances that have the greatest predictive capability on a test set different from the training set (cf. figure 1).

Theoretically, the type of representations inferred can vary between the two limiting cases, consisting respectively of a set of only abstract prototypes (one per class), up to a set consisting of all the exemplars that constitute the dataset. Empirically, in previous studies (Gagliardi, 2008; 2011; Gagliardi, Angelini, 2013), this algorithm has shown that in many cases on real datasets, the set of inferred representative instances is made up of a mixture of prototypes and exemplars.

In this context, the number of representative instances inferred from the PEL-C and the percentage ratio relative to the total dataset size—the "compression ratio"—can be used as the model interpretability metrics to distinguish between prototype-based and exemplar-based categorization.

A higher number of representative instances and a lower compression ratio indicate a categorization based on increasingly less abstract instances, that is, exemplars; conversely, a lower number of representative instances and a higher compression ratio indicate a categorization based on more abstract instances, that is, prototypes (e.g. table 2).

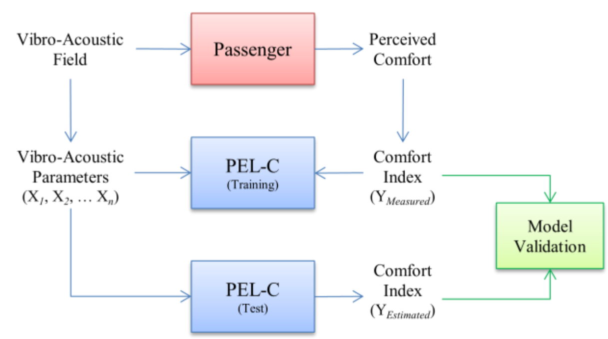


Figure 1. Diagram of the empirical and computational modeling activities performed in this study.

## The dataset

The collected data relating to the vibro-acoustic field and the comfort perceived by the passenger constitute the dataset used for the training and the subsequent testing of the computational model (cf. figure 1). The input features vector represents the vibro-acoustic field, while the output vector represents the comfort index.

In particular, in the aircraft there is a vibro-acoustic field that can be measured at various frequencies, obtaining a spectrum in which the intensity of the sound and vibrations varies as a function of the frequency. The human perception of comfort is conditioned by various characteristics of the vibro-acoustic field (Fastl, Zwicker, 2007), first of all, the loudness, which represents the level or amplitude of the sound and is expressed in dB, but also by temporal variations of the field itself and the amplitude modulations.

A multispectral and multiband analysis of the acoustic field was carried out considering a sequence of 9 spectra, each lasting 5.81 ms interspersed with 17.43 ms; for each

[1] Note that in the literature the term instance-based learning is mainly used to refer only to exemplar-based methods (e.g., Aha, *et al.*, 1991); in this work, we prefer to use this term to refer uniformly to both methods based on prototypes and those based on exemplars (see Gagliardi, 2011).

spectrum, the 1/3 octave bands between 16 Hz and 630 Hz[2] were considered, grouping the first 8 bands, from 16 Hz to 80 Hz, the 3 bands from 100 Hz to 160 Hz, and the two bands 200 Hz and 250 Hz, respectively, into three features, thus obtaining for each spectrum 7 features measured in dB (Quehl, 2001; Sorrentino, 2003).

In addition to these 63 acoustic features (7 features for 9 bands), the vibrations to which the passenger is subjected were measured following the ISO 2631-1:1997 standard considering vertical vibrations in the 1-300Hz range; according to this standard, vibrations are also expressed in dB.

The input feature vector $X_i$ is therefore made up of 64 elements, expressed in decibels (*dB*), of which the first represents the vibration level, and the remaining elements represent the acoustic intensity levels.

The comfort index perceived by the experimental subjects was subject to a discretization of the values into 7 classes; to avoid an unbalanced distribution of data in the classes, an equal-frequency binning was carried out (Witten, *et al.*, 2016) which guarantees that different classes present the same number of instances so that each class is equally represented. This choice was made following some well-known cognitive aspects, for which there is a limit to the extension of the range of values in which a person can express an absolute judgment, determined by the limit to the quantity of information that a person is capable of receiving and processing (e.g., Miller, 1956). Therefore, to evaluate the quality or otherwise of comfort, we can consider, under Miller's famous work, that a scale of 7 values is sufficient to adequately express the gradation of judgment of a human subject.

Ultimately, the available experimental data concern 772 observations or associations between vibro-acoustic feature vectors and comfort index; each input vector is composed of 64 numerical attributes measured in dB, while the output consists of an integer numerical value in the range [1, 7] (table 1).

Table 1: Characteristics of dataset.

| Characteristic | Number |
|---|---|
| Observations | 772 |
| Features | 64 |
| Classes | 7 |
| Missing values | 0 |

## The experimental results

The experimental performances were validated using the leave-one-out cross-validation technique (Witten, *et al.*, 2016) with which the entire dataset is used to test the computational model since one input pattern is considered at a time as a test and the remaining dataset is used for model training; this procedure is repeated for each pattern in the dataset and the performances are then evaluated (cf. figure 1).

The PEL-C obtained an accuracy of 99.48% on the dataset considered; the performances obtained were also compared with two other instances-based classification techniques, the Nearest Prototype Classifier (NPC) and the Nearest Neighbour Classifier (NNC) (see Gagliardi, 2011) for which the same cross-validation procedure was used.

The results obtained are reported in table 2; both the PEL-C and the NNC obtain excellent performances, the PEL-C also has an excellent compression factor, 16.18% of the data set, using on average around 125 instances compared to the 772 of the entire data set used by the NNC.

Table 2: Performances of the classification systems.

| | NPC | PEL-C | NNC |
|---|---|---|---|
| Accuracy | 32.77 % | 99.48 % | 99.48 % |
| Representative instances | 7 | 124.75 | 772 |
| Compression ratio | 0.90 % | 16.18 % | 100.00 % |
| Precision | 31.41 % | 99.49 % | 99.49 % |
| Recall | 32.83 % | 99.48 % | 99.48 % |

These results about the type of representative instance inferred by the system show a clear prevalence of the exemplar theory over the prototype theory in modeling the perception of comfort.

On the other hand, the number of instances selected by PEL-C (equal approximately to only 16% of the entire dataset) shows also a clear selection of the exemplars; the exemplar-based categorization can rely also on selective mechanisms of exemplar relevance and not just on mere memorization.

## Conclusions

In this work, we have addressed the modeling and analysis of comfort categorization by passengers of civil commercial aircraft. Using experimental data obtained through a test campaign conducted with human subjects under highly realistic flight conditions, we have developed comfort categorization models employing three types of cognitively plausible classifier systems.

The results demonstrate how instance-based classifiers can serve as cognitive-computational models of the processes underlying the subjective evaluation of comfort by humans. These computational models prove valuable both for advancing the understanding of the categorization processes in the human mind (cf. Gagliardi, 2009; 2014) and as a supportive tool in aeronautical design, integrating the perception of comfort by passengers.

The type of representative instances inferred by the two systems with higher accuracy (PEL-C and NNC) demonstrates a clear predominance of exemplar-based categorization in modeling the perception of comfort, at least within the experimental setting considered.

[2] Where not otherwise indicated, we refer to the central values of the 1/3 octave band.

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