

# Classification of Hearing Aids Into Feature Profiles Using Hierarchical Latent Class Analysis Applied to a Large Dataset of Hearing Aids

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**Objectives:** We developed a framework for objectively comparing hearing aids, independent of brand, type, or product family. This was done using a large dataset of commercially available hearing aids. To achieve this, we investigated which hearing aid features are suitable for comparison, and are also relevant for the rehabilitation of hearing impairment. To compare hearing aids objectively, we distinguished populations of hearing aids based on a set of key hearing aid features. Finally, we describe these hearing aid subpopulations so that these could potentially be used as a supporting tool for the selection of an appropriate hearing aid.

**Design:** In this study, we used technical (meta-)data from 3911 hearing aids (available on the Dutch market in March 2018). The dataset contained about 50 of the most important characteristics of a hearing aid. After cleaning and handling the data via a well-defined knowledge discovery in database procedure, a total 3083 hearing aids were included. Subsequently, a set of well-defined key hearing aid features were used as input for further analysis. The data were split into an in-the-ear style hearing aid subset and a behind-the-ear style subset, for separate analyses. The knowledge discovery in databases procedure was also used as an objective guiding tool for applying an exploratory cluster analysis to expose subpopulations of hearing aids within the dataset. The latter was done using Latent Class Tree Analysis, which is an extension to the better-known Latent Class Analysis clustering method: with the important addition of a hierarchical structure.

**Results:** A total of 10 hearing aid features were identified as relevant for audiological rehabilitation: compression, sound processing, noise reduction (NR), expansion, wind NR, impulse (noise) reduction, active feedback management, directionality, NR environments, and ear-to-ear communication. These features had the greatest impact on results yielded by the Latent Class Tree cluster analysis. At the first level in the hierarchical cluster model, the two subpopulations of hearing aids could be divided into 3 main branches, mainly distinguishable by the overall availability or technology level of hearing aid features. Higher-level results of the cluster analysis yielded a set of mutually exclusive hearing aid populations, called modalities. In total, nine behind-the-ear and seven in-the-ear modalities were found. These modalities were characterized by particular profiles of (complex) interplay between the selected key features. A technical comparison of features (e.g., implementation) is beyond the scope of this research.

**Conclusions:** Combining a large dataset of hearing aids with a probabilistic hierarchical clustering method enables analysis of hearing aid char-

acteristics which extends beyond product families and manufacturers. Furthermore, this study found that the resulting hearing aid modalities can be thought of as a generic alternative to the manufacturer-dependent proprietary “concepts,” and could potentially aid the selection of an appropriate hearing aid for technical rehabilitation. This study is in line with a growing need for justification of hearing aid selection and the increasing demand for evidence-based practice.

**Key words:** Cluster analysis, Evidence-based practice, Hearing aid features, Hearing aids, Hearing aid selection, Latent class analysis, Latent class trees analysis.

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## INTRODUCTION

Hearing aids are the primary tools for the rehabilitation of hearing impairment. Objective selection of and rehabilitation with hearing aids has been considered important since the earliest days of hearing aid fitting (Carhart 1950) and remains important to this day (Anderson et al. 2018). Today’s hearing care professionals and audiologists can choose from an overwhelming number of different types and brands of hearing aids to accommodate the needs of the hearing impaired individual. Presently, most hearing aid brands offer several product families, aiming for a wide price range and scope of rehabilitation purposes. Factors such as competition among hearing aid manufacturers and the development of complex hearing aids with a wide range of features have led to the need for manufacturers to distinguish themselves, for example, by using their own terminology to describe comparable hearing aid characteristics.

Hearing aid characteristics are commonly referred to as features and are the building blocks of the hearing aid, essentially defining the properties of the hearing aid. Although there are many differences between hearing aid features, such as the precise implementation of a feature and terminology used, hearing aid features can easily be grouped together by purpose. For instance, within hearing aid brands or even product families, there are many types of single-microphone noise reduction (NR) concepts. All these NR concepts share the same purpose, which is to improve speech-to-noise ratio and listening comfort (Brons et al. 2014). Currently, new developments in hearing aid technologies are usually presented in terms of proprietary “concepts,” which are combinations of features rather than isolated features (Le Goff 2016; Carlile 2017; Rodrigues 2019). However, the component features may still be recognized as known features, such as directionality or wind NR (WNR). These proprietary “concepts” are mainly used to outline the interplay of several existing features, but in contrast to commonly known and understood features, proprietary “concepts” are manufacturer dependent. Therefore, it becomes more challenging to

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compare hearing aid characteristics both between and within different brands.

### Hearing Aid Selection

A considerable amount of research has been conducted with focus on effectiveness and relevance of specific hearing aid features, such as compression (Verschuure et al. 1996; Jenstad & Souza 2005; Bor et al. 2008; Alexander & Rallapalli 2017; May et al. 2018), NR (Bentler & Chiou 2006; Hoetink et al. 2009; Brons et al. 2013, 2014; Desjardins & Doherty 2014; Wu et al. 2018), various modes of directionality (Leeuw & Dreschler 1991; Bentler et al. 2004; Picou et al. 2014; Wu et al. 2018). In general, these studies focus exclusively on the evaluation of one hearing aid feature, usually in great detail. To our knowledge, a comparable mixture of several objectively defined hearing aid features, across a wide selection of brands and types of hearing aids, has to date not been examined. Attempts have been made to assess differences between hearing aids (Cox et al. 2014, 2016; Kates et al. 2018; Wu et al. 2018), but these are rather limited and do not focus on the interplay between different features.

Over the past decades, the process of hearing aid selection has gradually shifted from a selection driven primarily by the amplification characteristics of hearing aids (Studebaker 1982; Cox 1985; Byrne 1996), toward a selection method that besides amplification takes into account the availability of more complex signal processing and overall level of technology (Meister et al. 2010; Northern 2011; Gioia et al. 2015). A recent study by Anderson et al. (2018) shows that the availability of specific (signal-processing) hearing aid features is an important aspect of selection among audiologists. The hearing aid selection process is prone to various types of bias: for example, selection could be influenced by previous experiences of the hearing aid dispenser (Johnson et al. 2009; Gioia et al. 2015). A caveat regarding hearing aid selection is the absence of an objective method for comparing hearing aids. If our goal is to select the hearing aid, which best accommodates the patients' rehabilitation needs, then there is a need for a tool for objectively comparing hearing aids (Anderson et al. 2018). In particular, we should be able to objectively compare relevant hearing aid features between different brands and types of hearing aids.

### Data Mining

There has been an increase in research that focuses on the application of data mining, also in the field of audiology. For instance, data-mining techniques have been used to explore the possibility of improving hearing aid fitting and validation through the use of large datasets (Mellor et al. 2018a). The strength of data-mining techniques is their potential to reveal important hidden relations within databases (Kaur & Wasan 2006). For this reason, and given the reasonable number of available hearing aids, the application of data mining to assess hidden relationships between the features of hearing aids seems promising. The term "modality" has been coined to define these relationships between features, and to characterize a population of closely related hearing aids. We hypothesize that variation within and differences between hearing aid populations in the form of hearing aid modalities, can be modeled using a well-defined subset of key features.

### Goal of the Study

The aim of our study is to devise a structure that enables comparisons between hearing aids, in an objective manner independent of brand, type or product family, and based on their key features. We used the technical (meta-)data, provided by hearing aid manufacturers to achieve this.

We formulated several research questions (1) which hearing aid features can be considered to be key features, (2) can we distinguish populations of hearing aids (i.e., modalities) based on key hearing aid features, and (3) is there any brand-dependency among the modalities?

Comparison of individual features (or how these features might be implemented) is beyond the scope of this research. Furthermore, our knowledge is currently insufficient to enable us to relate technical features to patient needs, but this could be a goal for future research.

## METHODS

In this study, we focused on (hidden) relations between hearing aid features. These relations, called modalities, could arise coincidentally or could be the result of deliberations in the R&D departments of manufacturers. In the process of defining hearing aid modalities, several steps were undertaken that will be explained in detail in this section. In short, publicly available technical hearing aid data were gathered, including information on the availability and adaptability of various hearing aid features. Hearing aid populations in the form of modalities could be modeled using information about specific hearing aid features. The benefit of this approach is that hearing aid modalities can be defined, independent of brand or type. A possible drawback of this method is that manufacturer-defined availability and adaptability are not always compatible between the different brands and even sometimes between different types of hearing aids within the same brand.

### Database

We utilized a database used by Dutch hearing care professionals for selection of hearing aids. It contains the most important characteristics of the hearing aids that were available on the Dutch market in March 2018 [in Dutch: "ZN-hoortoesstellendatabase," managed by the Platform for Audiological Clinical Testing (PACT) foundation<sup>\*</sup>]. The dataset used in this research included technical information from 3911 hearing aids, containing all major, and some lesser-known hearing aid manufacturers. The database comprised a mixture of different types of data: not only technical information but also data such as date of introduction, several identifiers, and functional information such as water resistance. For each hearing aid, a total of 50 unique hearing aid-related variables were registered using publicly available information provided by manufacturers and verified and supplemented by independent audiologists on behalf of PACT; a full list of the database attributes can be found in Appendix B in Supplemental Digital Content, <http://links.lww.com/EANDH/A652>.

<sup>\*</sup>The PACT foundation represents a scientific collaboration of almost all Dutch Audiological Centers.

### The Knowledge Discovery in Databases Process

As a consequence of having different data measure types (ordinal, nominal, interval) in our database, a systematic and well-defined approach was needed for data processing procedures, data analysis, and interpreting results. The method we used for deducing knowledge from data is referred to as Knowledge Discovery in Databases (KDD) and is explained in depth by Fayyad et al. (1996). They describe it as “the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data.” KDD is an iterative process that consists of five distinct stages which we explain briefly in this article. Each stage of the KDD can be evaluated after execution and newly gained insights can be applied directly. A more thorough description of KDD in relation to audiology can be found in Mellor et al. (2018b).

### Selection

The first step in the KDD process is selection of a dataset using a subset of variables and/or a selection of data samples. The selection is driven by prior knowledge and predetermined goals. Understanding of the application domain is therefore essential. Following this step, the list of database attributes listed in Appendix B in Supplemental Digital Content, <http://links.lww.com/EANDH/A652>, was reduced based on expert opinion (“prior knowledge”). This was done by asking a panel of (6) experienced audiologists and researchers to select, in mutual agreement, a subset of audiological relevant variables. The term “audiologically relevant” was defined as hearing aid features that have an (direct or indirect) effect on the functioning of the hearing aid without influence from the user. Table 1 shows the subset made based on expert opinion selection. Further reduction of variables was attained by the iterative

character of the KDD process. For instance, a variable could be removed when intermediate analysis results indicated that there was no significant contribution. This would be the case for a variable which showed a considerable correlation to one or more other variables. The final list of hearing aid features used in the data mining stage is described in the Results section. In addition, two predefined exclusion criteria were applied to the data; exclusion of (1) bone conduction hearing aids, pure Contralateral Routing Of Signals devices, hearing aid glasses, and body-worn hearing aids; (2) hearing aid brands that were not available via regular distributors in the Netherlands.

### Preprocessing

Due to fundamental differences between behind-the-ear (BTE) type hearing aids and in-the-ear (ITE) type hearing aids, the data were split into two subsets based on the style of hearing aid. The primary reason for this is the difference in design constraints between the two types, which cause different sets of features to be prioritized. The data in these subsets consisted of continuous and categorical variables, the latter being both ordinal (interval) and dichotomous. In the preprocessing stage, data were cleaned of noise (e.g., outliers, faulty data) and missing data. We dealt with this by defining missing data and outliers, and then creating rules for handling data which matched these definitions. We decided to completely remove all data that had missing or invalid data points on any of the variables used in the (final) analysis at the data mining stage. Outliers were identified as anomalies (e.g., values that could reasonably be assumed to be incorrect, eg, a value that was an order of magnitude larger than comparable values). Identification and removal of invalid data were important steps as it could have a considerable effect, especially when applying categorical data to classification analysis. As a result of the rigorous exclusion policy, the final dataset did not contain any records that had missing or invalid data.

**TABLE 1.** List of audiological relevant “ZN-hoortoestellendatabase” database attributes

Name	Type/Scale
OSPL 90 (max output)	dB
OSPL 50 (max gain)	dB
OSPL 60 (max reference)	dB
Upper limit bandwidth	Hz
Adjustable compression channels	Number
Adjustable MPO channels	Number
Signal processing channels	Number
Directionality	Y/N
Automatic directionality	Y/N
Adaptive directionality levels	Number
Natural “ear like” directionality	Y/N
Binaural beamforming	Y/N
Noise reduction levels	Number
Noise reduction environments	Number
Wind noise reduction levels	Number
Passive feedback levels	Number
Active feedback levels	Number
Expansion levels	Number
Impulse reduction levels	Number
Ear to ear feature synchronization	Y/N
Ear to ear sound streaming	Y/N
Frequency lowering levels	Number
Environmental steering	Y/N

### Transformation

Data transformation procedures can serve many purposes, although a general aim is to further reduce any potential bias that could originate from dominating values in any variable of the dataset (Mellor et al. 2018b). Data exceeding the 75 percentile of the variable were grouped together in a “greater than or equal to” value. This was done to handle some extreme cases in the upper ranges of the scales within the data.

Hidden structures within a dataset can be exposed with the use of exploratory cluster analysis. An important condition for such a method is a limited interdependence of variables. Although this cannot be eliminated completely in most real datasets, efforts should be made to minimize dependency between variables. In our dataset, we identified two groups of hearing aid features whose members were closely related in a complementary fashion, namely directionality and ear-to-ear communication. For directionality, the compound variable was assembled from the following hearing aid features: directionality, automatic directionality, adaptive directionality, and beam forming directionality. Initially, the hearing aid feature adaptive directionality was an ordinal scaled variable, but was transformed to a dichotomous variable that indicated the availability of this feature. The other directionality features were already dichotomous variables. In addition, the four directionality features as described above were found to be redundant (e.g., if automatic



directionality was present, directionality was also present). Similarly, a compound ear-to-ear communication variable was constructed using the hearing aid features: ear-to-ear feature sync and ear-to-ear sound streaming. The resulting compound variables comprised, respectively, 5 and 3 levels, increasing in complexity. For example, a hearing aid with a level 4 directionality featured all types of directionality except a beam forming directionality.

### Data Mining

Knowledge discovery is at the root of the data mining stage and goals that arise from it can be subdivided into two types: verification and discovery (Fayyad et al. 1996). Our research is primarily focused on the discovery of patterns in data: a form of cluster analysis seemed to be most suitable to meet the conditions of our research aim. Han et al. (2011) defined cluster analysis as follows: “the process of partitioning a set of data objects (or observations) into subsets.” This can be viewed as a data modeling technique that provides for concise summaries of the data (Berkhin 2006), without a priori knowledge (Mellor et al. 2018b).

The data mining stage of the KDD process often includes repeated iterative application of particular data mining methods (Fayyad et al. 1996). During the iterative process, a multitude of latent class models were fitted to the data which resulted in a further reduction of variables. Essentially, only variables that contributed to the model fit and interpretation of the model were included in the final analysis.

**Latent Class Analysis** • Latent Class Analysis (LCA) is a model-based, nondeterministic, clustering/classification method which has its roots in structural equation modeling (Oberski 2016a) and is presently used in multiple fields of science for analyzing multivariate discrete (categorical) data (Oberski 2016b). LCA has several powerful advantages over traditional cluster analysis techniques (Magidson & Vermunt 2002), and has shown to be a very useful tool for exploratory purposes (Oberski 2016a). Classification using LCA is based on membership probabilities estimated from the model, unlike the all-or-none based classification seen in cluster analysis such as k-means or DBSCAN. A more detailed description explaining the mechanism of LCA can be found in Appendix A in Supplemental Digital Content, <http://links.lww.com/EANDH/A652>.

Deciding on the number of classes that best fits the data is done in an exploratory setting. Depending on the dataset, it is not uncommon to end up with a large number of classes (Van Den Bergh et al. 2018). Such a result can become exceedingly complicated and difficult to interpret, reducing the practical use of the model. To overcome this problem, Van Den Bergh et al. (2017) suggested an extension to LCA, which they called Latent Class Trees (LCT) analysis.

**Latent Class Trees** • LCT analysis was developed to provide a solution to some common difficulties when interpreting LCA results, such as the absence of a distinct optimum number of classes that fits a model or the fact that it is often unclear how different model results are interconnected. LCT addresses these problems by imposing a hierarchical structure on the latent classes (Van Den Bergh et al. 2017). In short, LCT is defined by a structure of mutually linked classes that are formed by sequentially splitting classes into two subclasses (using LCA with weighted membership probabilities). This allows for a substantive interpretation of the relation between classes of different

levels, and so of how classes are formed and related. A detailed description explaining the mechanism of LCT can be found in Appendix A in Supplemental Digital Content, <http://links.lww.com/EANDH/A652>. Estimation of the latent class models was made using Latent Gold 5.1 (Vermunt & Magidson 2016), and the recursive procedure of the LCT method was applied using customized R scripts (RStudio Team 2016. RStudio: Integrated Development for R. RStudio, Inc., Boston, MA).

### Interpretation/Evaluation

The LCT method (as an extension of the LCA method) was used to discover hidden profiles of hearing aid features, which will be referred to as hearing aid modalities. As the LCT method was applied in an exploratory setting, the aim was not to find the “true” number of hearing aid modalities, but to define a set of modalities that describes the data reasonably well and, moreover, is easy to interpret.

Despite the described advantages of the KDD process, dimensionality reduction due to selection, transformation, or data cleaning always results in a loss of detail. Obviously this is done to enhance interpretation, however, results should be interpreted in this context.

## RESULTS

Originally the data consisted of 50 distinct hearing aid features variables. Reduction of these variables was guided by the KDD process. First, a panel of experienced audiologists and researchers were asked to agree on a subset of variables as being audiologically relevant (KDD: data selection stage); the processed and/or transformed variables were checked for interdependency, which was considered an unwanted property (KDD: preprocessing stage). Remaining variables were processed and several variables were merged into compound hearing aid features variables (KDD: transformation stage). Finally, variables that did not contribute to the model fit and interpretation of the model were removed (KDD: data mining and interpretation stages). Note that due to the iterative nature of the KDD process, the above-mentioned steps were not necessarily executed only once each.

As a result of the KDD process, a total of 10 hearing aid features were identified as fundamental: compression (C), sound processing (SP), noise reduction (NR), expansion (Ex), wind NR, impulse (noise) reduction (IR), active feedback management (FBM), directionality (Dir), noise reduction environments (NRe), and ear-to-ear communication (ETE). Table 2 lists these fundamental hearing aid features, along with a brief description of the variable. Spearman’s rank-order correlations between all fundamental hearing aid features were examined, and all proved to be positive and significant ( $p < 0.01$ ). This indicates that as the number of levels or bands of a certain feature increases, all other features showed an increase in bands or levels as well. It can be seen from Table 3 that most results did not exceed a weak to moderate ( $0.3 < \text{Spearman’s } \rho < 0.5$ ) correlation, although in 3 cases, a moderate correlation was found. The strongest correlation found was between the features C and Spearman’s  $\rho = 0.69$ ). Other notable correlations were found between the following pairs of features: ETE and C (Spearman’s  $\rho = 0.51$ ), and ETE and Dir (Spearman’s  $\rho = 0.51$ ).

**TABLE 2. A list of fundamental key features**

Feature	Domain	Brief Description
N of compression channels	Signal processing	Number of adjustable signal compression channels
N of sound processing channels	Signal processing	Nominal number of channels in which gain could be adjusted
Noise reduction	Signal processing	Number of adjustable noise reduction levels
Expansion	Comfort	The availability, and if so, number of adjustable levels of suppression of weak sounds in a silent surrounding
Wind noise reduction	Comfort	The availability, and if so, the number of adjustable wind noise reduction levels
Impulse noise reduction	Comfort	The availability, and if so, the number of adjustable levels to suppress sudden loud sounds
Active feedback manager	Comfort	The availability, and if so, the number of adjustable levels in which feedback could be actively corrected
Noise reduction environments	Adaptation	The ability to recognize different acoustical environment (on which to apply noise reduction); the availability, and if so, the number of recognizable environments
Directionality compound	Adaptation	NP = no directionality L1 = fixed directionality L2 = automatic directionality L3 = adaptive directionality L4 = beam forming directionality Compound variable is redundant to its lower levels
Ear-to-ear compound	Adaptation	Communication between a matched pair of similar hearing aids: NP = no ear-to-ear communication L1 = feature sync L2 = sound streaming Compound variable is redundant to its lower levels

Key-features were grouped into the domains: Signal Processing, Comfort and Adaptation. These domains were chosen to indicate in which direction these features operate.

Data from 3083 of the original 3911 hearing aids remained after applying the exclusion criteria and the KDD process. Of the 828 hearing aids removed from the analysis, 303 were removed as a result of the predefined exclusion criteria. Another 19 were removed during the KDD process because of faulty feature data, and 506 were removed based on missing data. Most (n = 417) of the hearing aids removed during the KDD process came from three hearing aid brands. For the three brands involved, this means a percentage reduction in hearing aids that could contribute to the analysis of 16%, 29%, and 56%, respectively.

Additionally, the data were split according to the style of the hearing aid, n = 2106 for BTE and n = 977 for ITE. The resulting hearing aid features could be grouped in terms of a common domain in which the features operate, this introduces a specific order and was purely done for the ease of interpretation.

**TABLE 3. Spearman ranked-order correlations of 10 fundamental hearing aid features**

	C	SP	NR	Ex	WNR	IR	FBM	Dir	NRe
SP	<b>0.69</b>								
NR	0.37	0.22							
Ex	0.34	0.32	0.35						
WNR	0.28	0.18	0.17	0.10					
IR	0.40	0.08	0.36	0.05	0.22				
FBM	0.39	0.35	0.48	0.49	0.12	0.19			
Dir	0.36	0.30	0.34	0.15	0.24	0.18	0.08		
NRe	0.34	0.34	0.46	0.11	0.12	0.20	0.22	0.32	
ETE	<b>0.51</b>	0.32	0.36	0.05	0.17	0.32	0.17	<b>0.51</b>	0.38

Correlations  $\geq 0.50$  are in bold. Features:

C, compression; Dir, directionality; ETE, ear-to-ear communication; Ex, expansion; FBM, active feedback management; IR, impulse (noise) reduction; NR, noise reduction; NRe, noise reduction environments; SP, sound processing; WNR, wind noise reduction.

However, the naming of the domains and the grouping was subjective and an attempt by the authors to interpret differences between groups of hearing aid features.

**Latent Class Tree Analyses**

In the KDD process which led to the LCT presented in this section, over 80 different LCT’s were built and evaluated; each model was constructed by using a unique combination of hearing aid feature data. This procedure was an essential part of the selection of the 10 final features. Evaluation and selection of the best fitting model were based on model measures but also on whether the model was meaningful in terms of content. It is not feasible to present each LCT analysis and all intermediate results here.

**Model •** Hearing aid data were split into a BTE and an ITE subset. Independent LCT analyses were performed for each subset. The decision process for the number of primary splits of the LCT is crucial and was guided by the relative improvement measure. This measure signifies the improvement in terms of reducing the Bayesian Information Criterion for an increase in the number of splits (see also Appendix A in Supplemental Digital Content, <http://links.lww.com/EANDH/A652>).

Relative improvement results for the primary node for both BTE and ITE data are shown in Table B.2 of Appendix B in Supplemental Digital Content, <http://links.lww.com/EANDH/A652>. The premise here is the smallest possible number of initial splits. The relative improvement measure indicated that a 3 split primary node was optimal for both subsets. This means that additional splits showed either a similar or smaller relative improvement measure.

Graphical representations of the complete BTE and ITE models are shown in Figure 1. For each model, the first split represents the most dominant structures in the data and is coded

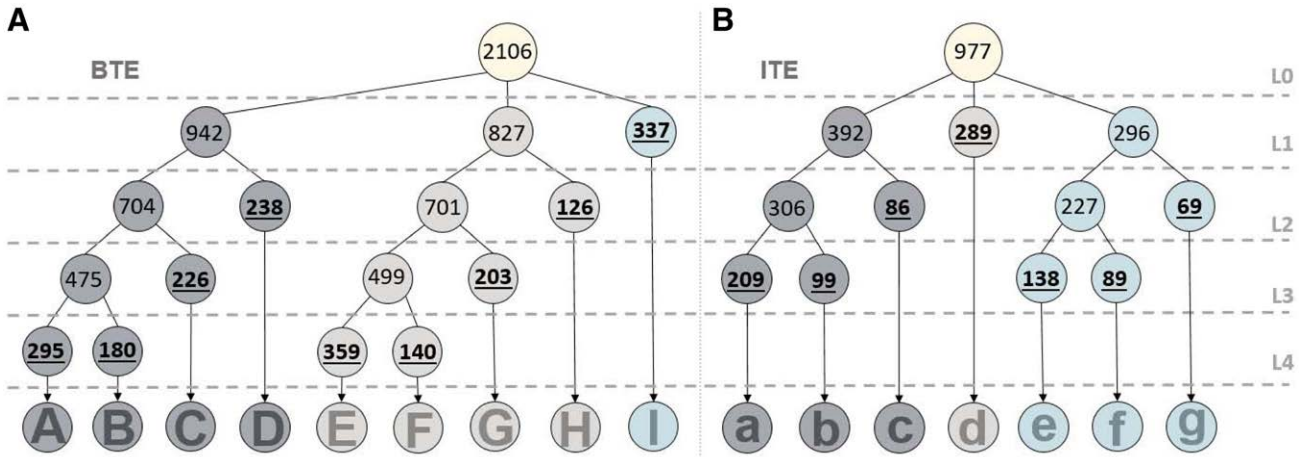


Fig. 1. Graphical representation of the final LCT results: (A) the BTE subset, and (B) the ITE subset. The top node for each model is the starting point for the model at level 0, the modalities are at the lowest level at the end of the tree. The underlined numbers inside the nodes correspond to the number of allotted hearing aids. The allocation of hearing aids to a class is based on probabilities. Therefore, slight deviations could occur between the sum of child nodes and the parent node. BTE indicates behind-the-ear; ITE, in-the-ear; LCT, Latent Class Trees.

similarly for both subsets. The order in which the branches of the BTE and ITE tree are presented, was specifically chosen to support comparison between the two subsets by emphasizing similarities at the primary split level. The number in each node on either side represents the number of hearing aids assigned to a particular node at some level. Consecutive splits were made at different levels for each branch, eventually ending in BTE and

ITE specific modalities. Each split represents a two class (LCA) model at some level  $k, L_k$ , and each model was dependent on the result of a prior “parent” model at level  $L_{k-1}$ ; Figure 2 exemplifies this dependency by showing the hierarchical relation of the second branch for the BTE subset. The feature profile emphasized in the top left graph of Figure 2 was considered an intermediate result. Next, corresponding model results at this level

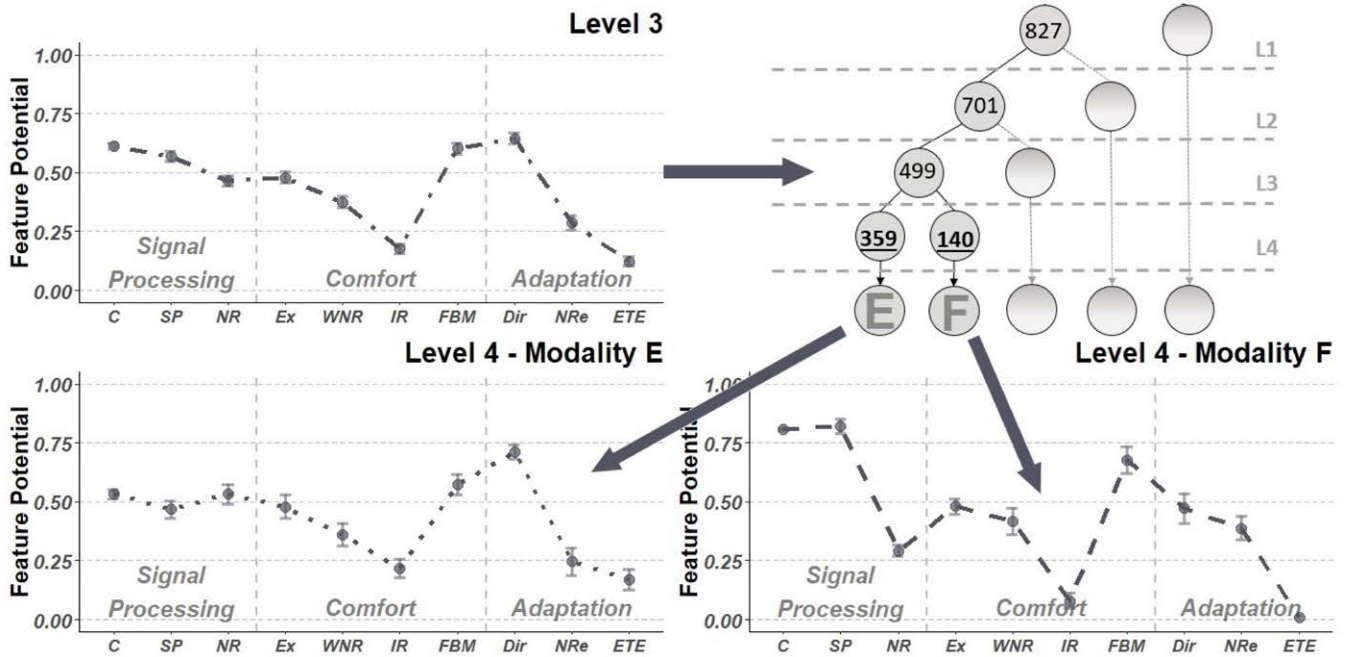


Fig. 2. Example showing the dependency of hearing aid feature profiles on prior “parent” models; each LCA model in the tree is dependent on (all) prior LCA model results up to the lowest level at the end of the tree. The bottom profile plots show the formation of two different profiles within the first BTE branch. In this example, a “parent” model at level 3 (striped dark grey line; highlighted in the top left panel) splits into two “child” nodes (schematically shown in the top right panel). As there were no further splits from the models at the bottom panels onward, the results at this level were considered BTE modality E and F. Mean hearing aid feature data were rescaled between 0 and 1 to enable a straightforward comparison between different scaled variables. Features were ordered according the three domains: signal processing, comfort, and adaptation. Whiskers show a 95% confidence interval of the specific feature. The lines between the points do not refer to a dependency between adjacent features, but were included to interpret and compare the feature profiles between modalities. Labels x axis: compression (C), sound processing (SP), noise reduction (NR), expansion (Ex), wind noise reduction (WNR), impulse (noise) reduction (IR), active feedback management (FBM), directionality (Dir), noise reduction environments (NRe), ear-to-ear communication (ETE). BTE indicates behind-the-ear; LCA, Latent Class Analysis.



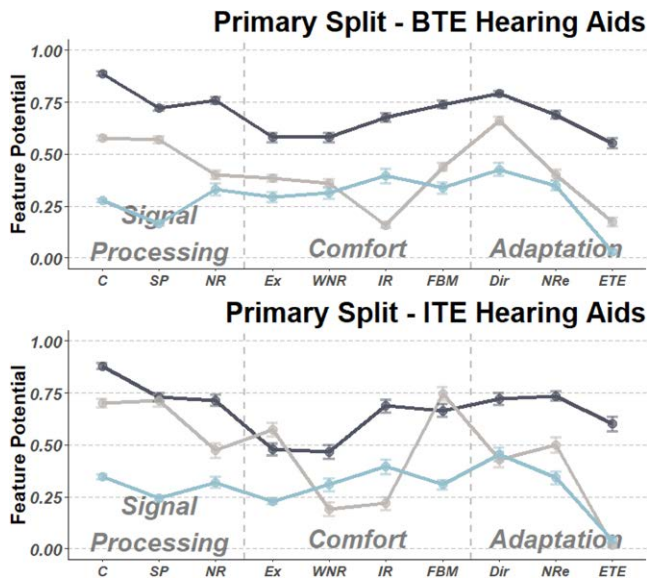


Fig. 3. Profiles plots primary node, for the BTE subset (upper panel) and the ITE subset (lower panel): profile 1 (dark grey), profile 2 (light grey), profile 3 (blue). For axis configuration, see also Figure 2. BTE indicates behind-the-ear; ITE, in-the-ear.

were used to construct a “child” model yielding two distinct profiles, presented in the two graphs at the bottom of Figure 2. In this example, no further splits were made after level  $L_3$ ; both resulting feature profiles were recognized as a final result and are referred to as modality E and F.

The size of the terminal node was considered the main termination criterion for the LCT model, as suggested by Pelaez et al. (2019) and Nasserinejad et al. (2017). Furthermore, model statistics and predefined additional rules for all intermediate levels up to level 4 were used to shape the final LCT results, and are found in Appendix A in Supplemental Digital Content, <http://links.lww.com/EANDH/A652>.

**Modalities BTE** • Focusing on the primary split, Figure 3 (upper panel) visualizes the three most dominant structures of the BTE subset. These three profiles outline the basis on which the LCT for the BTE subset was built, and thus the direction in which the final modalities evolved. Hearing aid feature data were rescaled between 0 and 1 to enable a straightforward comparison. Table 4 shows the means, SD and rescaled means for the BTE subset primary node profiles for each hearing aid feature. Rescaled mean levels at the primary node show that BTE devices allotted to profile 1 (upper panel Fig. 3; dark gray) consisted on average of a high feature potential, with rescaled means ranging between 0.55 and 0.89. Hearing aids belonging to profile 2 (upper panel Fig. 3; light gray) and especially profile 3 (upper panel Fig. 3; blue) on the other hand, show on average a more limited feature potential profile with rescaled means ranging between 0.16 and 0.66 for profile 2, and 0.03 and 0.43 for profile 3.

The nine modalities that resulted from the BTE subset LCT analysis could be characterized by means of their profile plots (Fig. 4), which show the profiles of the modalities resulting from the different hearing aid features, and allows for a detailed analysis. About half (44.7%) of all BTE hearing aids were associated with the first branch, which covered modalities A to

D. These modalities were defined by an overall intermediate to high feature potential for the hearing aid features on all three feature domains. Table 5 shows that there were large differences between rescaled means concerning the different modalities. For example, modality A and B evolved along the same branch, but differed notably between feature potential for IR (rescaled means for modality;  $A = 0.78$ ;  $B = 0.53$ ) and active feedback management (rescaled means for modality;  $A = 0.57$ ;  $B = 1.00$ ). Similar differences occur between particular features for the other modalities of the first branch, yet the largest differences between the modalities of the first branch were found for the features in the adaptation domain (Fig. 4).

The second branch contains 39.3% of all BTE hearing aids, and covers modalities E to H. These modalities shared a limited feature potential for most features. Despite this, the feature profile for modality F also shows a high feature potential for C and SP with rescaled means of 0.81 and 0.82, respectively. For modality H, a high feature potential was observed for the features SP, Dir, and NR environments, with rescaled means of 0.79, 0.82, and 0.86, respectively. The third branch resulted in a single modality, I, which represented 16.0% of the total BTE data. This modality was characterized by an overall low feature potential, most evident for the hearing aid features related to the domains signal processing and adaptation.

**Modalities ITE** • Comparable with the BTE analysis, the LCT obtained for the ITE subset resulted in a primary split, exposing the most dominant structures in the ITE subset. Figure 3, lower panel, shows the three profile plots at the primary node. It can be seen that these profiles share some resemblance to the BTE results, which is reflected by the mean, SD, and rescaled means tabulated in Table 6. The first branch (Fig. 3, lower panel, dark gray) accounts for 40.1% of the ITE data, and resulted in modalities a, b, and c. This branch is characterized by modalities with an above average feature potential (rescaled means between 0.88 and 0.47). The largest variation between feature potential for modalities a and b was found in the features in the adaptation domain, as illustrated by Figure 5. Modality c shows a very unique feature profile and contained only hearing aids with the maximum adjustable levels to suppress sudden loud sounds (Table 7, IR: mean = 5, SD = 0, rescaled mean = 1). Likewise, modality b only contained hearing aids that were fitted with all four levels of directionality (Dir: mean = 5, SD = 0, rescaled mean = 1).

The second branch (Fig. 3, lower panel, light gray) relates to 29.6% of all ITE hearing aids and resulted in a single modality. This modality, d, shows an average feature potential for the features in the signal processing domain, yet contained only hearing aids with almost no ability for wireless communication (ETE: mean = 1.04, SD = 0.19, rescaled mean = 0.02). The third branch (Fig. 3, lower panel, blue) contained 30.3% of all ITE hearing aids, and resulted in modalities e to g. Most of the features within these modalities showed limited feature potential: in particular hearing aids within modality g were found to be very limited (rescaled means ranging from 0 to 0.36), with regard to available feature potential, compared with the total subset of ITE hearing aids.

## Secondary Analyses

Thus far, we did not use any additional (meta) data such as information about the brands of the hearing aids or the date of

**TABLE 4. Mean, SD, and rescaled mean feature levels for each primary node profile for the BTE subset (including the total BTE subpopulation) and hearing aid feature**

Branch	C		SP		NR		Ex		WNR		IR		FBM		Dir		NRe		ETE	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
1	9.9	1.5	14.7	3.6	6.3	1.8	3.3	1.3	2.7	1.0	3.7	1.3	4.7	1.4	4.2	0.8	5.8	2.0	2.1	0.8
2	6.8	1.6	11.8	3.9	3.8	1.8	2.5	1.3	2.1	1.0	1.6	1.4	3.2	1.2	3.7	0.9	3.8	2.1	1.4	0.7
3	3.8	1.0	4.1	3.4	3.3	1.6	2.2	1.1	1.9	0.9	2.6	1.1	2.7	1.4	2.7	0.9	3.4	1.8	1.1	0.6
Total	7.7	2.7	11.9	5.3	4.9	2.3	2.8	1.2	2.4	1.0	2.7	1.5	3.8	1.6	3.7	1.1	4.7	2.4	1.6	0.8

Branch	Rescaled Mean										
	C	SP	NR	Ex	WNR	IR	FBM	Dir	NRe	ETE	
1	0.89	0.72	0.76	0.58	0.58	0.68	0.74	0.79	0.69	0.55	
2	0.58	0.57	0.40	0.38	0.36	0.16	0.44	0.66	0.40	0.17	
3	0.28	0.16	0.33	0.29	0.31	0.39	0.34	0.43	0.35	0.03	

Features:  
 BTE indicates behind-the-ear; C, compression; Dir, directionality; ETE, ear-to-ear communication; Ex, expansion; FBM, active feedback management; IR, impulse (noise) reduction; NR, noise reduction; NRe, noise reduction environments; SP, sound processing; WNR, wind noise reduction.

introduction. In our opinion, the features and modalities are much more important than specific brands or the dates of introduction. Nevertheless, associations involving the latter variables may provide additional insights.

**Hearing Aid Introduction Date** • The introduction date was defined as the date (month and year) when the hearing aid became commercially available on the Dutch market. For this analysis, we used the data of the 3083 hearing aids that were also used for the BTE and ITE LCT model analyses. For 604 hearing aids, the date of introduction was unknown, however

the absence of an introduction date was not a formal exclusion criteria. Most devices were introduced between 2010 and 2017; dates before 2009 were omitted, as there were only a few hearings aids representing these dates. Although there were differences between the median introduction dates of the different hearing aid brands, no notable effects were found between brands and modalities. Figure 6 shows the (fitted) progression of feature potential related to the three feature domains over time: the data were grouped by the year of introduction. Separate analyses were done for the BTE subset and the ITE subset.

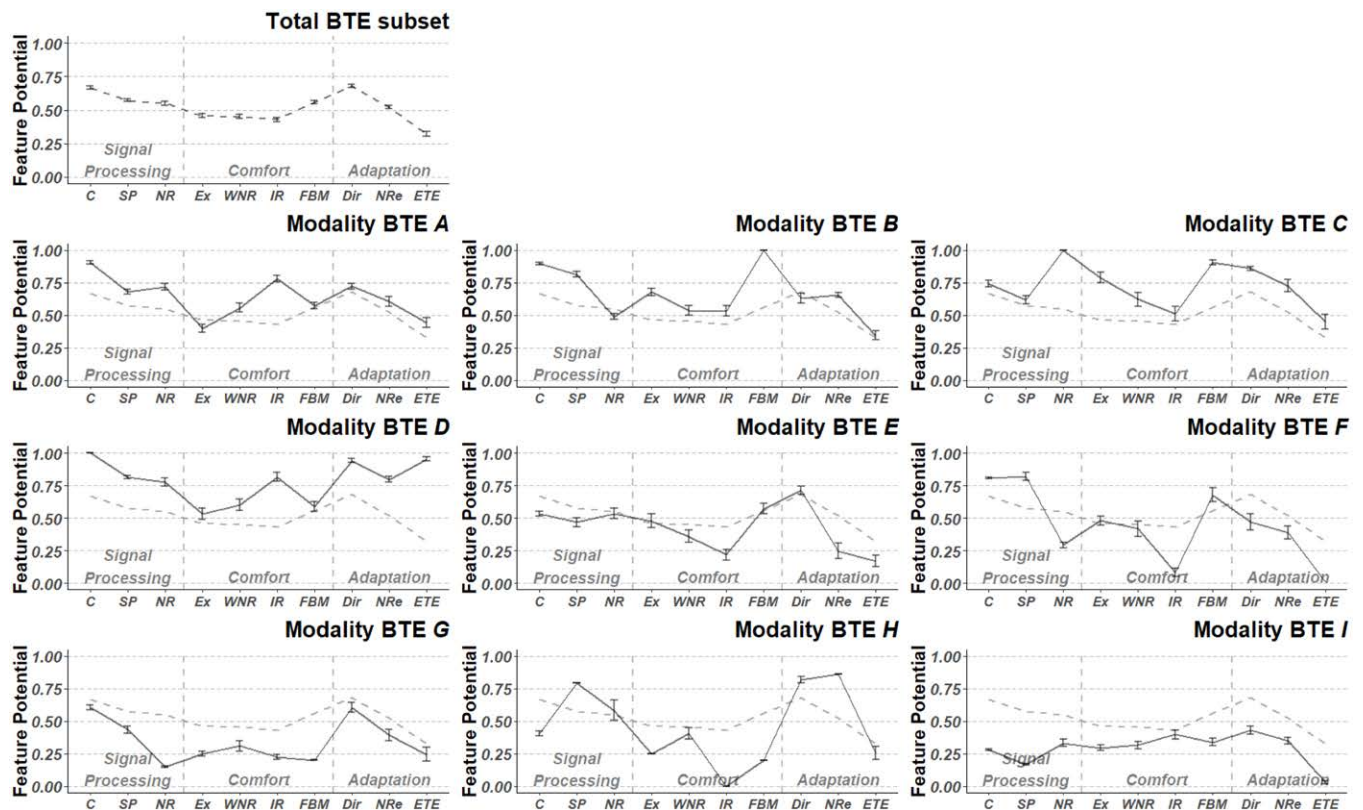


Fig. 4. Profile plots of nine final BTE modalities A to I: solid lines represent mean features measures for the specific modality, while dashed lines show mean feature measure of all devices in the dataset. For axis configuration, see also Figure 2. BTE indicates behind-the-ear.



TABLE 5. Mean, SD, and rescaled mean (res M) feature levels for all BTE modalities and the complete BTE subset

	C	SP	NR	Ex	WNR	IR	FBM	Dir	NRe	ETE
All										
M	7.68	11.89	4.85	2.83	2.35	2.72	3.79	3.73	4.65	1.64
SD	2.66	5.29	2.33	1.22	0.98	1.49	1.63	1.11	2.39	0.77
res M	0.67	0.57	0.55	0.46	0.45	0.43	0.56	0.68	0.52	0.32
A										
M	10.04	13.91	6.02	2.59	2.67	4.12	3.87	3.88	5.22	1.88
SD	1.20	3.27	1.49	1.07	0.94	0.89	1.10	0.72	2.20	0.66
res M	0.90	0.68	0.72	0.40	0.56	0.78	0.57	0.72	0.60	0.44
B										
M	9.95	16.43	4.42	3.71	2.61	3.12	6.00	3.52	5.57	1.68
SD	0.67	3.04	1.07	0.78	0.77	1.08	0	1.06	0.97	0.47
res M	0.89	0.81	0.49	0.68	0.54	0.53	1.00	0.63	0.65	0.34
C										
M	8.43	12.7	7.97	4.13	2.86	3.03	5.50	4.43	6.07	1.90
SD	1.89	4.29	0.40	1.28	1.22	1.73	0.67	0.51	2.48	0.85
res M	0.74	0.62	1.00	0.79	0.62	0.51	0.90	0.86	0.72	0.45
D										
M	11.00	16.47	6.44	3.13	2.80	4.26	3.94	4.76	6.58	2.91
SD	0	1.99	1.82	1.43	1.07	1.07	1.60	0.43	1.26	0.29
res M	1.00	0.81	0.78	0.53	0.60	0.82	0.59	0.94	0.80	0.95
E										
M	6.33	9.87	4.73	2.91	2.08	1.87	3.86	3.85	2.73	1.34
SD	1.15	4.08	1.76	1.22	0.85	0.93	1.29	0.75	2.43	0.52
res M	0.53	0.47	0.53	0.48	0.36	0.22	0.57	0.71	0.25	0.17
F										
M	9.07	16.61	3.05	2.92	2.25	1.32	4.39	2.89	3.71	1.01
SD	0.31	3.12	0.88	0.72	0.94	0.67	1.51	1.34	1.88	0.12
res M	0.81	0.82	0.29	0.48	0.42	0.08	0.68	0.47	0.39	0.01
G										
M	7.03	9.25	2.03	1.99	1.93	1.88	1.99	3.41	3.72	1.49
SD	1.41	3.83	0.31	0.53	0.87	0.52	0.10	1.07	2.21	0.79
res M	0.60	0.43	0.15	0.25	0.31	0.22	0.20	0.60	0.39	0.24
H										
M	5.03	16.00	5.07	2.00	2.21	1.00	2.00	4.27	7.00	1.51
SD	1.09	0	3.04	0	0.77	0	0	0.54	0	0.55
res M	0.40	0.79	0.58	0.25	0.40	0	0.20	0.82	0.86	0.25
I										
M	3.78	4.13	3.31	2.18	1.94	2.58	2.69	2.71	3.43	1.06
SD	0.67	0.88	1.86	0.86	0.75	1.32	1.27	1.22	1.47	0.24
res M	0.28	0.16	0.33	0.29	0.31	0.39	0.34	0.43	0.35	0.03

Legend for index noncompound variables: (1) feature not present, (2) low potential, (3) intermediate potential, (4) high potential. Directionality: (1) no directionality, (2) fixed directionality, (3) automatic directionality, (4) adaptive directionality, (5) beam forming directionality. Ear-to-ear communication compound: (1) no ear-to-ear communication; (2) feature sync; (3) sound streaming.

Features:

BTE indicates behind-the-ear; C, compression; Dir, directionality; ETE, ear-to-ear communication; Ex, expansion; FBM, active feedback management; IR, impulse (noise) reduction; NR, noise reduction; NRe, noise reduction environments; SP, sound processing; WNR, wind noise reduction.

For the BTE subset, only the adaptation domain showed a significant (positive) trend ( $p = 0.018$ ,  $r^2 = 0.52$ ) between the year of introduction and level of feature potential. The ITE data show a significant (positive) relation between the date of introduction and the domains signal processing ( $p = 0.013$ ,  $r^2 = 0.56$ ) and adaptation ( $p = 0.006$ ,  $r^2 = 0.62$ ). For both BTE and ITE data, the comfort domain did not yield a significant relation between feature potential and date of introduction.

**Hearing Aid Brand Analysis** • In this analysis, we looked at the relationship between the BTE and ITE modalities and different hearing aid brands. Again, separate analyses were done for the BTE subset and the ITE subset. The total dataset contained 44 hearing aids brands (including private labels), from which a subset was selected consisting of the 8 most commonly

used hearing aids brands in the Netherlands: Bernafon (Bern, Switzerland), Oticon (Copenhagen, Denmark), Phonak (Stäfa, Switzerland), Resound (Ballerup, Denmark), Siemens/Sivantos (Erlangen, Germany), Starkey (Eden Prairie, MN), Unitron (Kitchener, Canada), and Widex (Lyngø, Denmark) (in alphabetical order). This subset includes 2173 hearing aids of the 3083 hearing aids of the total dataset (70%). Figure 7A shows the distributions for each modality across the eight hearing aid brands (columns) for the BTE subset (left) and the ITE subset (right). Likewise, Figure 7B shows the distribution of each brand across each of the modalities (rows). It should be noted that the absolute numbers of hearing aids are dependent on both modality size as well as the hearing aid brands associated with the modality. Consequently, percentages of the same brand-modality combination do not translate well between Figure 7A and B.

**TABLE 6. Mean, SD, and rescaled mean feature levels for each primary node profile for the ITE subset (including the total ITE subpopulation) and hearing aid feature**

Branch	C		SP		NR		Ex		WNR		IR		FBM		Dir		NRe		ETE	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
1	9.8	1.6	14.9	3.8	6.0	1.9	2.9	1.2	2.4	1.0	3.8	1.3	4.3	1.5	3.9	1.1	6.2	1.6	2.2	0.7
2	8.0	1.4	14.6	3.1	4.3	1.9	3.3	1.2	1.6	1.1	1.9	1.2	4.7	1.7	2.7	1.0	4.5	1.5	1.0	0.8
3	4.5	1.0	5.6	3.5	3.2	1.8	1.9	1.1	1.9	1.1	2.6	1.0	2.5	1.6	2.8	1.0	3.4	1.4	1.1	0.7
Total	7.7	2.7	12.0	5.7	4.7	2.2	2.7	1.1	2.0	1.0	2.8	1.4	3.9	1.7	3.2	1.3	4.8	2.3	1.5	0.8

Branch	Rescaled Mean										
	C	SP	NR	Ex	WNR	IR	FBM	Dir	NRe	ETE	
1	0.88	0.73	0.72	0.48	0.47	0.69	0.66	0.72	0.74	0.60	
2	0.70	0.71	0.47	0.57	0.19	0.22	0.75	0.43	0.50	0.02	
3	0.35	0.24	0.32	0.23	0.31	0.40	0.31	0.46	0.34	0.04	

Features: C, compression; Dir, directionality; ETE, ear-to-ear communication; Ex, expansion; FBM, active feedback management; IR, impulse (noise) reduction; ITE, in-the-ear; NR, noise reduction; NRe, noise reduction environments; SP, sound processing; WNR, wind noise reduction.

For example, BTE hearing aids of brand 7 accounted for 89.5% of modality *B* and 71.2% of modality *F* (Fig. 7A). Yet, the combination of brand 7 and modality *B* accounted for 53.6% of the 239 hearing aids of brand 7, whereas the combination brand 7 and modality *F* amounts to 33.0% of all brand 4 hearing aids (Fig. 7B). The percentages in Figure 7A add up to 100% for each modality (rows), so it becomes clear what the distribution of hearing aid brands is per modality. Similarly, the percentages in Figure 7B add up to 100% for each brand (column). The different brands were not evenly distributed overall modalities, and some modalities consisted almost completely of one particular brand (e.g., BTE modality *B*, and *H*; ITE modality *G*). Other modalities showed a wider selection of different brands. However, for each modality there seems to be one or two dominating

brand(s) that accounts for more than 50% of the devices within that modality.

**DISCUSSION**

The main focus of this research was to define a framework for objective comparisons between groups of hearing aids that share a similar level of feature potential. The framework is intended to be independent of brand, type, or product family and preferably based on key hearing aid features. To achieve this, it was necessary to explore which hearing aid features could be considered key features. Subsequently, these key features were used to distinguish groups of hearing aids (i.e., modalities), that were related to each other by a comparable level of feature potential. The data used in this research were obtained

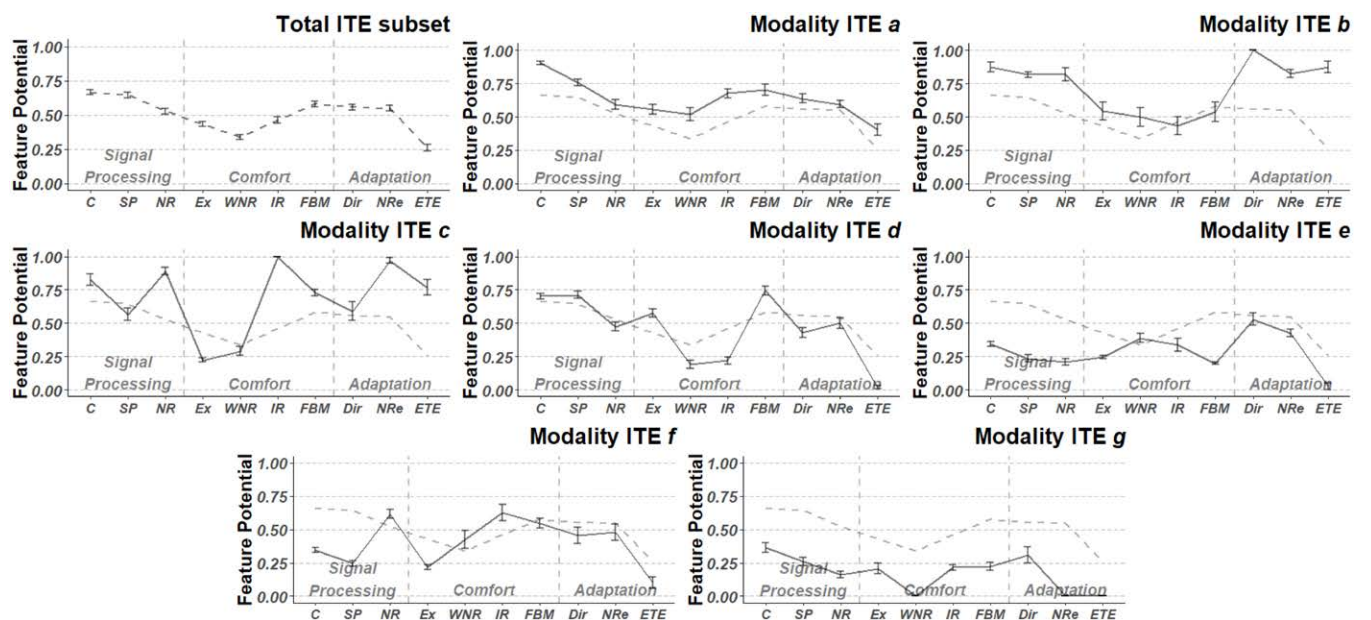


Fig. 5. Profile plots of seven final ITE modalities a to g: solid lines represent mean features measures for the specific modality, while dashed lines show mean feature measure of all devices in the dataset. For axis configuration, see also Figure 2. ITE indicates in-the-ear.

**TABLE 7. Mean, SD, and rescaled mean (res M) feature levels for all ITE modalities and the complete ITE subset**

	C	SP	NR	Ex	WNR	IR	FBM	Dir	NRe	ETE
<b>All</b>										
<i>M</i>	7.65	11.96	4.67	2.72	2.01	2.84	3.90	3.22	4.83	1.52
<i>SD</i>	2.70	5.69	2.23	1.14	0.97	1.44	1.65	1.30	2.26	0.75
<i>res M</i>	0.67	0.64	0.52	0.43	0.34	0.46	0.58	0.55	0.55	0.26
<b>a</b>										
<i>M</i>	10.03	15.4	5.15	3.22	2.57	3.71	4.50	3.57	5.17	1.80
<i>SD</i>	0.97	3.50	1.78	1.07	1.06	1.02	1.55	0.97	1.38	0.66
<i>res M</i>	0.90	0.76	0.59	0.56	0.52	0.68	0.70	0.64	0.59	0.40
<b>b</b>										
<i>M</i>	9.75	16.52	6.73	3.17	2.49	2.74	3.68	5.00	6.77	2.75
<i>SD</i>	1.94	1.96	1.83	1.41	1.07	1.40	1.88	0	1.14	0.46
<i>res M</i>	0.87	0.82	0.82	0.54	0.50	0.43	0.54	1.00	0.82	0.87
<b>c</b>										
<i>M</i>	9.28	11.74	7.23	1.90	1.87	5.00	4.65	3.36	7.79	2.53
<i>SD</i>	2.08	4.08	0.94	0.31	0.45	0	0.61	1.30	0.62	0.55
<i>res M</i>	0.83	0.57	0.89	0.22	0.29	1.00	0.73	0.59	0.97	0.77
<b>d</b>										
<i>M</i>	8.01	14.55	4.32	3.29	1.57	1.87	4.73	2.72	4.49	1.04
<i>SD</i>	1.77	4.92	2.12	1.09	0.84	1.03	1.47	1.26	2.31	0.19
<i>res M</i>	0.70	0.71	0.47	0.57	0.19	0.22	0.75	0.43	0.50	0.02
<b>e</b>										
<i>M</i>	4.43	5.46	2.46	1.98	2.17	2.35	1.99	3.12	3.97	1.05
<i>SD</i>	1.09	2.97	0.99	0.33	0.61	1.19	0.27	1.09	1.19	0.28
<i>res M</i>	0.34	0.23	0.21	0.24	0.39	0.34	0.20	0.53	0.42	0.03
<b>f</b>										
<i>M</i>	4.45	5.66	5.31	1.87	2.27	3.51	3.74	2.83	4.35	1.20
<i>SD</i>	0.99	1.94	1.14	0.34	0.96	1.23	0.89	1.18	2.05	0.40
<i>res M</i>	0.34	0.25	0.62	0.22	0.42	0.63	0.55	0.46	0.48	0.10
<b>g</b>										
<i>M</i>	4.62	5.88	2.13	1.83	1.00	1.86	2.12	2.23	1.00	1.00
<i>SD</i>	1.53	2.45	0.77	0.71	0	0.35	0.70	1.06	0	0
<i>res M</i>	0.36	0.26	0.16	0.21	0	0.21	0.22	0.31	0	0

Legend for index noncompound variables: (1) feature not present, (2) low potential, (3) intermediate potential, (4) high potential. Directionality: (1) no directionality, (2) fixed directionality, (3) automatic directionality, (4) adaptive directionality, (5) beam forming directionality. Ear-to-ear communication compound: (1) no ear-to-ear communication; (2) feature sync; (3) sound streaming. Features:

C, compression; Dir, directionality; ETE, ear-to-ear communication; Ex, expansion; FBM, active feedback management; IR, impulse (noise) reduction; ITE, in-the-ear; NR, noise reduction; NRe, noise reduction environments; SP, sound processing; WNR, wind noise reduction.

by collecting technical (meta-)data, provided by hearing aid manufacturers.

The strength of the resulting modalities is twofold. First, it provides a simple overview of comparable hearing aids, based on technical (meta-)data. In the future, knowledge can be obtained about the relationship between patient problems, and effective technical features to solve these problems. Relating patient problems to beneficial technical features would enable the audiologist to select a suitable hearing aid in a way which could lead to a more rapid and well-targeted fitting. In the absence of evidence-based knowledge, this framework could be used to collect practice-based evidence. Second, despite the absence of such knowledge, modalities could be useful when an initial fitting is not found to be beneficial. Distinct hearing aid modalities would allow the audiologist to “try something different” with confidence that a hearing aid representing another modality is really different.

Thus, hearing aid modalities offer the possibility to investigate the relations between technical features and patient needs. Without the need to benchmark all available hearing aids in a modality, fitting and/or rehabilitation results from individual hearing aids can be generalized for the entire population of

hearing aids within a particular modality. Expanding the possibilities of comparing hearing aids, fits well within a growing need for justification of hearing aid selection and the demand for evidence-based practice (Anderson et al. 2018). A good example of this demand is the growing interest in patient-reported outcome measures concerning hearing aid rehabilitation, which are used to assess and evaluate the added value of a hearing aid fit (Humes et al. 2009; Vestergaard Knudsen et al. 2010; Perez & Edmonds 2012; Ferguson et al. 2017). Hearing aid modalities defined in this research may potentially be matched to patterns of individual hearing problems measured by rehabilitation outcomes, such as described by Lansbergen et al. (2018).

Recently, there have been some attempts to compare hearing aids based on the level of technology (Humes et al. 2009; Cox et al. 2016; Johnson et al. 2018; Wu et al. 2018). However, these comparisons were driven by user output (objectively measured using performance scores or subjectively using self-reported outcome measure) and do not directly measure differences in technology within the hearing aid. The LCT analysis facilitates comparison of hearing aids on a lower level, by focusing on elementary differences between hearing aids; comparing either the availability of a feature or the number of levels or bands by



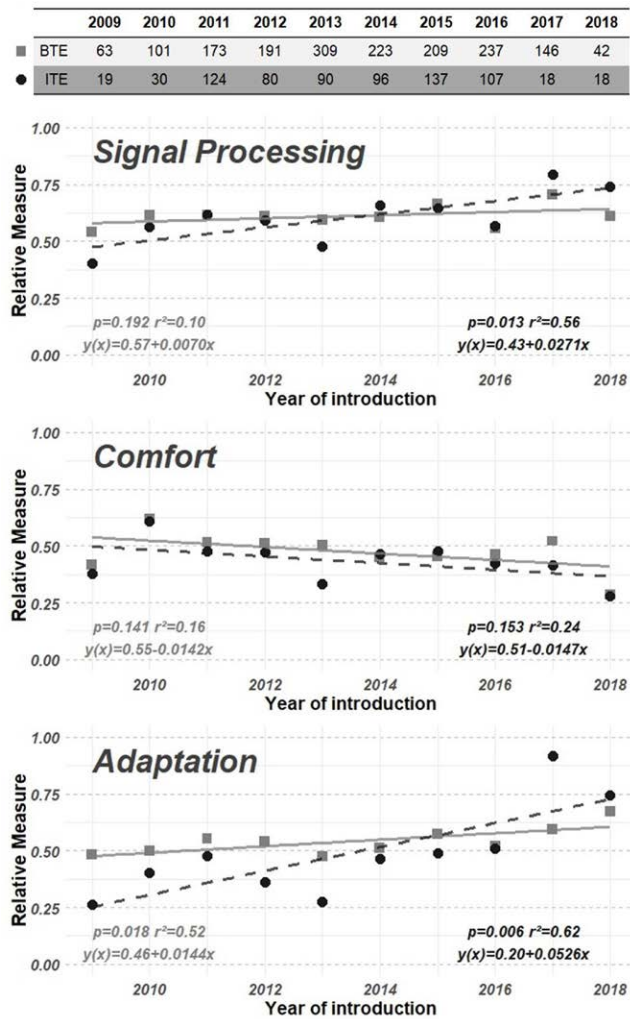


Fig. 6. Top of the table shows the number of hearing aids included in the analysis, for each year of introduction and hearing aid style type. The three graphs show rescaled mean hearing aid feature potential per domain ( $y$  axis) for grouped hearing aids (BTE: light grey squares; ITE: dark grey dots), plotted against the year of introduction ( $x$  axis) from 2009 up to and including 2018. The  $x$  axes of all three graphs share the same grouped hearing aids per year of introduction, and a linear model was fitted on each of the domain-specific data. The top graph shows the domain signal processing. The middle graph shows the domain comfort, and the bottom graph shows the domain adaptation. BTE indicates behind-the-ear; ITE, in-the-ear.

which features could be adjusted (e.g., the number of compression bands or levels of NR). An important aspect is that the LCT analysis also takes into consideration specific combinations of technologies in terms of profiles that go beyond individual features or functionalities. In addition, the modalities were obtained using a probabilistic model instead of deterministic, and within the current results, there are measures of uncertainty.

### Modalities

This study describes a (statistical) framework that applied LCT to a large dataset of hearing aids, and led to the formation of mutually exclusive hearing aid modalities. A hearing aid modality is characterized by a pattern of feature potential;

or to put it differently, modalities characterize populations of closely related hearing aids. Modalities could be thought of as a generic alternative to the manufacturer-dependent proprietary “concepts” that comprise a specific interplay between certain features. Modalities are in essence not manufacturer specific, nor a substitute to their “concepts”; they have been developed to be generic and always include information about a given set of features.

Before the LCT results presented in this article, the data went through several KDD stages. An important decision was to split the data based on the style of hearing aid. Consequently, two separate LCT analyses were performed. In the process of the LCT analysis, the dataset was split unconditionally at the first LCA, developing three separate branches of modalities, for both the BTE and ITE subset. These branches were defined by the most dominant structures in the data. Finally, nine BTE and seven ITE modalities could be distinguished, each characterized by a specific feature configuration.

It is interesting to note that the primary split yielded fairly comparable profile plots for the three branches (Fig. 3) for both the BTE and ITE subsets. This result is important for two reasons: splitting the data and running two separate LCT models could be considered as an alternative to cross-validation; second, there are only small and specific differences between BTE and ITE hearing aids on a basic level with respect to hearing aid feature potential. The latter can also be derived by observing similarities in the mean BTE subset and ITE subset feature plots of Figures 4 and 5.

The LCT analysis resulted in several modalities with large variation between hearing aid features. For example, hearing aids related to ITE modality  $c$  all have high IR feature potential, but only limited feature potential for Ex and WNR. This seems to be a nontrivial result considering the weak correlations between these modalities, which might be an intentional choice of design. There seems to be no research that has directly investigated or referred to specific nontypical feature configuration, investigating rehabilitation in relation to these modalities could reveal interesting insights in the effectiveness of this configuration.

An important advantage of identifying hearing aids modalities with distinct feature profiles is that devices related to a certain modality could serve a very different and specific type of rehabilitation demand when compared with devices related to another modality. Such specific details on the combination of features within hearing aid populations could support the demand for an evidence-based selection method (Anderson et al. 2018). In practice, modalities might serve as estimators for selecting hearing aids with a particular set of feature potential. For instance, when a practitioner would like to select a hearing aid to fit a large hearing loss with ski-sloping threshold values, a BTE style hearing aid with an emphasis on signal processing domain features, such as modality  $D$  might be a valid first choice. At this point, however, modalities have not been matched to rehabilitation outcomes and there is no evidence that particular modalities perform better than others. Besides, Anderson et al. (2018) demonstrates that audiologists rely on the manufacturers’ first fit for the fitting of hearing aid features (with the exception of frequency-specific gain), which certainly increases the importance of an objective selection method for a particular configuration of hearing aid features.

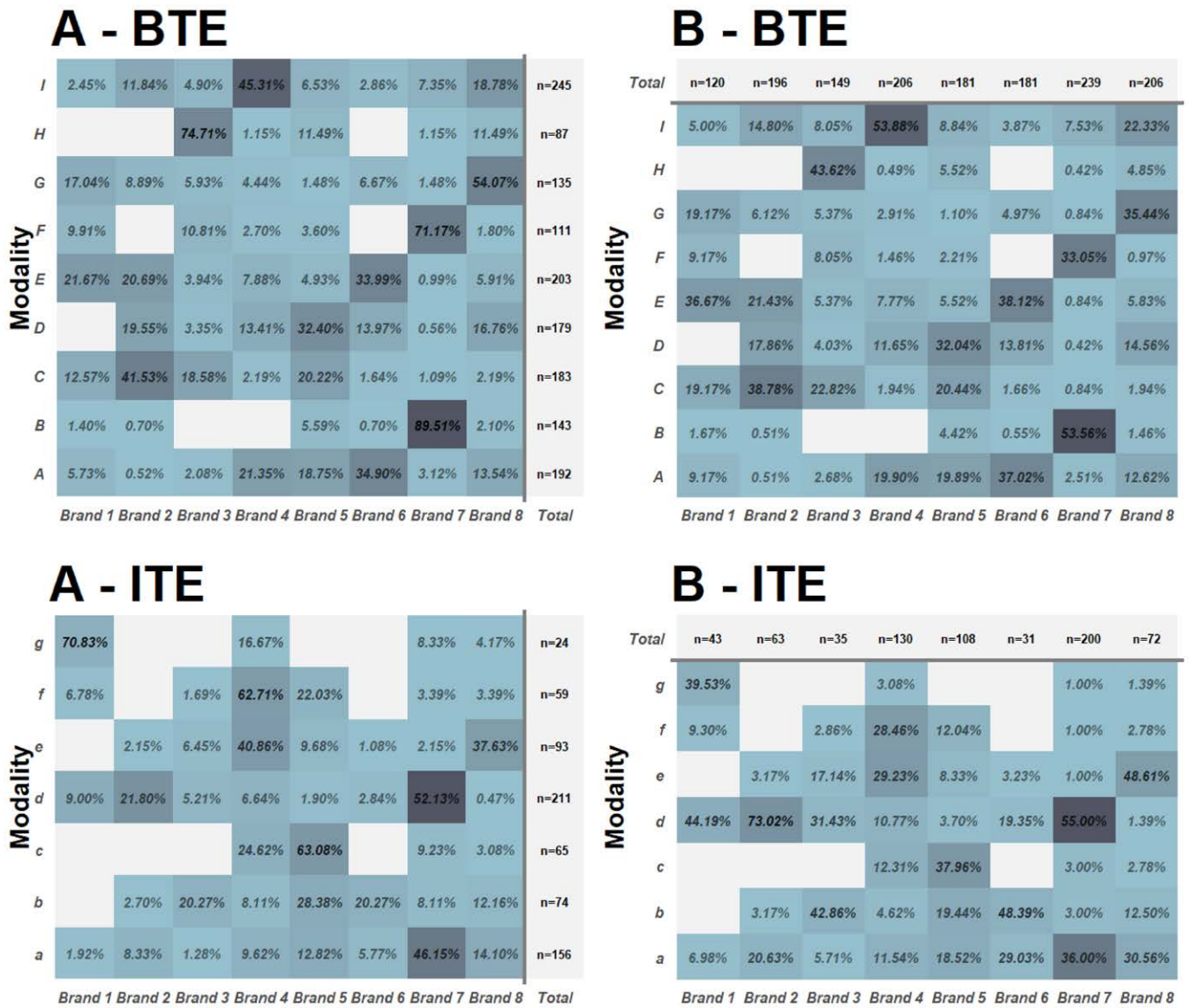


Fig. 7. Distribution of the BTE subset (upper panels) and ITE subset (lower panels), based on a selection of eight hearing aid brands (in random order). The percentages in (A) represent the distribution for each modality (row), while the percentages in (B) represent the distribution for each brand (column). The surface tone gives an indication of the underlying number. BTE indicates behind-the-ear; ITE, in-the-ear.

**BTE ITE Subset Comparison** • Similarities between the BTE and ITE subset were already briefly reviewed when the primary split results were discussed. Taking a step back, it is also interesting to investigate differences in the data of the two subsets. Considering Tables 4 and 6, it can be seen that on average, differences were most pronounced in the features WNR, Dir, and ETE. For these features the BTE subset showed a higher feature potential. Differences were also evident when examining the hierarchy of the LCT model (Fig. 1). The final number of modalities and termination depth of the nodes differed between the BTE and ITE analyses. Despite the fact that main stop criterion for terminating a node (and thus defining modalities) was proportional to the size of the subset. It seems that besides the most dominant structures, there are differences between BTE and ITE feature potential profiles on a higher (and more explicit) level. For a cross-validation approach of the data, the results of the primary split seem to be a good first-order approximation. However, it is important to bear in

mind that the split between BTE and ITE data did not result in equally sized samples, and obviously the samples were not randomly distributed.

The feature domains results (Figs. 4 and 5) show that there is a positive relation between the signal processing domain and the two other domains comfort and adaptation. This suggests there is a distinct relation between the level of technology of one set of features and the features related to other domains. Nevertheless modality-specific differences remain, which implies that the formation of the modalities cannot simply be dismissed as a positive correlation between the level of feature technology.

**Key Features**

The formation and partitioning of the 10 key hearing aid features can also be considered a valuable result, if only for the fact that the analysis is as strong as the input variables that were used. Unmistakably, the choice of hearing aid features that were

considered for this research is not a complete list of features that could be marked as audiological relevant for rehabilitation. Results should therefore be interpreted considering the inclusion of specific hearing aid features. Additionally, hearing aid features excluded as a result of the KDD process held little to no information that could be beneficial to the LCT analysis.

Some hearing aid features were expressed in terms of number of levels (e.g., Ex) or channels (e.g., compression). There is a general assumption that a larger range of adjustable channels or levels is analogous to an overall higher level of technology. Results of the BTE and ITE modalities projected on the domains of functionality already showed a positive relation between mean feature potential between the domains. Furthermore, it is reasonable to assume that higher feature potential (i.e., a larger the number of levels or channels) relates to more technologically advanced devices that can be fitted with a higher level of sophistication. Even though correlations between individual features were not evident, most key features did not strongly depend on the level of other features, yet showed a positive dependency with the overall level of technology. This will probably not hold for each individual hearing aid, however, in general, the number of levels and channels and the level of technology in hearing aids tend to be associated.

### Year of Introduction

The three feature domains (signal processing, comfort, and adaptation) were used to analyze the relation between the year of introduction of the device and level of feature potential over the period of a decade. For the BTE subset, only the adaptation domain showed a significant and strong effect of year of introduction on feature potential level. For the ITE subset, significant positive relations were found between the year of introduction and the feature domains signal processing and adaptation. It is interesting to note that for these domains, the increase in feature potential for ITE hearing aids is stronger compared with BTE hearing aids. It could be argued that miniaturization of technical resources enables manufactures to increase feature potential in the limited space and power supply of the ITE, to the point that ITE devices approach the feature potential of BTE hearing aids. In contrast to the features related to the dimensions of signal processing and comfort, the features of the adaptation domain are fairly new and emerging. For the BTE hearing aids, these results seem to suggest that there has been only limited development in the level of feature potential over the past decade. On the other hand, it might also be true that functionality of existing features improved without an additional increase in feature potential. Such could for example be achieved by increasing emphasis on the combined usage of features by manufacturers (i.e., concepts). A note of caution is due here since a considerable portion (19.5%) of the data lacked any information about the date of introduction.

### Relation to Hearing Aid Brands

The interplay between hearing aid features fulfills an important role in the hearing aid fitting process. It is unlikely that the precise connection and dependency between features will be fully understood by each hearing aid clinician (Mellor et al. 2018a), partly because the complexity and methods of implementation of the features are hidden in most cases. In addition, the increasing

use of manufacturer proprietary “concepts” contributes strongly to this issue. The ability to distinguish between configurations of hearing aid features, without the burden of manufacturer-specific terminology and “concepts,” would be of value in relation to the prediction of rehabilitation outcomes/success.

We analyzed the relationship between BTE and ITE modalities and different hearing aids brands, using a selection of hearing aid brands that consisted of the eight most commonly used hearing aids brands in the Netherlands. Results of these analyses revealed several modalities that included brand transcending configurations, while other modalities turned out to be more brand-specific. The latter group seems to mainly include hearing aids from one or two brands (e.g., BTE modality *B* and *H*, or ITE modality *C* and *G*). However, these brands were not limited to these modalities. This could imply that some product families within a particular brand have a very distinct composition of features that seems to deviate from other types of hearing aids from the same brand. For example, BTE modality *B* is almost completely dominated by brand 7, and therefore could be considered as an almost exclusive brand 7 modality. However, brand 7 is not exclusively associated with modality *B*, as 33.1% of all devices of brand 7 were also associated with modality *F*. Also, each brand (that was included in the subset) was on average present in 6.75 modalities, which demonstrates that most modalities were not directly associated with one specific brand. Such diversity increases the usability of the modalities as a more objective selection tool for an appropriate hearing aid selection.

### Limitations

The major limitation of this study is the absence of knowledge on how patient needs relate to technical features categorized into hearing aid modalities. Without this information, hearing aid modalities are of limited use. Whether the current approach of clustering a large population of hearing aids was a success in relation to the research aim, depends on how the results are considered. Despite its exploratory nature, this study offers some insight into the coherence of feature potential between selected hearing aid features.

Another potential shortcoming of this model is that it was designed only to reveal patterns between hearing aids present in the current database. Therefore, the model may need to be extended for future hearing aids. This approach was chosen intentionally, as we did not want to anticipate technical developments taking place in new hearing aids. The main argument here is that we cannot foresee how novel modalities and interactions could fit into or be explained by the present model. Although it would be possible to assign some new hearing aids to the existing profiles based on individual feature profiles, even if a measure of some feature is different from the measure ranges within the present database. Due to the size of the dataset, it would be highly unlikely that the currently presented modalities would alter as a result of the addition of several new hearing aids, nor that the modalities would not apply to new hearing aids. However, it is advisable to repeat the analysis as more and more new hearing aids become available (and consequently replace outdated devices).

Although a selection of important key features was defined during the initial KDD process and further used for the LCT analysis, it is still a simplification and approximation of the complete description of the potential of each hearing aid.



It is not possible to define generalized categories that capture the whole variety of different concepts and features present in modern hearing aids. Even when a concept is broadly used among hearing aids from different manufacturers, the implementation of a concept could lead to differences that at best complicate comparability.

It should be mentioned that quantitative measures such as the clustering of hearing aids by modeling particular combination of features does not and should not replace the interpretation of a specific feature configuration as is common practice in a clinical setting. The large individual variability in patient characteristics makes a full “Expert-System” not feasible. The modalities described can be characterized as a hearing aid selection guiding system to support the selection of an appropriate device or a comparable group of devices for an individual hearing-impaired person. Complementary research that addresses questions about the relationship between the proposed modalities and patient needs could reassert the usefulness of the current method.

## CONCLUSIONS

The general assumption that hearing aids can be grouped by a low or high level of technology (sometimes referred to in terms of basic and premium devices) seems to be valid only as a first-order approximation. This research shows that it is possible to group hearing aid populations based on a much more detailed configuration of hearing aid features. In total nine BTE and seven ITE modalities were defined, each with a particular feature configuration, which accommodated a total of 3083 different hearing aids. These modalities could be thought of as a generic alternative to the manufacturer-dependent proprietary “concepts,” and could potentially support the selection of an appropriate hearing aid for rehabilitation of hearing loss. This study will form the basis for bringing together quantitative results in audiological rehabilitation and will provide an objective structure for the technical classification of the hearing aids of the past decade, without the burden of manufacturer-specific terminology.

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