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SKILL PROGRESSION AND ERROR REDUCTION IN NOVICE INTERPRETERS OF AUDITORY BRAINSTEM RESPONSES (ABR)

Contributions:
A Study design/planning
B Data collection/entry
C Data analysis/statistics
D Data interpretation
E Preparation of manuscript
F Literature analysis/search
G Funds collection

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Abstract

Introduction: Auditory brainstem response (ABR) is a key objective diagnostic method in audiology; however, the interpretation of recordings – especially estimating hearing thresholds – is challenging for novices. The aim of this preliminary descriptive study was to document the learning process of novices in ABR threshold interpretation in preparation for the ABR.AI project.

Material and methods: Seven students with varying levels of baseline theoretical knowledge participated in the training. The program consisted of a multi-stage cycle including theoretical lectures, individual analysis of ABR recordings, independent practice with available expert consultation, and case-based discussions. The students' hearing threshold estimations were compared with expert assessments across three clinical datasets (115–122 cases each). Results were presented as the percentage of full agreement (0 dB difference), minor discrepancies (≤ 10 dB), and large discrepancies (> 10 dB) relative to the expert's assessment.

Results: Across the three training stages, mean full agreement with the expert increased from 55% (Set 1) to 60% (Set 3), while major discrepancies decreased from 9% to 6%. Despite individual differences in learning dynamics, the majority of participants demonstrated a consolidation of interpretive skills and a reduction in large diagnostic errors. Most deviations were ≤ 10 dB, indicating that discrepancies were generally small and clinically acceptable.

Conclusions: This preliminary descriptive study demonstrated that multi-stage, expert-guided training was associated with an improvement in ABR threshold estimation accuracy, and most importantly, with a clinically meaningful reduction in large discrepancies (>10 dB) from the expert's assessment. These findings highlight the importance of structured, feedback-based learning in the education of audiology professionals.

Keywords: medical education • auditory brainstem response • hearing threshold • ABR interpretation • speech therapy students

POSTĘPY W NABYWANIU UMIEJĘTNOŚCI I ZMNIEJSZENIE LICZBY BŁĘDÓW U POCZĄTKUJĄCYCH OSÓB INTERPRETUJĄCYCH WYNIKI BADANIA SŁUCHOWYCH POTENCJAŁÓW WYWOŁANYCH (ABR)

Streszczenie

Wprowadzenie: Słuchowe potencjały wywołane pnia mózgu (ABR) stanowią podstawową metodę diagnostyki obiektywnej w audiologii, jednak interpretacja zapisów – szczególnie przy szacowaniu progów słyszenia – jest trudna dla osób początkujących. Celem tego wstępnego badania opisowego było udokumentowanie procesu uczenia się nowicjuszy w zakresie interpretacji progów ABR w ramach przygotowań do projektu ABR.AI.

Materiał i metody: W szkoleniu wzięło udział 7 studentów o zróżnicowanym poziomie początkowej wiedzy teoretycznej. Program obejmował wieloetapowy cykl z wykładami teoretycznymi, indywidualną analizą zapisów ABR, pracą własną z możliwą konsultacją ekspercką oraz omawianiem przypadków. Oceny progów słyszenia wykonane przez studentów porównano z ocenami eksperta w trzech zestawach danych klinicznych (każdy po 115–122 przypadki). Wyniki przedstawiono jako odsetki pełnej zgodności (0 dB) oraz rozbieżności względem oceny eksperta: niewielkie (≤ 10 dB) i znaczne (> 10 dB).

Wyniki: Średni poziom pełnej zgodności z ocenami eksperta wynosił 55,4% w zestawie 1. i wzrósł do 60,0% w zestawie 3., a odsetek znacznych rozbieżności (> 10 dB) spadł z 8,7% do 5,8%. Mimo indywidualnych różnic w dynamice nauki, u większości uczestników zaobserwowano konsolidację umiejętności interpretacyjnych i zmniejszenie liczby istotnych błędów diagnostycznych.

Wnioski: Niniejsze wstępne badanie obserwacyjne wykazało, że rezultatem wieloetapowego szkolenia prowadzonego przez ekspertów była poprawa dokładności szacowania progów ABR, a przede wszystkim istotna klinicznie redukcja znacznych rozbieżności w porównaniu z oceną eksperta (>10 dB). Wyniki te podkreślają znaczenie ustrukturyzowanej nauki z informacją zwrotną w procesie kształcenia kadr audiologicznych.

Słowa kluczowe: edukacja medyczna • słuchowe potencjały wywołane pnia mózgu • próg słyszenia • interpretacja wyników ABR • studenci logopedii

Introduction

The auditory brainstem response (ABR) is a key method in objective audiological diagnostics, used to assess neural conduction latencies along the auditory pathway [1] and to estimate frequency-specific hearing thresholds [2], making it particularly useful when behavioral testing is unreliable or infeasible. ABR recordings display a characteristic sequence of waves (typically labelled I–VII), each reflecting synchronous neural activity at different levels of the auditory pathway. For example, wave I arises from the distal portion of the cochlear nerve, wave III from the cochlear nucleus, wave V from the inferior colliculus, and waves VI–VII likely originate from still higher auditory centers [3]. Among these, wave V is generally considered the most robust and clinically relevant component [4], therefore becoming the primary indicator for estimating hearing threshold [5]. Threshold assessment in ABR testing involves recording responses to stimuli presented at progressively lower intensities and determining the lowest sound level at which wave V remains detectable. The stimuli most commonly used are clicks and tone bursts at 500, 1000, 2000, and 4000 Hz, allowing evaluation of hearing sensitivity across different frequency regions.

Accurate identification of wave V plays a crucial role in the threshold determination. However, interpretation of ABR waveforms remains particularly challenging [6] due to variability in morphology [7] and recording conditions [8]. The morphology of ABR waves is affected by stimulus parameters such as frequency and intensity [9], as well as by subject-related factors including age, hearing status, and neural synchrony [10]. In contrast, variability in recording conditions arises primarily from technical and environmental factors [11], including electrode placement [12] and background noise [13]. Given the interplay between these sources of variability, reliable threshold estimation requires both technical proficiency and clinical experience in waveform interpretation. Nevertheless, variability can persist even with substantial expertise.

Even among experienced clinicians, inter-rater variability in threshold estimation can be substantial [14]. Differences in individual judgment may lead to threshold discrepancies of up to 10–20 dB, particularly in recordings with low signal-to-noise ratio or atypical wave morphology [15]. This variability illustrates the subjective nature of ABR interpretation and the importance of clear, standardised evaluation criteria. To address these challenges, recent research has increasingly turned toward machine learning (ML) as a potential solution [16]. The use of ML algorithms is being explored to enable objective, consistent, and rapid analysis of ABR recordings, supporting or even in some extent replacing human evaluation in threshold determination. Various ML approaches have been explored for this purpose [17], ranging from classical classifiers [18,19] to advanced deep learning architectures [20–22].

Despite the broad use of ABR in clinical practice and ongoing research on automated detection methods, relatively little attention has been paid to the learning process of novice interpreters. In particular, there is limited evidence on how quickly students can acquire the skills needed for ABR threshold estimation, how closely their judgments align with expert evaluations, and what types of errors are most frequent during training. Previous studies have shown that direct, face-to-face training tends to be more effective [23] than computer- or simulator-based instruction in developing interpretive accuracy. Understanding these aspects is important for improving educational strategies and preparing future clinicians for diagnostic challenges in audiology.

This educational study was conducted as part of the ABR. AI project, which was initiated to develop an AI-based application for the automated assessment of ABR waveforms [24]. Building and validating such an algorithm requires a large, high-quality, human-annotated database of recordings. To achieve this, a group of novice trainees was engaged to support the expert team in dataset preparation. It is critical to clarify that while the overarching project is AI-focused, the educational process described in this paper was entirely traditional (human-to-human). No AI tools, automated feedback, or machine learning algorithms were utilised during the training or evaluation of the students. This dual purpose – supporting dataset development while providing supervised training – created a unique opportunity to document the learning curve of novice interpreters.

The present paper reports on this educational component of the project. It describes the multi-stage training workflow, the methods used to assess student performance, and the progression of their interpretive accuracy on the following tasks. By documenting both the learning curve and the challenges encountered, this study seeks to illustrate how novice interpreters develop their skills in ABR threshold estimation under expert supervision. The main objectives of this preliminary descriptive study were to document students' learning progress across successive training stages, observe changes in their performance over time, and compare their ABR interpretation accuracy with expert judgements. While the instructional sequence itself follows a standard clinical teaching model, the novelty of this study lies in providing objective, empirical data on the actual learning trajectory of novices. By quantifying how quickly interpretation skills consolidate and identifying the specific types of errors that persist – particularly the clinically significant >10 dB deviations – this research addresses a notable gap in the audiological literature regarding the evidence-based training of electrophysiology interpreters.

Material and methods

This study was conducted with the approval of the Bioethics Committee of the Institute of Physiology and Pathology of Hearing in Warsaw (approval no. KB.IFPS 6/2025, 27 March 2025). It was carried out under a grant to ABR.AI (no. 2024/ABM/03/KPO/KPOD.07.07-IW.07-0222/24-00 – An AI-based system for estimating hearing thresholds from intensity series of wave V responses) funded by the Polish Medical Research Agency (Agencja Badań Medycznych, ABM).

Participants

Within the ABR.AI project, 7 students (2 from medicine and 5 from the speech therapy with audiology program) participated as trainees. The selection of these specific disciplines reflects the organisational structure of audiological care in Poland. In the Polish healthcare system, objective hearing assessments, including ABR, are a shared clinical competency. They are routinely performed and interpreted not only by dedicated audiophonologists but also extensively by medical doctors specialising in otolaryngology or audiology, as well as professionals graduating from speech therapy with audiology programs. Because these students will be directly responsible for performing and interpreting such examinations in their future clinical practice, they were specifically included in this training project. The trainees entered the project with varying levels of baseline theoretical knowledge regarding auditory brainstem responses (ABRs), ranging from no prior exposure to basic coursework-level familiarity. The expert panel included experienced audiologists and electrophysiologists, among them a pioneer of ABR threshold evaluation methods in Poland (co-author K.K.), who has had longstanding clinical and research experience in auditory evoked potentials since the 1980s.

Procedures

Data

All ABR recordings used for the training datasets were obtained from consecutive patients undergoing routine audiological diagnosis. The clinical material was not pre-selected or stratified based on specific auditory pathologies. This approach ensured that the datasets reflected the natural variability, technical artifacts, and typical diagnostic challenges encountered in everyday clinical practice, rather than being an artificially designed progression of difficulty. All stages of the education process are shown in **Figure 1**.

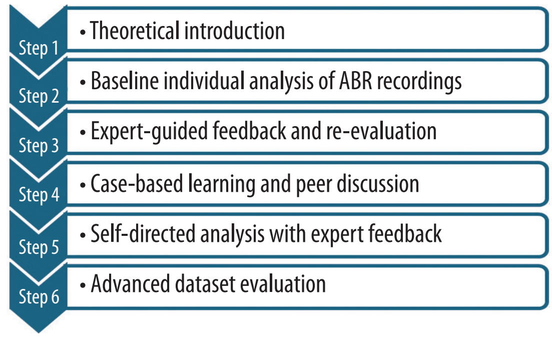

Figure 1. Six-step training process for students in ABR interpretation

Step 1 – Theoretical introduction

First introductory expert-led lecture included theoretical section which addressed the physiological and physical foundations of the ABR, including the generation mechanisms of waves I–V, the basilar membrane response to changes in stimulus intensity, neural firing rate adaptation, and the application of averaging techniques in signal processing. Based on this framework, practical strategies for the detection of wave V were presented, with particular focus on its clinical significance for threshold estimation. After an hour the session ended with a guided analysis of representative recordings, during which thresholds were determined collectively under expert supervision and alternative interpretations were discussed.

Step 2 – Baseline analysis of ABR recordings

Following this theoretical introduction, participants received their first dataset comprising ABR recordings from 30 patients (117 ear-specific cases using both click and tone-burst stimuli at 500, 1000, 2000, and 4000 Hz). Students were instructed to estimate auditory thresholds based on the presence of wave V. Their results were compared with expert evaluations, and discrepancies were quantified as the percentage of instances of complete agreement with expert judgments, the percentage of estimates within 10 dB of the expert thresholds, and the percentage of estimates deviating by more than 10 dB.

Step 3 – Expert-guided feedback and re-evaluation

In subsequent sessions, participants received structured feedback on their performance. Each meeting began with a presentation of summary statistics, including the proportion of responses in complete agreement with expert thresholds and the distribution of deviations. The most challenging cases for students were then selected for detailed discussion. An expert prepared a number of case-based presentations and explained the rationale for the correct threshold determination, highlighting key features important for reliable wave V identification. Alternative interpretations were discussed collectively, and potential

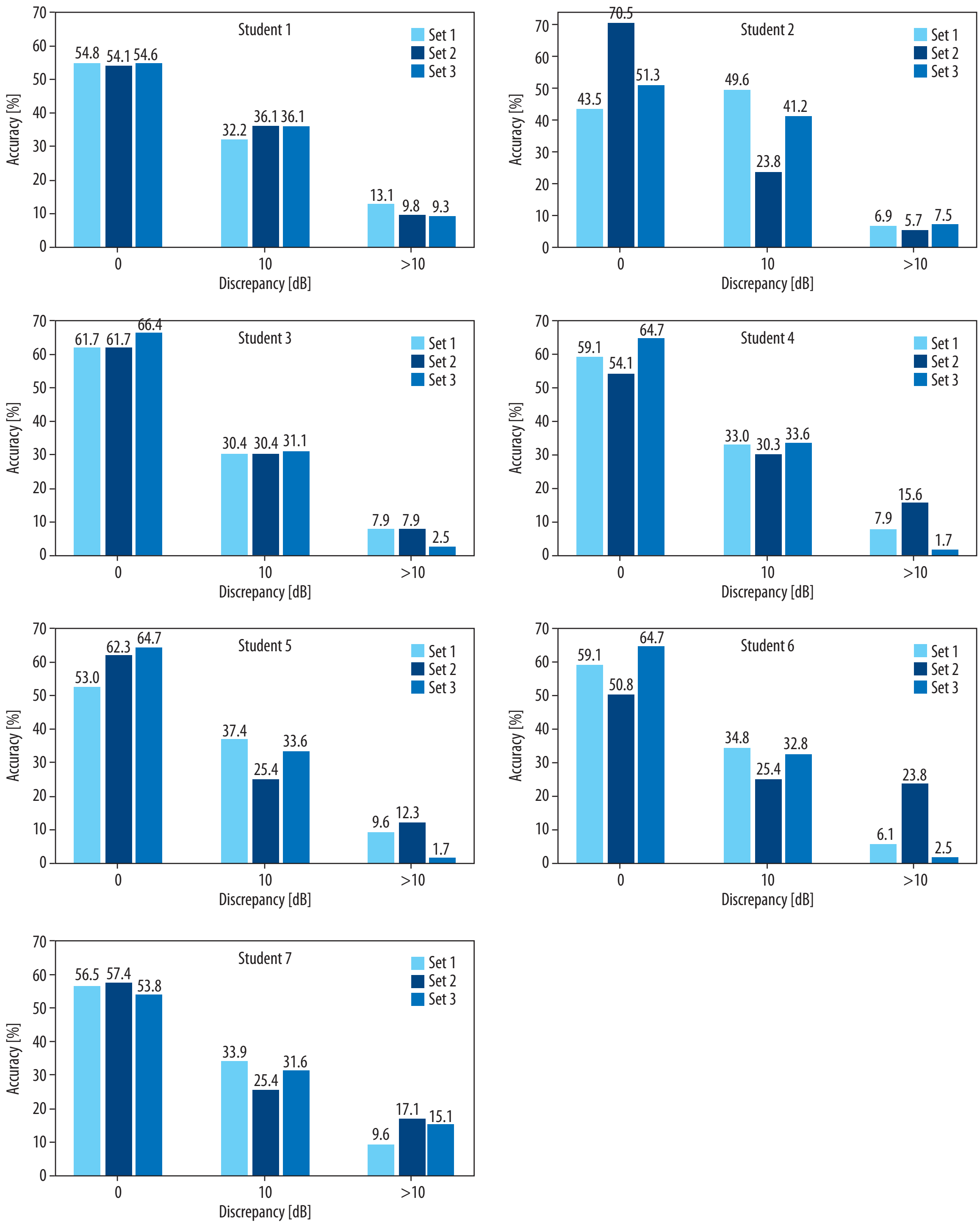

Figure 2. Mean performance of 7 students across 3 sets of ABR interpretations

sources of error were clarified. This interactive format not only reinforced the rules for wave V identification but also provided practical guidance for resolving ambiguity in complex cases. A second dataset, including recordings from 30 patients (122 cases) was subsequently distributed and analysed using the same procedure. Results were assessed in relation to expert judgments, after which group discussions addressed common sources of discrepancy.

Step 4 – Case-based learning and peer discussion

To support further learning, an expert-prepared catalogue of ABR examples was provided, including normal-hearing cases and ears with different types of auditory pathology. The catalogue included principles of frequency specificity, threshold testing procedures, and common errors in interpretation. Using this resource, students selected three

Table 1. Discrepancies (dB, absolute values) in the ratings of 115 ABR records in set no. 1 between students and the expert; values are presented as percentages [%]

Discrepancy [dB]	Student						
	1 [%]	2 [%]	3 [%]	4 [%]	5 [%]	6 [%]	7 [%]
0	54.8	43.5	61.7	59.1	53.0	59.1	56.5
10	32.2	49.6	30.4	33.0	37.4	34.8	33.9
20	9.6	6.0	7.9	7.0	6.1	5.2	6.1
30	2.6	0.9		0.9	1.7	0.9	1.7
40					0.9		0.9
50	0.9						
80					0.9		0.9

Table 2. Discrepancies (dB, absolute values) in the ratings of 122 ABR records in set no. 2 between students and the expert; values are presented as percentages [%]

Discrepancy [dB]	Student						
	1 [%]	2 [%]	3 [%]	4 [%]	5 [%]	6 [%]	7 [%]
0	54.1	70.5	54.9	54.1	62.3	50.8	57.4
10	36.1	23.8	28.7	30.3	25.4	25.4	25.4
20	6.6	4.1	9.8	7.4	9.8	13.9	9.8
30	1.6	1.6	4.9	6.6	2.5	7.4	4.9
40	0.8		1.6	1.6		2.5	1.6
50	0.8						0.8

particularly challenging or informative cases from their daily tasks – such as technical errors, atypical morphology, or diagnostic ambiguity – and presented them during a seminar session for collective discussion.

Step 5 – Self-directed analysis with expert feedback

Throughout the project, participants engaged in independent practice with continuous access to expert evaluations, which allowed them to compare their judgments with expert results and review differences in wave V identification. They discussed their interpretations within the group, and unresolved cases were clarified through consultation with the expert.

Step 6 – Advanced dataset evaluation

After 4 months of training, a final dataset comprising 21 patients (120 cases) was introduced to assess progress. Although not deliberately selected for difficulty, this consecutive clinical sample naturally happened to include more complex cases (e.g., lower signal-to-noise ratio, atypical morphology). This presented an unplanned but valuable additional challenge for the trainees, while maintaining a comparable total number of cases to earlier sessions. This approach enabled a direct comparison with previous exercises, while controlling for sample size, and thus allowed assessment of the effect of systematic training on student performance in advanced ABR analysis.

Results

Set no. 1

Set no. 1 comprised 117 recordings. The expert provided valid assessments for 115 cases, while 2 cases were deemed unsuitable for evaluation. Therefore, the analyses were conducted with $N = 115$. In this set, the differences between the students' and the expert's assessment ranged from 0 to 80 dB (**Table 1**), with a mean difference of 11.7 dB (SD = 10.4). Full agreement (0 dB difference) ranged from 43.5% to 61.7% across students, while differences of 10 dB occurred in 32.2–49.6% of cases. Differences above 10 dB were observed in 6.1–13.1% of cases.

Set no. 2

Set 2 comprised 122 ABR recordings, all of which were assessed by the expert. In set no. 2, the differences between the students' assessments and the expert's assessment ranged from 0 to 50 dB (**Table 2**), with a mean difference of 11.1 dB (SD = 10.5). Full agreement was observed in 50.8–70.5% of cases. Differences of 10 dB occurred in 23.8–36.1% of cases. Differences above 10 dB were observed in 5.7–17.1% of cases.

Table 3. Discrepancies (dB, absolute values) in the ratings of 119 ABR records in set no. 3 between students and the expert; values are presented as percentages [%]

Discrepancy [dB]	Student						
	1 [%]	2 [%]	3 [%]	4 [%]	5 [%]	6 [%]	7 [%]
0	54.6	51.3	66.4	64.7	64.7	64.7	53.8
10	36.1	41.2	31.1	33.6	33.6	32.8	31.1
20	5.9	6.7	2.5	1.7	1.7	2.5	13.4
30	3.4	0.8					1.7

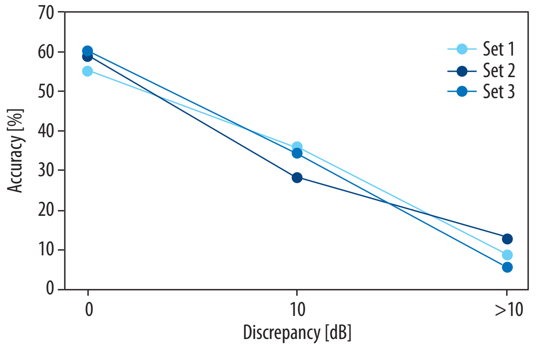

Figure 3. Changes in students' agreement with the expert across 3 successive sets of ABR assessments

Set no. 3

Set no. 3 comprised 120 recordings. The expert provided valid assessments for 119 cases, while 1 case was deemed unsuitable for evaluation. Therefore, the analyses were conducted with $N = 119$. In this set, the differences between the students' assessments and the expert's assessment ranged from 0 to 30 dB (**Table 3**), with a mean difference of 10.1 dB (SD = 7.3). Full agreement ranged from 51.3 to 66.4% across students, while differences of 10 dB occurred in 31.1–41.2% of cases. Differences above 10 dB were observed in 1.7–15.1% of cases.

General student performance

Overall, participants demonstrated measurable improvement in ABR threshold estimation over the course of the training (**Figure 2**). The mean accuracy relative to expert assessments (0 dB difference) increased slightly across the three datasets, from 55.4% in Set 1 to 58.7% in Set 2, and 60.0% in Set 3. This gradual rise indicates a steady enhancement in students' ability to correctly identify the ABR threshold.

At the same time, the proportion of responses differing by more than 10 dB from the expert benchmark decreased markedly, from 8.7% in Set 1 to 5.8% in Set 3, reflecting a meaningful reduction in major errors. Minor discrepancies (≤ 10 dB) fluctuated slightly –35.9%, 28.1%, and 34.2% for Sets 1–3, respectively – suggesting that while some variability persisted, students became more consistent in distinguishing near-threshold responses.

Taken together, these observations suggest that structured expert guidance was associated with an improvement and a clinically meaningful reduction in large errors in ABR interpretation, even though small inter-individual variability remained.

Individual student progress

To examine the learning progress of individual students, the percentage of full agreement with the expert's assessments (0 dB difference) and size of differences were analysed across the three sets. This allowed for the evaluation of both inter-individual variability and changes in accuracy over time.

Figure 3 shows that there were varying learning dynamics among the trainees. While some participants demonstrated steady, progressive improvement in full agreement with the expert (e.g., students 3, 4, and 5), others exhibited more fluctuation across the successive datasets (e.g., students 2 and 6). However, despite these individual variations in exact threshold matching, a common trend emerged: for the majority of participants, repeated practice and guided feedback were associated with a distinct consolidation of skills and a marked reduction in large discrepancies (>10 dB) by the final assessment.

Discussion

The results of this preliminary descriptive study indicate that the multi-stage training process was associated with an improvement in accuracy and a clinically meaningful reduction in large errors during ABR threshold estimation. Full agreement (0 dB difference) was achieved in 43.5–70.5% of cases, with the highest concordance observed in Set 2, while discrepancies within 10 dB occurred in approximately one-third of cases across all sets, suggesting that most deviations were small and clinically acceptable. Large discrepancies (>10 dB) were relatively infrequent, with the mean frequency across all students decreasing from 9.4% in Set 1 to 6.6% in Set 3, despite a temporary increase to 12.6% in Set 2, likely due to more challenging or complex cases. This reduction in major errors reflects a gradual improvement in consistency and supports the potential value of systematic, expert-led practical training, which is particularly important clinically to ensure reliable hearing threshold estimation and reduce the risk of misdiagnosis.

Analysis of individual and group performance revealed measurable improvement across all students. Overall mean accuracy relative to expert assessments increased from 55.4% in Set 1 to 60.0% in Set 3. All participants, despite varying levels of baseline theoretical knowledge prior to the project, demonstrated measurable improvement. This highlights that systematic, supervised practice can enhance interpretive accuracy and reduce errors in novice learners.

The greatest progress was observed between set 2 and set 3, mainly due to a reduction in large errors (>10 dB). This improvement highlights the potential utility of strategies such as direct expert feedback, case-based discussions, and regular comparison of students' assessments with expert evaluations over a longer period of time. This approach facilitated faster reduction of large errors and supported the consolidation of interpretive skills. Early, intensive application of case-based learning and interactive correction sessions appeared particularly beneficial, proving more effective than relying only on oral instructions [25], which may provide only limited improvement in interpretive accuracy without hands-on practice and individual feedback.

These findings are consistent with previous reports on learning ABR interpretation. Dzulkarnain and colleagues [24] showed that direct, interactive expert-led training is more effective than simulator- or computer-based instruction. Our descriptive observations support the notion that structured, multi-stage training may help enhance accuracy in ABR interpretation and reduce the incidence of large errors. At the same time, the literature on training novice ABR interpreters remains limited, and our observations provide a useful contribution to the development of educational strategies in audiology.

It is important to note that even among experts, some degree of disagreement exists in ABR threshold estimation. As some studies suggest [14,26], inter-expert differences can exceed 10 dB in certain cases, indicating that complete agreement among students with expert assessments is unrealistic. This variability leaves room for artificial intelligence (AI) systems, which, once properly trained, might provide more consistent and objective threshold evaluations [27], reducing the subjectivity inherent in human interpretation.

While the present study focused exclusively on traditional, expert-guided learning to establish a human-annotated baseline, in the future ML and AI systems could play a significant role in supporting student education [28,29], for example by offering real-time guidance or highlighting key ABR features in recordings. Such tools could accelerate the reduction of large errors [30] and shorten the time needed to acquire proficiency in ABR threshold estimation.

Overall, the study met its objectives: it was found that students demonstrated measurable progress across successive training stages, the multi-stage training was associated with enhanced ABR interpretation accuracy, and the students' performance could be reliably compared with expert judgements, highlighting the importance of structured, feedback-based learning.

Limitations

There are several limitations of this study. First, the small number of participants ($N = 7$) limits the generalisability of the results. Second, since the recordings consisted of consecutive clinical cases, the difficulty of the datasets was not controlled. Thus, the third dataset contained more complex recordings and was reported by students as being the most challenging, and therefore would have affected the recorded differences and rules out direct comparison of progress across datasets. Future studies should aim to standardise dataset difficulty to allow better assessment of training effectiveness.

Conclusions

This preliminary descriptive study demonstrated that structured, expert-guided multi-stage training was associated with a modest improvement in students' exact agreement with expert ABR threshold estimations, alongside a clinically meaningful reduction in large errors (>10 dB). These findings add to the limited literature on training novice ABR interpreters and indicate that AI systems may in the future support both educational processes and the standardisation of threshold assessment. Despite limitations related to sample size and unequal dataset difficulty, the study highlights the potential of structured training and ML/AI support to accelerate the learning curve and improve the reliability of ABR interpretation.

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