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Original article

Utilizing Artificial Neural Networks for Establishing Hearing-Loss Predicting Models Based on a Longitudinal Dataset and Their Implications for Managing the Hearing Conservation Program

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ABSTRACT

Background: Though the artificial neural network (ANN) technique has been used to predict noise-induced hearing loss (NIHL), the established prediction models have primarily relied on cross-sectional datasets, and hence, they may not comprehensively capture the chronic nature of NIHL as a disease linked to long-term noise exposure among workers.

Methods: A comprehensive dataset was utilized, encompassing eight-year longitudinal personal hearing threshold levels (HTLs) as well as information on seven personal variables and two environmental variables to establish NIHL predicting models through the ANN technique. Three subdatasets were extracted from the afirementioned comprehensive dataset to assess the advantages of the present study in NIHL predictions.

Results: The dataset was gathered from 170 workers employed in a steel-making industry, with a median cumulative noise exposure and HTL of 88.40 dBA-year and 19.58 dB, respectively. Utilizing the longitudinal dataset demonstrated superior prediction capabilities compared to cross-sectional datasets. Incorporating the more comprehensive dataset led to improved NIHL predictions, particularly when considering variables such as noise pattern and use of personal protective equipment. Despite fluctuations observed in the measured HTLs, the ANN predicting models consistently revealed a discernible trend.

Conclusions: A consistent correlation was observed between the measured HTLs and the results obtained from the predicting models. However, it is essential to exercise caution when utilizing the model-predicted NIHLs for individual workers due to inherent personal fluctuations in HTLs. Nonetheless, these ANN models can serve as a valuable reference for the industry in effectively managing its hearing conservation program.

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1. Introduction

In 2019, approximately 430 million people experienced disabling hearing loss, and it is anticipated that this figure will exceed 700 million by 2050 [1]. Hearing loss can have various causes, such as genetics, birth complications, infections, medication, aging, and prolonged exposure to loud noise. About 16% of adult disabling hearing losses are attributed to prolonged workplace noise exposure, making noise-induced hearing loss (NIHL) a prevalent global occupational condition [2]. NIHL is both preventable and irreversible, and it is particularly common in noisy sectors such as steel-making, mining, and construction [3]. Besides prolonged exposure to excessive noise, environmental factors, such as solvents, asphyxiants, nitriles, and metals can exacerbate the issue [4,5].

Workers exposed to excessive noise initially experience hearing losses in the 3,000- to 6,000-Hz range, irrespective of specific noise patterns [6]. However, fluctuating noise exposure can lead to higher hearing threshold levels (HTLs) than steady noise at the same level [7]. Unhealthy behaviors such as smoking, alcohol consumption, the absence of personal protective equipment (PPE), and obesity are associated with sensorineural hearing loss [8–10]. Studies suggest PPE as a preventive measure against occupational hearing loss [11,12]. Given the multifaceted nature of NIHL, including factors such as age, employment year, smoking, alcohol consumption, blood pressure, noise exposure, noise pattern, and PPE, the development of NIHL prediction models would be beneficial for industries in managing hearing conservation programs.

Numerous studies have explored the relationship between NIHL and noise exposure level, as well as various covariate risk factors (e.g., predisposing characteristics, employment-related factors, and personal habits) using multivariate logistic regression and Cox regression models [8,13–15]. However, existing regression models may not fully capture the intricate interactions among these factors and their impact on NIHL outcomes. Recently, artificial neural networks (ANNs) have gained prominence for predicting complex phenomena in various fields, utilizing multiple learning algorithms, and interconnected adaptive processing elements known as artificial neurons or nodes [16,17].

In audiology, ANNs have been increasingly used for various applications related to hearing and speech processing [18,19]. ANNs are computational models inspired by the structure and functioning of the human brain. They have shown promise in addressing complex tasks in audiology and have been applied in areas such as speech recognition, hearing-aid optimization, diagnosis of hearing disorders, development of noise reduction algorithms, automation of audiometric testing, and personalizing approaches to tinnitus management. ANNs can be utilized for the diagnosis and prediction of hearing loss based on various input data, such as audiometric measurements, exposure history, and personal factors [20,21]. They can help analyze complex patterns and relationships within data to predict the likelihood or severity of NIHL. Using ANNs' application in predicting NIHL has achieved promising results in some studies (such as achieving 80% accuracy in the excess noise exposure group [21], predicting pure-tone thresholds with approximately 85% accuracy [22], and obtaining high accuracies for normal hearing across different frequencies based on distortion product otoacoustic emissions [23]).

ANNs outperformed multivariate logistic regression in a study conducted in a steel factory [20]. However, it should be noted that the afirementioned ANN studies typically relied on cross-sectional datasets, overlooking NIHL's association with long-term cumulative noise exposures. Additionally, crucial personal and environmental factors such as alcohol consumption, body mass index (BMI), diastolic blood pressure (DBP), systolic blood pressure (SBP), and noise pattern were often omitted. When utilizing ANN techniques, therefore, it is imperative to incorporate longitudinal HTLs and comprehensively consider personal and environmental factors to enhance prediction accuracy.

In the present study, an eight-year follow-up on personal HTL measurements was conducted on 170 steel-making industry workers, together with the collection of the information of nine variables, including two environmental factors (noise level and noise pattern) and seven personal factors (age, smoking, alcohol consumption, BMI, DBP, SBP, and use of PPE) that are recognized for their significant influence on HTLs [6–12,15]. The ANN technique was used to predict workers' NIHLs. The benefits of incorporating complete personal and environmental variable information in predicting HTLs were assessed. Finally, implications of the ANN technique for managing the occupational hearing conservation program were discussed.

2. Materials and methods

2.1. Study population and data collection

This study included all workers with a minimum of 1 year of experience in the steel bar manufacture, the electric generators department, and the air compressors department of a steel-making industry in southern Taiwan. Exclusions were made for workers potentially exposed to organic solvents, polycyclic aromatic hydrocarbons, a history of head injury, ontological disease, ototoxic drug use, noise exposure during leisure time, congenital deafness, or pre-employment hearing impairment. Study participants (n = 170 male workers) underwent structured questionnaire interviews, otoscopic examinations, impedance tympanometry, pure tone audiometry (PTA), and personal noise measurements with an approval from the Institutional Review Board of National Cheng Kung University Hospital, Tainan, Taiwan (B-ER-108-436).

Demographic characteristics, work history, health habits (smoking and alcohol consumption), medical conditions, and the uses of medications, dietary supplements, and hearing protection were annually collected through a structured questionnaire interview. Moreover, BMI, DBP, and SBP were measured during the annual medical examination. The face-to-face interviews were conducted by trained interviewers before the audiological examination for each worker. The pack-year smoking was computed by multiplying the number of smoking years by the daily tobacco consumption [24].

2.2. Noise exposure assessment

The TES-1355 Noise Dose Meter (TES Electrical Electronic Corporation, Taipei, Taiwan), complying with the American National Standard Institute (ANSI) specifications [25], assessed personal noise exposure from 7:00 a.m. to 4:00 p.m. during the work shift. Dosimeters measured sound levels at 10-minute intervals across various frequencies, converting the data into a continuous equivalent A-weighted sound-pressure level (Leq) based on the equal energy principle (3-dB rule). The time-weighted average (TWA) Leq for the 8-hour shift (Leq-8h) was then calculated for each worker. Additionally, if a worker used PPE during the shift, the corresponding Leq-8h was adjusted according to the noise reduction rating (NRR) specified for the worn PPE.

In the present study, the exposed noise pattern for each selected worker was decided using a sound-level meter (TES-52, TES Electrical Electronic Corporation, Taipei, Taiwan) positioned at a height equivalent to the worker's hearing zone (155 cm). This instrument adhered to ANSI specifications for sound-level meters [26]. A-weighted noise levels were measured in Leq (applying the 3-dB rule) throughout the work shift. The exposed noise patterns were then categorized based on noise-level variation, with variations exceeding 5 dBA classified as fluctuating noise and variations of 5 dBA or less classified as steady noise [27].

Considering the minimal changes in manufacturing processes and facilities (e.g., workplace layout, facility types, and work tasks) over recent decades, we assumed that the daily exposed noise levels collected in this study would accurately represent past exposures. Thus, we evaluated each worker's total noise exposure by examining their work history, which included consecutive job titles and departments throughout their entire career. The TWA exposure over the years (Leq-total, dBA-year) was utilized to calculate the cumulative noise exposure level over their job duration. Leq-total was computed by logarithmically summing the TWA noise levels as follows:

$$Leq - total = 10 \cdot \log\left[\Sigma \mathrm{Ti} \cdot 10^{(Leq-8hi/10)}\right]$$

where *Ti* is the *i*th work period in the entire work history, and *Leq-8hi* is the TWA noise exposure during *Ti*.

2.3. Audiological assessment

Workers were instructed to avoid from workplace noise exposure for at least 48 hours before audiological assessments. These assessments occurred between 06:30 and 07:30 a.m. An otolaryngologist evaluated the workers' outer and middle ear status using an otoscope, whereas middle ear function was assessed by a trained technician through impedance tympanometry (Grason Stadler GSI-37 Auto Tymp; Gordon N. Stowe and Associates, Inc., Wheeling, IL, USA). Pure-tone audiometry was conducted by an audiologist using a Grason-Stadler GSI 68 audiometer (Gordon N. Stowe and Associates, Inc., Wheeling, IL, USA) within a sound-attenuating chamber meeting International Organization for Standardization 8253-1 testing conditions [28], with examination frequencies encompassing 500, 1,000, 2,000, 3,000, 4,000, 6,000, and 8,000 Hz. Permanent threshold shift (PTS-6) hearing levels, defined as the average at 500 Hz, 1,000 Hz (twice), 2,000 Hz (twice), and 4,000 Hz, were used to determine hearing impairment, classified when hearing levels exceeded 25 dB (>25 dB) [29]. Audiological assessments were conducted annually throughout the study period for each worker.

2.4. The establishment of experiment datasets

In this study, a comprehensive dataset was established based on the measures outlined in the previous sections, and three subdatasets were further derived from it for comparative purposes. Each serves distinct objectives:

Complete dataset: containing 8-year longitudinal HTL records and information on nine variables (age, smoking, alcohol consumption, BMI, DBP, SBP, use of PPE, exposed noise exposure level, and exposed noise pattern).

Subdataset A: containing 1-year cross-sectional HTL records and information on four variables (age, smoking, exposed noise exposure level, and use of PPE), aligning with a study by Aliabadi et al. [20].

Subdataset B: containing 8-year longitudinal HTL records and information on four variables identical to those in subdataset A. The purpose is to assess the benefits of using longitudinal data in predicting NIHL compared to the results from subdataset A.

Subdataset C: containing 8-year longitudinal HTL records and information on seven variables, mirroring the complete dataset but excluding noise pattern and use of PPE variables. The aim is to

Table 1
Demographic and personal characteristics of the individuals by factory workplaces

Variable	Steel bar manufacture ($n = 80$)*		Electric generators ($n = 46$)†		Air compressors ($n = 44$)‡		All	
Quantitative	Median	IQR§	Median	IQR	Median	IQR	Median	IQR
Age (years)	52.72	49.10, 54.59	49.85	43.60, 53.90	44.44	37.71, 51.90	51.08	43.89, 53.97
Employment (years)	28.75	25.96, 30.58	26.58	20.75, 30.71	21.08	11.92, 28.25	27.33	20.75, 30.27
Body mass index (kg/m^2)	25.50	23.69, 27.24	25.42	25.42, 25.42	25.42	25.42, 25.42	25.42	25.13, 25.81
Diastolic blood pressure (mmHg)	85.00	78.00, 87.00	85.00	85.00, 86.25	85.00	85.00, 85.00	85.00	84.75, 86.00
Systolic blood pressure (mmHg)	131.00	124.25, 136.00	134.00	134.00, 134.00	134.00	134.00, 134.00	134.00	131.00, 134.00
Tobacco smoking (pack-year)	0.01	0.00, 21.75	0.00	0.00, 10.38	0.00	0.00,7.13	0.00	0.00, 16.00
Cumulative noise exposure (Leq-total; dBA-year)	88.67	86.16, 106.45	87.98	86.32, 99.36	88.98	86.12, 96.73	88.40	86.21, 103.28
Hearing threshold levels (dB)	21.25	15.83, 28.96	19.79	14.17, 25.52	18.75	13.75, 23.23	19.58	15.00, 26.25
Categorical	No.	%	No.	%	No.	%	No.	%
Smoking tobacco								
Yes	29	36.25	8	17.39	11	25.00	48	28.24
Used to	12	15.00	9	19.56	7	15.91	28	16.47
No	39	48.75	29	63.00	26	59.09	94	55.29
Alcohol consumption								
Yes	14	17.50	8	17.39	7	15.91	29	17.06
No	66	82.50	38	82.61	37	84.09	141	82.94
Use of PPE								
Yes	45	56.25	38	82.61	43	97.73	126	74.12
No	35	43.75	8	17.39	1	2.27	44	25.88
Exposed noise patterns								
Steady	66	82.50	13	28.26	1	2.27	80	47.06
Fluctuating	14	17.50	33	71.74	43	97.73	90	52.94

Abbreviations: IQR, interquartile range; PPE, personal protective equipment.
* The involved main process was associated with manufacturing steel bars.
† The involved main facilities include electric generators, blowers, condensers, and boiler system (outside).
‡ The involved main facilities include air compressors, oxygen compressors, fractionating towers, storage tanks, and cooling towers.
§ IQR: interquartile range (lower quartile, upper quartile).

investigate the impact of noise pattern and use of PPE on predicting NIHL, in comparison with the complete dataset.

2.5. Artificial neural network model

Given their capacity to decipher intricate relationships across diverse scenarios (such as linear and nonlinear regression, classification, and mapping tasks) [30], ANNs can acquire relevant data from various distributions, including non-normal distributions [31]. In this study, ANNs were adopted for predicting NIHLs based on the collected personal and environmental factors. In ANNs, each neuron in the hidden layer of the networks can be viewed as a simple processing element that receives one or more inputs and generates one or more outputs. Neurons are interconnected via numerous weighted connections [32].

To ensure successful training and utilization of ANNs, a sufficiently large dataset is crucial [33]. The widely accepted guideline recommends a sample size of at least 10 times the number of variables in the ANN to ensure adequate performance [34]. In our study, we have nine variables and 170 data points, making it suitable for establishing predictive models with ANN. The complete dataset, along with the three extracted subdatasets (A, B, and C), were used to construct a three-layer feed-forward ANN for NIHL prediction. Each experimental dataset was further partitioned into three subsets: 70% for network training, 20% for testing the neural networks, and 10% for validation [17,20,35].

2.6. Statistical analysis

Coefficient of determination (R^2) and root mean square error (RMSE) were conducted to evaluate the developed prediction models by comparing predicted and measured HTLs. Higher R^2 and lower RMSE values indicate greater similarity and more accurate estimation [35]. All statistical analyses were conducted using MATLAB software (version R2019b, MathWorks, Inc., Natick, MA).

3. Results

3.1. Study population

Recruited 170 male workers were from three workplaces: 80 from steel bar manufacture, 46 from electric generators, and 44 from air compressors. Information regarding the involved main processes/facilities of the three selected workplaces is shown in Table 1.

3.2. Demographics, noise exposure patterns and levels, and measured HTLs

Table 1 shows participant characteristics, including a median age of 51.08 years, median work experience of 27.33 years, and median values of BMI (25.42 kg/m^2), DBP (85.00 mmHg), and SBP (134.00 mmHg). Smoking habits included 28.24% current smokers and 16.47% ex-smokers, whereas 17.06% consumed alcohol. Noise exposure patterns revealed 47.06% and 52.94% exposed to steady and fluctuating noise, respectively. Median cumulative noise exposure was 88.40 dBA-year, with a median HTL of 19.58 dB for both ears. Additionally, 74.12% reported wearing PPE.

3.3. Performance of the established predicting models

Results show that if the subdataset A was used, the best NIHL predictions were achieved using one hidden layer with fifteen neurons. Conversely, for the other three experiment datasets, the optimal predictions were obtained using one hidden layer with thirty-three neurons. Fig. 1 shows scatter plots depicting the measured versus ANN-model-predicted HTLs (including the training, testing, validation, and all datasets) for each of the four experiment datasets. Results show that the complete dataset (Fig. 1D) yielded the most accurate prediction (R^2 = 0.87, RMSE = 3.16) among all experimental datasets. Subdataset B

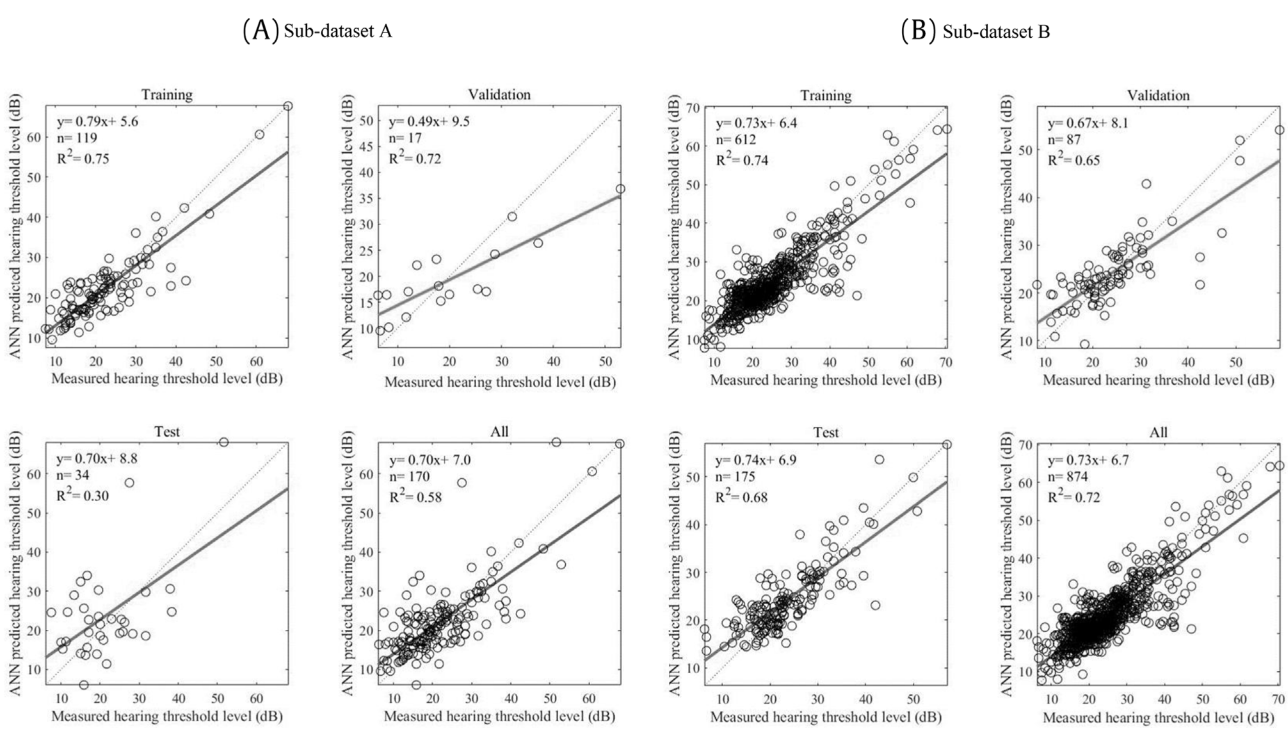

Fig. 1. Scatter plots of measured HTLs versus ANN model predicted HTLs for the four experiment datasets. (A) Subdataset A, (B) subdataset B, (C) subdataset C, and (D) complete dataset. Abbreviations: ANN, artificial neural network; HTL, hearing threshold level.

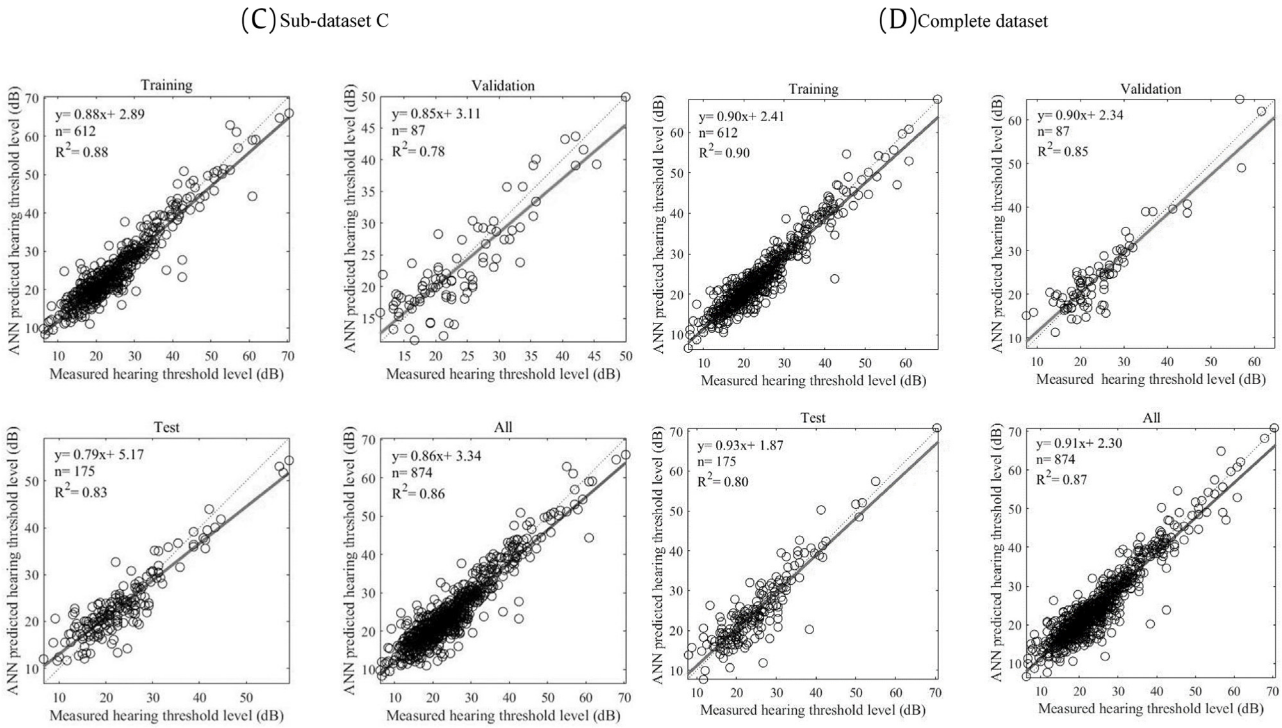

Fig. 1. (*continued*).

(Fig. 1B) outperformed subdataset A (Fig. 1A), with superior NIHL prediction performance (R^2 = 0.72, RMSE = 4.73 vs. R^2 = 0.58, RMSE = 6.58). Additionally, subdataset C (Fig. 1C) exhibited enhanced NIHL prediction (R^2 = 0.86, RMSE = 3.31) compared to subdataset B (Fig. 1B) (R^2 = 0.72, RMSE = 4.73).

3.4. *The implication of the established predicting models*

Table 2 presents demographic, personal characteristics, and exposure scenarios (i.e., exposed noise patterns and use of PPE) of the four selected workers for the illustration purpose. Fig. 2 shows their predicted and measured HTLs at different ages. Though fluctuation can be seen in measured HTLs for each selected worker, both the predicted and measured HTLs exhibit a similar trend.

For worker A (steady noise (Leq-total = 85.17 dBA)/with PPE), measured HTLs increased from 17.92 dB (at the 24.77th employment year) to 21.67 dB (at the 31.74st employment year), which are quite consistent with the corresponding predicted values (from 16.79 to 18.91 dB). It also can be estimated that on the 39.74th employment year (or at the age of 63.39 years old), worker A's HTL will exceed 25 dBA. This suggests a marginal acceptability for worker A if he retires at the age of 65 years of age (Fig. 2A).

Table 2
Demographic and personal characteristics of the four selected workers and predicted ages for HTL over the level of 25 dB

Feature	Worker A	Worker B	Worker C	Worker D
Age (years)*	48.42	43.90	46.21	41.5
Employment (years)*	24.77	21.22	24.77	20.63
Smoking tobacco (pack-year)*	0	0	0	27.00
Body mass index (kg/m^2)*	26.89	23.74	20.71	23.66
Diastolic blood pressure (mmHg)*	75	89	76	85
Systolic blood pressure (mmHg)*	109	132	132	134
Cumulative exposed noise level (Leq-total; dBA-year)*	85.17	84.80	88.98	105.38
Exposed noise patterns*	steady	steady	fluctuating	fluctuating
Use of PPE*	yes	no	yes	no
Alcohol consumption*	no	no	no	yes
Measured HTL range within recorded years (dBA)	17.92–21.67	14.58–20.00	22.08–25.41	17.92–29.17
Predicted HTL range within recorded years (dBA)	16.79–18.91	16.96–20.44	21.77–24.06	18.66–26.33
Employment year for HTL to exceed 25 dB after the last record (years)	8.00	3.00	2.00	0
Age for HTL to exceed 25 dB (years old)	63.39	53.92	55.12	48.56
Acceptability of noise exposure	marginal	no	no	no

Abbreviations: HTL, hearing threshold level; PPE, personal protective equipment.
* The values were shown at the 1st data record year.

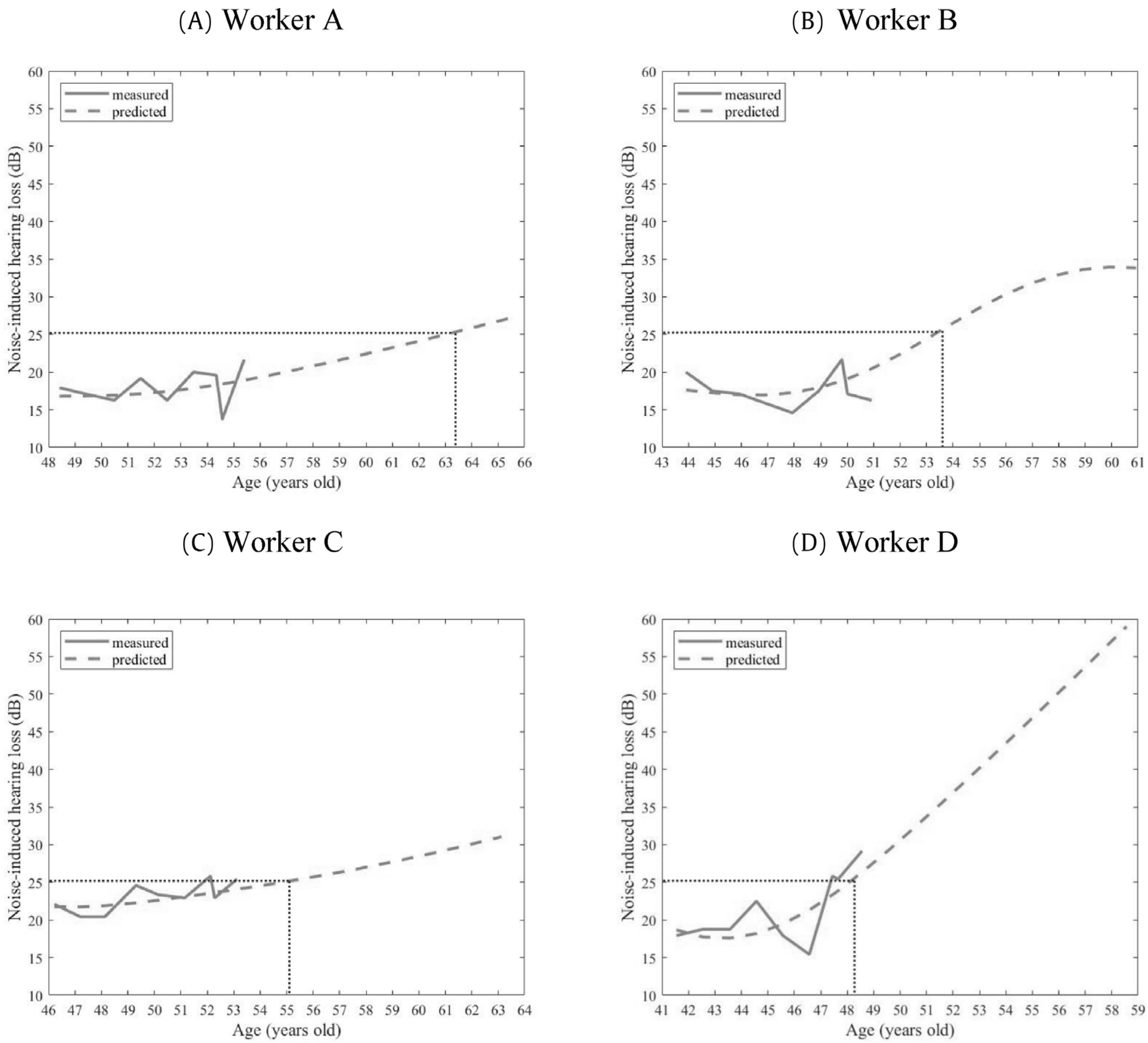

Fig. 2. Predicted and measured HTLs at different ages and the ages for HTL reaching 25 dBA for (A) worker A: steady noise and equipped with PPE, (B) worker B: steady noise and equipped without PPE, (C) worker C: fluctuating noise and equipped with PPE, and (D) worker D: fluctuating noise and equipped without PPE. Abbreviations: HTL, hearing threshold level; PPE, personal protective equipment.

For worker B (steady noise (Leq-total = 84.80 dBA)/without PPE), measured HTLs increased from 20.00 dB (at the 21.22st employment year) to 21.67 dB (at the 27.12th employment year) before decreasing to 16.25 dB (at the 28.24th employment year), closely matched predicted HTLs (increased from 17.61 to 20.44 dB). Worker B's HTL is projected to exceed 25 dB at the 31.24st employment year (or age 53.92), and therefore, is considered unacceptable if retirement occurs at age 65 (Fig. 2B).

For worker C (fluctuating noise (Leq-total = 88.98 dBA)/with PPE), measured HTLs increased from 22.08 dB (at the 24.77th employment year) to 25.41 dB (at the 32.67nd employment year) also closely matched predicted HTLs (ranging from 21.77 dB to 24.06 dB). Worker C's noise exposure is deemed unacceptable, with HTLs projected to exceed 25 dB at the 34.67th employment year (or age 55.12) if retiring at 65 (Fig. 2C).

Fig. 2D shows results for worker D (fluctuating noise (Leq-total = 105.38 dBA)/without PPE). Measured HTLs increased from 17.92 dB at the 20.63th employment year to 29.17 dB at the 27.66th employment year, mirroring predicted HTLs (increasing from 18.66 dB to 26.33 dB). Worker D's HTL is anticipated to surpass 25 dB at the 27.66th employment year (or age 48.56), rendering noise exposure unacceptable for retirement at age 65.

4. Discussion

To our knowledge, this is the first study using comprehensive longitudinal data to establish ANN models for predicting NIHL in the steel-making industry. Overall, our findings indicate that the ANN technique can be used for accurately predicting workers' NIHLs.

Fig. 1 illustrates that subdataset B (Fig. 1B) outperformed subdataset A (Fig. 1A) in NIHL predictions, with R^2 values of 0.72 and 0.58, and RMSE values of 4.73 and 6.58, respectively. This highlights the superiority of utilizing long-term longitudinal data over cross-sectional data when developing prediction models with the same chosen variables. This might explain some studies using ANN techniques for NIHL prediction but using cross-sectional data resulting in prediction accuracies ranging from 32% to 85% [21–23]. These results underscore the ANN technique's promise for NIHL prediction. Given the chronic nature of NIHL, longitudinal data provide a more representative foundation for prediction models. Our study demonstrated an improved prediction accuracy of 87% for the noise-exposed population (Leq-total = 88.40 dB) by utilizing 8-year longitudinal HTL records and a nine-variable dataset (Fig. 1D). Therefore, collecting longitudinal HTL data alongside comprehensive personal and environmental factors is a notable strength of our study.

The ANN technique is recognized for its ability to uncover complex relationships among variables through various learning algorithms, and utilizing a more comprehensive set of variables enhances predictive capabilities [17,20]. However, it has limitations, notably being labeled a black-box approach, which means that the inner workings of the hidden layers are not easily interpretable [36]. Nonetheless, this limitation does not hinder the widespread application of neural networks in scientific contexts, as they excel at accurately capturing operational characteristics [36]. Consequently, it is unsurprising that the complete dataset (Fig. 1D) yields the most accurate predictions (R^2 = 0.87, and RMSE = 3.16) among all study designs (Fig. 1A–C). However, the selection of these variables should be discussed.

In the present study, the impact of each selected variable on NIHL has been confirmed through literature reviews [8–10,14]. For instance, a longitudinal Cox proportional-hazards regression study identified high blood pressure as a significant hearing-loss risk factor [15]. Additionally, a 7-year follow-up study established a link between obesity and an increased risk of hearing loss [10]. Wang et al. demonstrated that longer noise exposure and greater smoking-pack-years were associated with higher hearing-loss risk [8]. Other studies suggest that smoking and alcohol consumption, in conjunction with occupational noise exposure, may synergistically contribute to NIHL [8,9].

In our study, the complete dataset was found to have better prediction (R^2 = 0.87, and RMSE = 3.16) than that of subdataset C (R^2 = 0.86, and RMSE = 3.31). These findings support the influence of noise pattern and use of PPE on workers' NIHL, as indicated in prior research. For instance, a study on PPE's impact on noise exposure attenuation revealed that PPE with an NRR value of 29 dB could reduce noise exposure by 11.87 dB [12]. Furthermore, an increase of 10% in PPE usage frequency was associated with a 3- to 5-dB reduction in HTL [37]. A cross-sectional study also suggested that fluctuating noise exposure, particularly at higher noise levels, may lead to more significant NIHL than non-fluctuating noise exposure [7].

In the present study, pure-tone audiometry was adopted to assess the hearing thresholds of the workers. However, pure-tone audiometry has limitations, including sensitivity to factors such as background noise, cross-hearing with loud sounds, ear canal issues, discomfort from wearing earphones, and challenges in hearing measurement [38]. Fig. 2 illustrates noticeable variations in measured pure-tone thresholds for the four selected workers over eight years. Nevertheless, these variations for each worker remained within 10 dB. It is worth noting that this level of variation differs from a previous study where most test–retest threshold differences were within 10 dB [39]. Despite these fluctuations, our predicted and measured HTLs exhibit a consistent trend (Fig. 2). Nevertheless, it is essential to exercise caution when utilizing the model-predicted NIHLs for individual workers due to inherent personal fluctuations in HTLs.

We set the NIHL warning level at 25 dB in this study. Fig. 2A indicates that the acceptability of noise exposure for worker A is marginal. Worker A, classified as obese with a BMI of 26.89, should consider weight management, as obesity is associated with an increased risk of hearing loss [10]. Similarly, worker B's noise exposure scenario is unacceptable (Fig. 2B), possibly due to inadequate PPE usage or enforcement. Implementing PPE consistently can help, as it may reduce HTLs by up to 5 dB [37]. Although worker C used PPE, their noise exposure remains unacceptable (Fig. 2C) due to exposure to fluctuating noise, which poses a higher NIHL risk than nonfluctuating noise exposure [7]. Implementing administrative controls such as work–rest schedules and job rotation can limit fluctuating noise exposure. Worker D's unacceptable hearing loss (Fig. 2D) is likely due to smoking, alcohol consumption, lack of PPE use, and exposure to fluctuating noise [7–9,12]. In addition to PPE, comprehensive training on promoting a healthy lifestyle should be part of control measures for worker D.

A recent study has unveiled several significant advancements, notably the ANNs, that can be used to enhance hearing conservation programs [40]. Here, two potential applications of ANNs are exemplified: (1) use information such as the age of first employment year, usage of PPE, and workplace noise levels of workers in the ANN predictive model for predicting the HTLs of workers in different years that can serve as a basis for implementing appropriate control measures (such as establishing a workplace rotating plan, reducing workplace noise levels, and selecting suitable PPE for workers) for preventing NIHLs and (2) applying the personal and workplace information of workers in the ANN predictive model to underscore the significance of using PPE in preventing NIHL, which would enhance the education and training of the workforce. Finally, it is essential to emphasize that the continuous accumulation of personal and workplace information over the years will contribute to refining the ANN predictive model. This refinement will result in improved predictions for future occurrences, reinforcing the efficacy of preventive measures against NIHL.

5. Conclusion

The feed-forward multilayer neural network accurately predicted NIHLs in the steel-making industry using comprehensive data, with long-term longitudinal data outperforming cross-sectional data. Adding variables, particularly noise pattern and use of PPE, enhanced accuracy. While individual trends in predicted vs. measured HTLs aligned, caution is needed due to measured HTL fluctuations. Regardless, this study offers valuable insights to improve the industry's hearing conservation program and reduce NIHLs among workers. Therefore, it is concluded that NIHL is a significant concern, and integrating ANNs into hearing conservation programs can improve early detection, prevention, and management.

Conflicts of interest

All authors declare that they have no conflict of interest.

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