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Title: Using a decision tree approach to determine hearing aid ownership in older adults

Running title: Decision tree for hearing aid ownership

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Abstract:

Purpose: The main clinical intervention for older adults with hearing loss is the provision of hearing aids. However, uptake and usage in this population have historically been reported as low. The aim of this study was to understand the hearing loss characteristics, from measured audiometric hearing loss and self-perceived hearing handicap, that contribute to the decision of hearing aid ownership.

Materials and methods: A total of 2833 adults aged 50+ years, of which 329 reported hearing aid ownership, were involved with a population-based survey with audiometric hearing assessments. Classification and regression tree (CART) analysis was used to classify hearing aid ownership from audiometric measurements and hearing disability outcomes.

Results: An overall accuracy of 92.5% was found for the performance of the CART analysis in predicting hearing aid ownership from hearing loss characteristics. By including hearing disability, sensitivity for predicting hearing aid ownership increased by up to 40% compared with just audiometric hearing loss measurements alone.

Conclusions: A decision tree approach that considers both objectively measured hearing loss and self-perceived hearing disability, could facilitate a more tailored and personalised approach for determining hearing aid needs in the older population.

Keywords: hearing loss, hearing aids, older adults, classification and regression tree, hearing disability, Hearing Handicap Inventory for Elderly Screening

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INTRODUCTION

Hearing loss is the most frequently occurring sensory deficit in human populations and a highly prevalent disability with age [1]. Mid-life hearing loss has been found to be associated with mild cognitive impairment [2], and recently identified as the biggest modifiable risk factor for a future dementia diagnosis [3]. Without intervention, adults with a hearing loss are at risk of higher rates of depression, anxiety, social isolation, and cognitive disorder [4-6]. Fortunately, some studies are showing improved hearing function to have mitigating effects on cognitive disorders by slowing the rate of cognitive decline and improving some cognitive skills in older adults [7,8]. For the majority of people who experience mid-life hearing loss there are existing and effective interventions to compensate reduced hearing function. The main clinical intervention for older adults with a mild to moderate hearing loss is the provision of hearing aids (HAs) [9]. However, only a relatively small portion of adults with an hearing impairment seek help for their hearing problems and only one in five adults with a hearing impairment wear HAs, hampering its effectiveness [10-12].

Untreated hearing loss leads to continued negative and disabling impacts on the lives of older adults [13]. Population screening is an important initiative that has been offered as a possible solution to the under-diagnosis and under-treatment of hearing loss in adults [14]. The World Health Organization (WHO) has listed having policy or legislation for hearing aid provision, as a relevant indicator that should be included for ear health care [15]. However, current eligibility for a HA in many international programs are often based on hearing ability alone. For example, using audiometric cut-offs for insurance coverage for HAs. In the Netherlands a pure-tone average cut-off of greater than 35 dB HL (decibel hearing loss) at the frequencies 1.0, 2.0 and 4.0 kHz is used to determine eligibility, and in Australia, the Hearing Services Program uses pure-tone average of greater than 23 dB HL at the frequencies 0.5, 1.0 and 2.0 kHz [16,17]. Despite measured audiometric hearing loss, there is still considerable HA under-usage [18]. Many studies have found self-reported hearing difficulties as the strongest correlate for HA use [10,19]. Gopinath et al. (2011) found having a self-perceived hearing handicap was associated with a 7% increase likelihood of incident HA use, demonstrating that it is not just measurable hearing loss but also self-perceived hearing difficulty that may contribute to the decision-making around HAs.

Given that the help-seeking behavior for hearing healthcare is likely to start with an individual's self-perception of their hearing loss, research is needed to reconcile the discrepancies between perceived hearing difficulties and measurable audiometric loss to enhance our understanding and facilitate potential behaviour change for hearing aid uptake [20]. An accurate, easy, and inexpensive method to detect the objective and subjective hearing loss characteristics that are important in determining HA ownership is needed for practical applications such as hearing screening to identify those in need of HAs. This paper aims to examine the associations between self-perceived hearing difficulties and audiometrically measured hearing loss with determining HA ownership. To the best of our knowledge, machine learning methods have not yet been applied in determining uptake of HAs. Through applying the machine learning strategy of classification and regression tree (CART) analysis using a decision tree model, we aim to elicit the decision pathways from measured audiometric hearing loss and self-perceived difficulties that predict HA ownership. Through the decision pathways we will also uncover optimal audiometric and hearing handicap cut-offs that can potentially be implemented to screen HA needs in the older population.

MATERIALS AND METHODS

Study population

The study population was from the Blue Mountains Hearing Study (BMHS) [21]. The BMHS is a population-based survey of age-related hearing loss in a representative older Australian community. During the period 1997-1999, 2956 older adults (ages 50+) who resided within the Blue Mountains area, west of Sydney, Australia, participated in the BMHS survey and had an audiometric examination. We examined data from 2833 participants from the Blue Mountains Hearing Study (BMHS), where data from the pure-tone audiometry and survey responses on hearing aid use and self-perceived hearing loss/handicap were available. The BMHS was conducted in accordance with the Declaration of Helsinki and was approved by The University of Sydney Human Research Ethics Committee (Reference: HREC 9826).

Audiometric Testing

Audiometric examination was conducted to obtain an audiometric measure of hearing loss. Pure-tone audiometry was administered by audiologists in sound treated facilities. The air conduction thresholds were obtained at 0.25-8.0 kHz using a Madsen OB822 audiometer (Madsen Electronics Copenhagen, Denmark) calibrated to Australian standards. Stimuli were presented through supra-aural headphones using standard TDH-39 earphones. Audiometric thresholds for air-conduction stimuli in both ears were established for frequencies at 0.25, 0.5, 1.0, 2.0, and 4.0 kHz. Both better and worse ear hearing were used in this study. For audiometric threshold comparisons we used the conventional hearing status in accordance with the WHO, using averaged pure-tone audiometric hearing thresholds at 0.5, 1, 2 and 4kHz. A four-frequency average hearing loss (4FAHL) greater than 25dB HL in the better hearing ear was used to define hearing loss. This defines hearing loss as bilateral.

Hearing Handicap Inventory for Elderly Screening (HHIE-S)

To obtain a measure of self-perceived hearing difficulty we used the Hearing Handicap Inventory for Elderly Screening (HHIE-S). The HHIE-S has been validated for screening hearing impairment in older adults and originally developed to assess perceived functional limitations associated with hearing impairment.[22,23] HHIE-S consists of five social or situational items and five emotional response items with a scoring of 4 points for “yes”, 2 points for “sometimes” and 0 points for “no” responses. According to the American Speech-

Language- Hearing Association (ASHA) guidelines, a total HHIE-S score of ≥8 indicates the presence of a hearing handicap [24].

Hearing Aid Ownership

To obtain information regarding HA ownership in the study population we used the question “Do you or have you ever worn a hearing aid?” from the BMHS survey. Response for this question was categorized as “Yes” or “No”. HA owners were defined as those reporting “Yes” that they have ever worn a HA, and conversely non-HA owners are those that responded “No”.

Classification and Regression Tree analysis

Decision trees are commonly used as a strategy to identify the pathways to a targeted goal. Decision tree algorithms are used for classification- or regression-based predictive models. CART analysis is a nonparametric supervised machine learning method used for classifying target conditions by learning simple decision rules from data [25]. We used CART analysis to build a clinically useful decision tree model that can classify different hearing loss characteristics to determine hearing-aid ownership. The decision tree approach starts with all the observations at the root node. It then splits the dataset at each node (internal nodes) based on certain conditions determined through a regression algorithm. At each node, the regression algorithm creates a threshold or cut-off for the decisions. A final decision is made at the terminal node (leaf), and pathways can be determined through navigating the decision tree from root to leaf. For this study, the best split for each of the nodes were determined through the Gini impurity which measures the degree of probability that the characteristics were wrongly classified when it is randomly chosen, it is a “loss” metric [26].

The decision tree was constructed from CART analysis performed in RStudio, R (version 4.0.4) using the caret package [27]. We used five frequencies, 0.25, 0.5, 1.0, 2.0 and 4.0 kHz, of audiometric pure tone in both better and worse ears and HHIE-S scores as the hearing loss characteristics for the decision tree. The classification output was HA ownership, "yes" or "no". To ensure that the model built can be interpretable and not over-fitted we set the model to have a minimum split of n=30 (that is, there must be at least 30 observations in each group for a split to occur), minimum bucket of n=30 (there must be at least 30 observation in each group at the last split or terminal node) and a maximum depth of 4 branches (which is the maximum number of splits or branching that occurs).

Performance of the model was validated using a leave-one-out cross-validation technique through leaving one data point out while building the model with the remaining dataset. This was repeated for all the data points. The model is tested against the data point that is left out and test accuracy and errors are calculated for all data points. This validation technique was chosen as it has the advantage of all data points being used for the model and test error rates not being overestimated [28]. Performance of the CART model was measured by an overall accuracy and Cohen's kappa. Accuracy is a measure of the number of correct classifications made divided by the total number of predictions, expressed as a percentage. Cohen's kappa measures the degree of agreement after adjusting for chance. In machine learning, the Cohen's kappa statistic measures the degree of agreement between the model's prediction and the actual value, it is used to deduce whether the classification from the model is better than, equal to or worse than a random model [29]. Kappa is a measure of reliability and values between 0-0.2 are considered poor or slight, 0.21-0.4 are fair, 0.41-0.60 are considered moderate, 0.61-0.8 are substantial, greater than 0.81 are almost perfect, and 1.0 is perfect [30,31].

Statistical Analysis

Statistical analyses were conducted using SPSS version 27 [32]. Descriptive statistics were calculated as means with standard deviations or frequencies and percentages. t-tests and chi-square tests were used to compare demographic and hearing characteristics between HA and no HA ownership. To examine the effectiveness of the decision tree in determining thresholds and predicting hearing aid ownership, we compared this technique to a conventional method using logistic regression analysis, adjusting for age and sex. Results were expressed as odds rations (OR) with 95% confidence intervals (CI).

We also compared the sensitivity, specificity, and accuracy, calculated from the classifications using logistic regression model results. We compared a model using conventional audiometric threshold for hearing loss (4FAHL≥25 dB) against the thresholds determined from the decision tree. Sensitivity, specificity, and accuracy were calculated form the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values. Sensitivity was defined as TP/TP+FN, specificity was defined as TN/TN+FP and accuracy was defined as TP+TN/TP+TN+FP+FN [33].

RESULTS

From the sample of 2833 there were 329 that reported owning a HA. Table 1 shows the demographic and hearing characteristics between the two groups. HA owners are significantly older and there were more males that owned HAs compared with females. Those who owned a HA versus those who did not, were more likely to have moderate level of bilateral hearing loss and mild to moderate self-reported hearing handicap.

Classification of HA ownership from the pure tone audiometric examination and HHIE-S were modelled using CART analysis. After excluding participants with missing audiometric data for some of the frequencies measured, a total of n=2785 were included in the CART model. The overall performance from the CART analysis for predicting HA ownership was evaluated, we found an overall accuracy of 92.5% and a Cohen's kappa of 0.61, demonstrating substantial reliability.

Figure 1 shows the decision tree breakdowns for where the decisions were made. The tree model suggested four splits (with five terminal node decisions) to classifying hearing aid ownership from measured hearing loss (pure-tone audiometry) and self-perceived hearing handicap (HHIE-S). Although frequencies for both better ear hearing and worse ear hearing were entered into the model, only better ear hearing frequencies were selected by the model for the decision tree. The five decisions were each determined by 5 possible pathways which can be traced from the top root node. The five pathways are: (1) audiometric threshold of <38 dB at 2.0 kHz, (2) audiometric threshold of ≥38 dB at 2.0 kHz, and HHIE-S score <8, (3) audiometric threshold of ≥38 dB at 2.0 kHz, HHIE-S score ≥8, audiometric threshold of <43 dB at 1.0 kHz, and audiometric threshold of <53 dB at 4.0 kHz, (4) audiometric threshold of ≥38 dB at 2.0 kHz, HHIE-S score ≥8, audiometric threshold of <43 dB at 1.0 kHz, and audiometric threshold of ≥53 dB at 4.0 kHz, and (5) audiometric threshold of ≥38 dB at 2.0 kHz, HHIE-S score ≥ 8, and audiometric threshold ≥43 dB at 1.0 kHz.

Table 2 shows the decision tree results at each of the splits. The root split shows the dataset at the start before any splits. There were 2785 observations and a default decision of "No". There were 301 "Yes" observations to HA ownership, and thus these will be considered a "loss" if a decision of "No" was made for all observations. For the other splits/decisions, "loss" measured the number of observations which were incorrectly classified at each split and probabilities measured the distribution of the classes (Yes/No) at each node.

The performance of the model using the thresholds determined by CART analysis was then examined using a logistic regression model. Table 3 shows the odds ratios for determining HA ownership. After adjusting for age and sex, participants reporting self-perceived hearing handicap were 7.4-fold more likely to own a HA. Moderate to severe hearing loss was also associated with 3.2 to 5.0 odds of HA ownership.

From the logistic regression model, sensitivity and specificity were obtained and calculated for the CART analysis thresholds. These were then compared with the conventional method for measuring hearing loss using 4FAHL of ≥ 25dB. Table 4 shows sensitivity, specificity, and accuracy for four models. The highest sensitivity and accuracy were found for the audiometric cut-offs determined by the CART analysis that included HHIE-S. The sensitivity of the model decreased by more than 5% when self-perceived hearing difficulties were not included in the model. There was virtually no sensitivity (ability to determine HA ownership correctly) in the model that used only pure-time audiometry data. Sensitivity increased by over 40% when the self-perceived difficulties (HHIE-S) response was included in this model.

DISCUSSION

This study is unique as it applied a novel decision tree methodology to successfully classify HA ownership from a combination of pure tone audiometry meaures and hearing handicap scores. A prediction accuracy of 92.5% was found with reliability kappa of 0.61, demonstrating that the classification obtained from the CART model was found to be substantially better than random. There were five decision-tree pathways modelled from four hearing loss characteristics. Audiometric pure tone hearing loss frequencies at 1.0, 2.0 and 4.0kHz from the better ear and HHIE-S scores were found to be the most important characteristics for classifying HA ownership. In addition, the regression algorithms within the CART analysis uncovered the cut-off thresholds for the hearing loss characteristics that determines HA ownership.

The pure tone audiometric frequencies identified by CART analysis (1.0, 2.0, and 4.0 kHz) were all considered as high frequencies for hearing loss [34]. At the first node, we found a pure tone at 2.0 kHz with a cut-off threshold of 38 dB HL as important for differentiating between HA owners and those who did own a HA. In fact, a large majority (86%) of the observations were classified as not owning a HA when they had <38 dB hearing loss at 2.0 kHz. This frequency of hearing loss was previously shown in other studies to be important for the screening of moderate hearing loss in adults, demonstrating for this study that moderate hearing loss is an important factor for HA uptake [25,35]. Pure tone audiometric frequencies at 1.0 and 4.0 kHz were also found as important characteristics for the classification of HA ownership. These audiometric measurements are all associated with high frequency hearing loss whereby high-frequency components of speech, such as consonant sounds are often missed, and there are increases in difficulties to understanding speech especially in background noise [34]. It is also reported that the most important frequencies for speech perception are often found between 1.0 and 2.0 kHz [36]. Given this range of frequencies were found to be important in the decision tree analysis, with subsequent regression analysis showing 3.2- to 5.0-fold greater odds of HA ownership at >38 to 58 dB HL in the frequencies 1.0, 2.0, and 4.0 kHz, it may be that speech perception problems could be a major driver for the decision to take up HAs.

Although audiometric results from both better and worse ear hearing loss were entered in the CART model, the resulting model selected only better ear frequencies. This indicates that it was bilateral hearing loss frequencies as opposed to unilateral hearing loss, that were indicators for HA ownership. This may have clinical implications for hearing aid fittings and whether it is the need for two HAs or innovations that enhances bilateral hearing that may provide the effectiveness required to encourage and motivate HA uptake and use, this needs further investigation. It is also likely for those with unilateral hearing loss that the remaining function in the contralateral ear might compensate for some of the hearing difficulties experienced. The impacts of unilateral hearing loss on hearing handicap has previously been shown to be less when compared with bilateral hearing loss especially for the social and emotional domains [37].

Self-perceived hearing handicap as determined by an HHIE-S was also an important factor for determining HA ownership in both the CART analysis and the logistic regression models. Interestingly, the cut-off threshold identified from the CART model for HHIE-S was the same as the ASHA guidelines with HHIE-S score ≥8 (ASHA, 1989). This indicates that the presence of a hearing handicap is a determining factor for HA ownership. HHIE-S captures self-perceived frustration, embarrassment and/or of disruptions to one's social and personal life as a direct consequence of having a hearing loss; by including hearing difficulty to the determination of HA ownership adds to the subjective perspective and potential motivation for the uptake of HA [38]. HHIE-S contributed to almost 8% increase in sensitivity of detecting HA ownership and a self-perceived hearing difficulty was associated with a 7.4 greater odds of HA ownership.

Currently, the most widely used threshold for hearing loss is in accordance with the WHO using averaged pure-tone audiometric hearing thresholds at 0.5, 1.0, 2.0 and 4.0 kHz (4FAHL) with hearing loss as greater than 25dB HL in the better hearing ear. We compared this to the cut-off thresholds that were determined from the regression algorithm in the CART analysis. The logistic regression model that included the associated cut-off thresholds from CART was found to have the highest accuracy and sensitivity in determining HA ownership. In comparison, the model that used the conventional 4FAHL threshold for audiometric hearing loss was unable to detect HA ownership, with sensitivity of only 0.3%. This cut-off was only able to detect not having a hearing-aid (specificity). Only through including HHIE-S into this model did sensitivity increase by 40%, demonstrating that HA ownership is not solely determined by measurable audiometric hearing loss alone, especially when using the conventional 4FAHL cut-off.

These results suggest that to adequately screen and identify individuals with hearing loss for optimal uptake of hearing devices, clinicians should consider the combined use of objective and subjective measures for hearing loss. Using a decision tree approach, the decision pathways point to an optimal audiometric cut-off of greater than 38dB HL and hearing handicap cut-off score of greater than 8 for distinguishing between those that have taken up

HA ownership and those that have not. Findings from decision tree analysis can potentially be used to assist audiologists in their decision-making to tailor aural rehabilitation to ensure optimal use of hearing aids. Through a targeted approach using the optimal cut-offs that consider both objective and subjective measures, recommendations for HA needs that are better suited to the needs of the hearing-impaired patient can be made. The CART results can also inform hearing policy to ensure the clinical effectiveness and cost-efficiency of existing hearing screening and HA programs in the older population, and thereby addresses the World Health Assembly Resolution on the Prevention of Deafness and Hearing Loss [39], which highlighted the urgent need for evidence to underpin the policy-making process for ear and hearing care. The cut-offs observed in our study are also in line with Ventry and Weinstein (1983) examining screening "failures" or cut-offs for both hearing handicap and audiometric measures. They found that a screen failure of 10 for hearing handicap was closest to 40dB HL at 1000 and 2000Hz [40,41]. Currently, HA eligibility is generally based on just audiometric measures alone and using this criterion may lead to HA issues such as infrequent usage and eventually device abandonment, especially in those that do not perceive any hearing difficulties. Edwards (2020), in his review has suggested that people that do not report any perceived hearing difficulties are not likely to seek help for their hearing loss. As such, other hearing innovations such as earphones or audio devices with augmented audio might need to be considered by clinicians as these may be better suited for people that do not report hearing difficulties [42].

Key strengths of this study include the utilisation of a representative population-based sample of older adults. In addition, they were surveyed before the introduction of a minimum hearing loss threshold for hearing aid eligibility was introduced for the Hearing Services Program in Australia. This indicates that hearing-aid ownership is likely to reflect adults that sought help for their hearing problems, and not an artifact from having a hearing loss level that was above a certain threshold. The results would therefore reflect the 'true' level of audiometric hearing loss and self-perceived hearing handicap that determines hearing-aid ownership. There are also study limitations that need mention. Although a wider frequency range for air-conduction stimuli was collected for the BMHS, ranging from 0.25 to 8.0 kHz, there were more missing values within the higher frequencies and the frequencies of 6.0 and 8.0 kHz and were not included in the CART analysis. Given that hearing loss in older adults start from higher frequencies it would be of interest to determine whether these frequencies are also important for determining hearing-aid needs.

Both measured audiometric hearing loss and self-perceived hearing difficulties contributed to the decision pathways used to classify HA from non-HA owners in this study, which is consistent with previous research from Sawyer and colleagues (2019). The current study demonstrated how a machine learning technique, specifically decision tree analysis, can be used in the hearing healthcare setting to meet the need for a parsimonious screening protocol to selectively provide hearing rehabilitation to those older adults most in need. Therefore, potentially offering an improved and cost-effective strategy for adult hearing loss screening and HA eligibility in the older population.

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TABLES:

Table 1: Demographic and hearing characteristics for hearing-aid and non-hearing-aid ownership

Characteristics		Hearing aid	No hearing aid	p-value
Age	M(SD)	74.3 (8.6)	66.5 (8.9)	<0.001
Sex:				<0.001
Male	N(%)	173 (52.6)	1046 (41.8)	
Female	N(%)	156 (47.4)	1458 (58.2)	
4FAHL-better ear	M(SD)	46.0 (19.0)	18.9 (11.1)	<0.001
HHIE-S	M(SD)	20.2 (9.7)	5.8 (7.4)	<0.001

Table 2: Decision tree results for nodes at each split

Split	Number of Observations	Loss*	Probabilities (No, Yes) #	Decision for hearing aid ownership
Root	2785	301	0.89, 0.11	No
Audiometric threshold of <38 dB at 2.0 kHz	2406	95	0.96, 0.04	No
Audiometric threshold of ≥38 dB at 2.0 kHz	379	173	0.46, 0.54	Yes
HHIE-S score <8	73	11	0.85, 0.15	No
HHIE-S score ≥8	306	111	0.36, 0.64	Yes
Audiometric threshold of <43 dB at 1.0 kHz	204	96	0.47, 0.53	Yes
Audiometric threshold of ≥43 dB at 1.0 kHz	102	15	0.15, 0.85	Yes
Audiometric threshold of <53 dB at 4.0 kHz	32	9	0.72, 0.28	No
Audiometric threshold of ≥53 dB at 4.0 kHz	172	73	0.42, 0.58	Yes

*Loss is a measure of the number of observations which were incorrectly classified at each split

#Probabilities are measuring the distribution of the classes (No/Yes) at each node

Table 3 Logistic regression model for hearing aid ownership using the hearing characteristics thresholds determined from CART model.

	Unadjusted Odds ratio (95%CI)	Age-sex adjusted Odds Ratio (95% CI)
HHIE-S score ≥8	6.8 (4.7, 9.9)	7.4 (5.1, 10.8)
Audiometric threshold of ≥38 dB HL at 2.0 kHz	5.2 (3.6, 7.6)	4.3 (2.9, 6.4)
Audiometric threshold of ≥43 dB HL at 1.0 kHz	5.2 (3.0, 9.0)	5.0 (2.9, 8.7)
Audiometric threshold of ≥53 dB HL at 4.0 kHz	3.7 (2.6, 5.3)	3.2 (2.2, 4.9)

Table 4: Sensitivity, specificity, and accuracies for the different audiometric hearing loss models

Logistic Regression Model	Sensitivity (%)	Specificity (%)	Accuracy (%)
CART audiometric thresholds + HHIE	56.7	96.8	92.4
CART audiometric thresholds only	49.2	96.9	91.7
4FAHL of ≥ 25dB + HHIE	41.0	96.1	89.7
4FAHL of ≥ 25dB only	0.3	100	88.4

Figure 1: Decision tree model for determining HA ownership. Final decisions (Yes/No), probabilities and percentage of observations are shown in the terminal nodes (1-5) for each of the 5 decision pathways. The darker shades of gray showed a more accurate prediction for that pathway. The hearing loss characteristics are shown in the nodes (in rectangles) and thresholds/ cut-offs (in dBs) are shown on the branches (dotted-lines) of the decision tree