applied sciences

MDPI

Article

Modelling of Earphone Design Using Principal Component Analysis

Lucas Kwai Hong Lui [1] and C. K. M. Lee [1,2,*]

[1] Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong, China; lucas.lui@connect.polyu.hk

[2] Research Institute for Advanced Manufacturing (RIAM), The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China

* Correspondence: ckm.lee@polyu.edu.hk; Tel.: +852-3400-3899

Abstract: This research investigated a mathematical model of earphone design with principal component analysis. Along with simplifying the design problem, a predictive model for the sound quality indicators, namely, total harmonic distortion, power of output, range of frequency response, signal-to-noise ratio, impedance of the speaker, and headroom, was formulated. (1) Background: Earphone design is a difficult problem requiring excessive experience and know-how in the process. Therefore, this research was developed to formulate a predictive model to facilitate the design process. (2) Methods: A simplified model for the design was developed in previous research, while the sound quality indicators were found to be connected to the eight material-specific parameters. Simultaneously, a principal component analysis (PCA) was utilized to decrease the number of input variables and create a more convenient and streamlined model. (3) Results: The principal component analysis-based approach obtained suboptimal predictive accuracy for the sound quality indicators, but a simplified formulation was obtained. (4) Conclusions: Based on the development and comparison of the modelling approach, it can be seen that principal component analysis can be utilized to simplify the mathematical model of the earphone design problem with a trade-off of accuracy.

Keywords: principal component analysis; earphone design; regression model; computer-aided design; sound quality

check for updates

Citation: Lui, L.K.H.; Lee, C.K.M. Modelling of Earphone Design Using Principal Component Analysis. *Appl. Sci.* **2023**, *13*, 9912. https://doi.org/10.3390/app13179912

Academic Editors: Douglas O'Shaughnessy and Lamberto Tronchin

Received: 20 June 2023
Revised: 14 July 2023
Accepted: 28 July 2023
Published: 1 September 2023

1. Introduction

Earphone design was found to be an art due to the infinite selection of materials and technologies, while the experience of the designers and developers was found to be essential in the process [1]. Although the arrangement was found to be an industrial norm, the practice was found to be a constraint for knowledge transfer [2], which may not be advisable for organizational growth [3]. Hence, the pioneer study on the formulation of the design problem was conducted [4] so that future suggestions for the development and design can be beneficial. Although linear regression was an effective solution for the predictive model, the vast number of variables hid the popularity of the computer-aided design [1]. Therefore, in the current work, principal component analysis [5] was applied in order to reduce the dimensions of the formulation in order to yield a handy tool for the prediction of the expected sound outcome based on the parameters [6], while it was expected that the formulation would be useful from a practical viewpoint even with a trade-off in the performance. Therefore, for the sake of demonstrating the problem-solving process, the goals and objectives of this project will be established to define the scope and guide the research implementation, along with explaining the motivation behind the work. Following this, a literature review will be performed on the design of earphone products and the definition of sound quality, drawing upon pioneering research studies for support. This will enable the formulation of the problem to be prepared with a strong foundation. Finally, the paper's layout will be mentioned to speed up the retrieval of the relevant content. Therefore, the first section of the paper consists of four subsections with the titles Aim and Objectives, Design Parameters, Sound Quality Performance and Organization of the Report, respectively, in order to present the related information systematically [7].

1.1. Aim and Objectives

The aim of this research was to employ statistical analysis to explore the correlation between earphone design parameters and sound quality outcomes, with the objective of developing a model-based approach to inform the design process. For the intention of achieving this purpose, five objectives were defined to guide the implementation of the research, motivated by the need to improve the inspection of earphone design, as follows.

1. To develop a simplified formulation of the earphone design problem in order to capture and characterize the design parameters and the expected sound quality outcomes.
2. To deduce the mathematical expression based on linear regression for the predictive model.
3. To develop a simplified mathematical model using the principal component analysis technique.
4. To contrast and compare the predictive performance of the two modelling approaches.
5. To give recommendations on the design of earphones based on the analytic findings of the research.

With reference to the defined five objectives, it can be observed that the first one was accomplished along with the reviewed design parameters and sound quality performance, while the current study will follow the research problem in the later development.

1.2. Design Parameters

With respect to the five objectives, the design parameters should be defined in order to support the formulation of the simplified modelling problem. Drawing on prior research conducted by Lui and Lee [4], it is possible to simplify the design of earphones into a selection problem comprising eight variables: the type, magnet, voice coils, and diaphragm of both the primary and secondary drivers ($4 \times 2 = 8$ parameters), while the depiction of a single driver can be observed in the Figure 1.

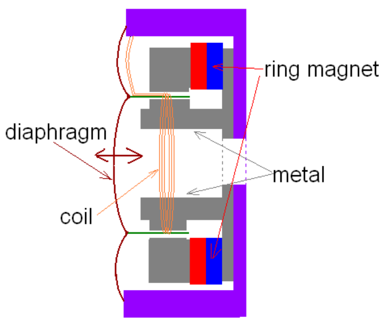

Figure 1. Depiction of the components for a single driver [8].

A concise overview of the primary components of the drivers and their associated options can be found below. At the core of earphone design are the drivers, which consist of a magnet and voice coil. The magnet's function is to produce a magnetic field that interacts with the voice coil, which then moves, producing sound. The type of magnet used can significantly impact the quality of sound produced by the earphones. A stronger magnet generates a more powerful air movement with the same number of turns of the coil, resulting in better coverage of the frequency range and enhancing the overall sound quality of the earphones. Conversely, a weaker magnet may result in suboptimal sound production, particularly in the lower frequency range. It is thus essential to carefully consider the type of magnet used in earphone design to achieve optimal results. In more detail, the magnet in the earphone driver is responsible for creating a magnetic field that interacts with the voice coils, which are essentially wires that are wrapped around a cylindrical former. The voice coils in earphone drivers become magnetized when an electrical current flows through them, allowing them to interact with the magnetic field produced by the magnet. As a result, the diaphragm moves, creating sound waves. The strength of the magnet used in earphone design can significantly impact the quality of sound produced [9].

Next, apart from the selection of types of magnets, the material of the coils is essential to earphone designs. Actually, the coils are in direct contact with the diaphragm and produce the driving force needed to vibrate the surrounding air through electromagnetic induction. Although most coils are made of copper, the quality of the copper used can vary and play a role in the earphones' sound quality. The conductivity of the material used in the coils affects the current generated with the same voltage, leading to a larger driving force [10].

Lastly, the diaphragm is an essential component of the earphone core, as it directly interacts with the air or conduction media. As the human ear perceives sound waves generated by the diaphragm, the interaction between the membrane's movement and the perception of humans is crucial for product design. However, the relationship between the two is complex and nonlinear, making it challenging to design earphones [11]. Additionally, the diaphragm is a crucial component of earphone drivers, responsible for converting the electrical signals from the voice coils into sound waves. The selection of materials for the diaphragm can significantly impact the sound quality of the earphones. Various materials are used in diaphragm construction, including mylar, titanium, paper, and carbon fiber, among others. Each material has its own unique properties and can produce a distinct sound profile. However, despite the wide range of materials available for diaphragm construction, the association between the material used and the resulting sound quality remains somewhat of a mystery. This is because the interaction between the diaphragm material and other components of the driver, such as the magnet and voice coils, is highly complex and not yet fully understood. Furthermore, the sound quality produced by earphones is also influenced by factors such as ear canal resonance, sound leakage, and environmental noise, making it challenging to isolate the impact of the diaphragm material alone. As a result, earphone designers must carefully balance various factors when selecting diaphragm materials, including cost, weight, durability, and sound quality. By carefully considering these factors and leveraging advancements in materials science and engineering, designers can create earphones that provide exceptional sound quality and a superior listening experience for users.

The three most common types of headphone drivers found in the market are dynamic units or moving coils, balanced armature units, and planar magnetic units [12]. Dynamic units or moving coil drivers are the most common and use a permanent magnet and a voice coil to generate sound. Balanced armature drivers use a smaller, more precise armature and a balanced magnetic field to produce sound. Finally, planar magnetic drivers use a thin film membrane with a conductive layer and an array of magnets to create sound [13]. Each type of driver has its own unique properties and can produce a distinct sound profile. For example, dynamic driver/moving coil drivers are known for their ability to produce deep bass tones, while balanced armature drivers are known for their precision and clarity in the mid- to high-frequency range. Planar magnetic drivers are known for their ability to produce a wide soundstage with exceptional detail and accuracy [12]. Earphone designers must carefully consider the strengths and weaknesses of each type of driver and balance them with other factors such as weight, cost, and overall sound quality when designing earphones. By leveraging advancements in driver technology and materials science, designers can create earphones that provide exceptional sound quality and a superior listening experience for users.

In addition to the drivers and the mentioned design parameters, other factors can also affect the sound quality of earphones. For example, the size and shape of the earphone housing can affect the soundstage and the perceived range of frequency response. The ear tips, which are in direct contact with the ear canal, can also affect the sound quality by altering the seal and the amount of outside noise that is blocked. Finally, the cable quality can also affect the sound quality by minimizing electrical interference and signal loss. Nonetheless, the influence of the related factors was found to be relatively small. Hence, due to the consideration of simplifying the problem formulation, the associated factors were omitted in the model so that an accomplishable formulation could be derived, while the variants and expansion will be included in the later development of the research.

1.3. Sound Quality Performance

Apart from the design parameters as inputs of the model, the dependent variables, which are the sound performance of the earphone design, will be defined in order to formulate the simplified expression of the prediction. Essentially, six indicators, namely, total harmonic distortion (THD), power of output, range of frequency response, signal-to-noise ratio (SNR), impedance of the speaker, and headroom, were adopted in the formulation of the mathematical model, while these metrics are utilized in the evaluation of the sound performance of the designed earphone.

Firstly, it is without any question that the expression of the original sound is one of the critical criteria for a sound system. Therefore, THD is found to be an important metric for evaluating the sound quality of designed earphones [14]. In essence, this factor quantifies the amount of distortion introduced by the earphone to the original signal, highlighting the contrast between the two. Therefore, a high-quality earphone should have low THD, indicating that it produces a faithful reproduction of the original signal [15]. To summarize, an earphone with high-quality sound should have a low THD rate. Earphone distortion rates are typically measured as a percentage of the total signal, with lower percentages indicating higher-quality sound reproduction. An excellent earphone system will have a distortion rate of less than 1%, while a moderately performing system will have a rate ranging from 1% to 5%. Conversely, a low-quality system may have a distortion rate as high as 10%. However, THD is not always a reliable metric for sound quality evaluation, as the nonlinear behavior of the human ear can limit its applicability, whereas the human sensation may have various sensitivities to sound with different loudness and frequency. Thus, reflecting the truth may be considered an evaluative dimension, but not a comprehensive scheme of quality measurement.

Secondly, apart from the distortion, the power of output is another important metric for the evolution of sound quality that determines the loudness and bass capabilities of an earphone [16]. It is typically measured in watts or milliwatts and reflects the maximum power that the earphone can handle before it starts to attenuate with the inverse square law. While loudness may not be directly related to sound quality, a good earphone should have a high power of output, especially in the low-frequency range, to produce clear and powerful bass so that the original sound can be expressed.

Thirdly, the range of frequency response [17] is a measure of an earphone's ability to reproduce different frequencies within the audible range [18]. The range of frequency response is typically measured in hertz (Hz) and indicates the range of frequencies that the earphone can produce [19,20]. Therefore, a good earphone should have a wide range frequency range in order to take care of the special needs of some extremely sensitive users [21]. For a full-range earphone system, it is essential to have a range of frequency responses that can accurately reproduce sound across the entire audible range for humans [22,23], which typically spans from 20 Hz to 20 kHz. Therefore, a high-quality full-range earphone system should be capable of responding to frequencies within this range. However, due to the physical limitations of earphones, they typically provide responses from 310 Hz to 12 kHz, with high-quality systems capable of a wider frequency range [24].

Fourthly, in addition to measuring distortion directly, the SNR is a crucial metric for evaluating earphone performance. It represents the ratio of the signal level to the noise level and is often used to determine the quality of the sound produced by the earphones. It is typically measured in decibels (dB) and indicates how much louder the signal is than the noise. A high-quality earphone should ideally have an SNR of 90 to 100 dB, indicating a low noise level and a clear, crisp sound. A higher SNR implies that the earphone can produce a more accurate and detailed sound by minimizing the amount of noise and interference that can degrade the quality of the audio signal. Therefore, a high SNR is a crucial factor to consider when evaluating the performance of earphones.

Fifthly, impedance is a measure of the resistance that an earphone offers to the flow of electrical current. On the other hand, the evaluative factor is similar to the power of output, which indicates the amount of power that the earphone can deliver to the listener. Both impedance and power of output are crucial factors to consider when selecting earphones, as they can significantly impact the overall sound quality and listening experience. In essence, impedance is typically measured in ohms and indicates how much power is lost as the current flows through the earphone. Low impedance indicates high quality, as it ensures that the earphone draws maximum power from the source.

Finally, apart from measurement with devices, headroom refers to the ability of an earphone to generate a short burst of sound without distortion or clipping. It is a subjective measure of the ability of the earphone to provide a thrilling experience to the listener, especially in the case of action movies or music with sudden loud sounds. High-quality earphones should have good headroom to deliver a powerful and exciting listening experience. It is worth noting that the same setting was preserved in the hosting company of the data in order to ensure reproducibility. Nonetheless, as the current work would like to gain inspiration for the design, alignment of the scale may not be an important concern, along with the slight diversity of the 388 sets of designs.

1.4. Organization of the Report

All in all, this paper aims to explore the connection between the design parameters and the sound quality of earphones. For this purpose, it is structured into five main sections: Introduction, Materials and Methods, Results, Discussion, and Conclusions. Each section is designed to provide a comprehensive analysis of the key factors that impact the sound quality of earphones, with the ultimate goal of improving the design and performance of these devices. In the first section, the goal of the current research for developing a proper model in characterizing the impacts of the design variables on sound quality outcomes is defined along with the required background information to lay the foundation for the comprehension of the current work. Then, the required materials, such as the dataset and the required formulation, are highlighted to illustrate the modelling process's configuration. Moreover, this study conducts a performance analysis of two formulae to compare the accuracy of their estimations using a testing set of data. The findings of this analysis are discussed and conclusions drawn. The discussion and conclusion include an evaluation of the model formulation and its performance, highlighting the implications of the study's results for the design and optimization of earphones.

2. Materials and Methods

This section begins by developing a research framework based on the building blocks reviewed in the previous section. This framework will be used to depict the formulation of the model. Subsequently, a practical procedure will be developed with reference to the defined framework. This procedure will guide the implementation of the research evaluation, ensuring that the study is conducted in a systematic and cohesive manner. Furthermore, as the model construction is required for the training data, an overview of the characteristics will be included to briefly review the adopted dataset. Lastly, subsequent to the description of the dataset, formulations with traditional and principal component analysis-based regression approaches are derived in order to support the performance analysis.

2.1. Development of Research Framework

The framework for the current work can be seen in Figure 2. It can be observed that the predictive model used in the current study consists of the eight design parameters for the primary and secondary drivers and the six sound quality outcomes defined in the previous section, while the ultimate study of the formulation was to develop a mechanism to map the independent and dependent variables. Actually, different techniques can be applied in the modelling process, while the current work stresses the linear model based on traditional regression and the principal component analysis-based regression. Additionally, recommendations and conclusions are drawn based on the research findings.

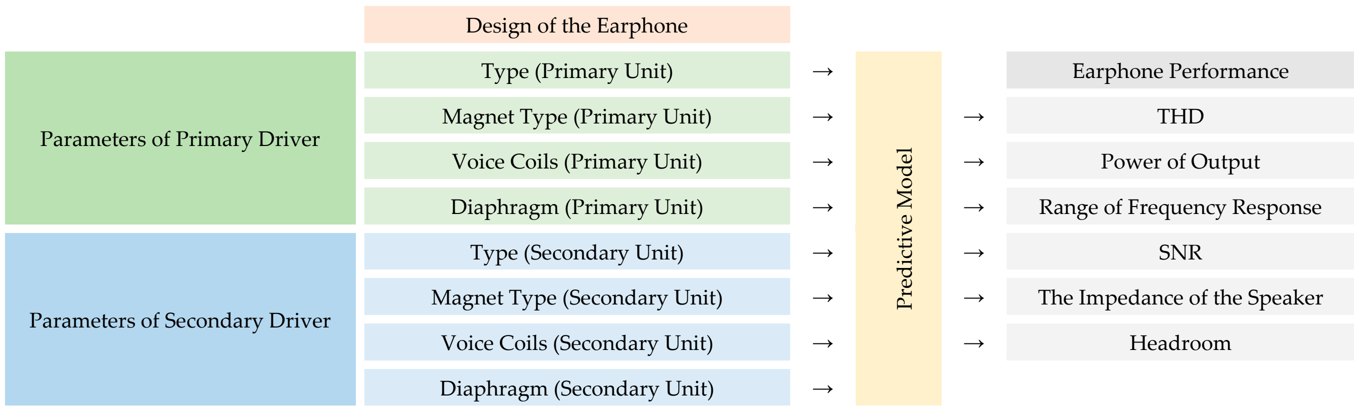

Figure 2. Research framework for the current study.

2.2. Steps of the Study

The practical steps of the study should be developed to depict the research procedure [25], and five steps were developed accordingly. First, the research started with the definition of the earphone design parameters and the outcomes of the sound quality in order to simplify the research problem for the formulation. Second, the training data were prepared for the development of the mathematical models that link the design parameters and sound quality performance. A total of 388 designs were revealed from the design database of the hosting company, while each design was characterized by the eight parameters and the six sound quality outcomes. According to the depiction of the hosting organization, the designed earphone was tested based on the standard IEC 60318-4, or 711-coupler. In essence, the related standard specifies an artificial ear designed for testing supra-aural and circumoral headphones, as well as other devices that rest against the pinna (outer ear). It simulates the acoustic impedance of the human ear and provides a uniform frequency response for measurements. Additionally, the input voltage and mechanical resonance frequency were 0.5 V and 100 Hz for the engineer to inspect the designs. Nonetheless, the testing parameters for the 388 designs may include slight alternates with respect to the requirement. Third, the formulations derived from the traditional regression technique and the application of principal component analysis were deduced based on the 388 designs. Fourth, the testing data were prepared in the same sense, while 168 designs were captured for the evaluation of the predictive performance. Finally, comparing the two formulations was conducted to benchmark the predictive accuracy based on the 168 unseen designs.

2.3. Overview of the Training Set

With respect to the defined steps, it can be seen that the development of the predictive model should start with the consolidation and clearance of the modelling data. Although it was impossible to list the data individually, an overview is provided to facilitate the understanding. Each earphone design was characterized by eight variables, while the corresponding options can be seen in Table 1. Additionally, 388 designs were involved in the modelling, and the number of samples and the corresponding percentages can also be observed in the table. It can be seen that the training set covered all categories of design parameters with a roughly even distribution. Thus, the dataset was appropriate for the development of the predictive model.

Table 1. Summary of the possible options of the design in the simplified formulation,, while the assigned values in the proposed formulation are also included in order to highlight the correspondence between the options and the represented values in the formulation. The distribution of the cases involved in the development of the model is included as well.

Parameters of the Design *	Possible Options	Assigned Values	N (Total = 388)	% (Total = 100%)
Type (Primary Unit)	Dynamic Unit/Moving Coil	1	196	50.52%
	Balanced Armature Unit	2	90	23.20%
	Planar Magnetic Unit	3	102	26.29%
Magnet Type (Primary Unit)	N35 Grade	1	119	30.67%
	N40 Grade	2	114	29.38%
	N45 Grade	3	85	21.91%
	N45 Grade	4	70	18.04%
Voice Coils (Primary Unit)	Copper Wire	1	161	41.49%
	Aluminum Wire with Copper Covered	2	106	27.32%
	Silver Wire	3	121	31.19%
Diaphragm (Primary Unit)	Polyethylene Terephthalate	1	141	36.34%
	Polyethene Naphtholate	2	98	25.26%
	Polyetheretherketone (PEEK)	3	77	19.85%
	PEEK + Polyurethane	4	72	18.56%
Type (Secondary Unit)	No Secondary Unit Included	0	86	22.16%
	Dynamic Unit/Moving Coil	1	83	21.39%
	Balanced Armature Unit	2	100	25.77%
	Planar Magnetic Unit	3	119	30.67%
Magnet Type (Secondary Unit)	No Secondary Unit Included	0	86	22.16%
	N35 Grade	1	80	20.62%
	N40 Grade	2	74	19.07%
	N45 Grade	3	78	20.10%
	N45 Grade	4	70	18.04%
Voice Coils (Secondary Unit)	No Secondary Unit Included	0	86	22.16%
	Copper Wire	1	127	32.73%
	Aluminum Wire with Copper Covered	2	71	18.30%
	Silver Wire	3	104	26.80%
Diaphragm (Secondary Unit)	No Secondary Unit Included	0	86	22.16%
	Polyethylene Terephthalate	1	83	21.39%
	Polyethene Naphtholate	2	75	19.33%
	Polyetheretherketone (PEEK)	3	75	19.33%
	PEEK + Polyurethane	4	69	17.78%

* The earphone was assumed to have at most two drivers, while the options of the design were finite.

Apart from the design parameters, the distribution of the quality outcomes of the sound of the design was included to enhance the comprehension of the data. Instead of the numerical values of the measurement, the sound quality indicators were classified with respect to levels so that a comparable scale could be deduced. The corresponding levels of sound performance and explanations can be observed in Table 2. The levels were assigned values to represent the design's excellence. For instance, the THD was divided into seven levels, while the assigned value's size indicated the performance scale's preference.

Table 2. Summary of the definition of sound quality performance and the assigned values in the formulation.

Sound Quality Performance	Performance Range	Remark	Assigned Values
THD (THD) Under Frequency Signal with 10 kHz	Serious Level of THD	This level of THD is considered to be a significant issue, as it can cause significant degradation of the audio quality and introduce unwanted artefacts into the sound. Hence, the distortion measured in the designed earphone was greater than 10%.	1
	Sensible Level of THD	This level of THD is noticeable but not necessarily problematic. It may be acceptable for some applications but not for others that require high-quality audio. Hence, the distortion measured in the designed earphone was approximately 9%.	2
	Slightly High Level of THD	At this level, the THD is slightly higher than ideal but may not be noticeable to all listeners. Thus, the distortion measured in the designed earphone was roughly 7%.	3
	Moderate Level of THD	This level of THD is noticeable and may affect the overall audio quality. It is generally considered to be suboptimal for most applications. As a result, the distortion measured in the designed earphone was approximately 5%.	4
	Slightly Low Level of THD	This level of THD is slightly lower than ideal but may not be noticeable to all listeners. Thus, the distortion measured in the designed earphone was roughly 3%.	5
	Insensible Level of THD	At this level, the THD is so low that it is imperceptible to most listeners. Then, the distortion measured in the designed earphone was approximately 1%.	6
	Zero Level of THD	This level of THD refers to a situation where there is no THD present in the audio signal. Thus, the distortion measured in the designed earphone was less than 1%.	7
Power of Output	Extremely Low Level of Power of Output	This level of power of output refers to a situation where the power of output of a device or system is exceedingly low, to the point where it is barely measurable or completely negligible. As a result, the measured power of output was less than 80 milliwatts.	1
	Low Level of Power of Output	At this level, the power of output of a device or system is still relatively low, but it can be measured and may be sufficient for some applications. However, it may not be sufficient for more demanding applications. Thus, the measured power of output of the designed earphone was approximately 100 milliwatts.	2
	Below-average Level of Power of Output	This level of power of output is slightly higher than a low level, but still below the average power of output of similar devices or systems. It may be suitable for some applications but not for others that require higher power of output. Hence, the measured power of output of the designed earphone was roughly 120 milliwatts.	3
	Moderate Level of Power of Output	This level of power of output is average or typical for similar devices or systems. It is sufficient for most applications, but may not be optimal for high-power applications. Thus, the measured power of output of the designed earphone was approximately 150 milliwatts.	4

Table 2. *Cont.*

Sound Quality Performance	Performance Range	Remark	Assigned Values
	Above-average Level of Power of Output	At this level, the power of output of a device or system is higher than average, making it suitable for more demanding applications that require higher power of output. Hence, the measured power of output of the designed earphone was approximately 180 milliwatts.	5
	Strong Power of Output	This level of power of output refers to a situation where the power of output of a device or system is high, making it suitable for demanding applications that require a strong and consistent output. Thus, the measured power of output of the designed earphone was approximately 200 milliwatts.	6
	Extremely Strong Power of Output	This level of power of output is the highest possible level, where the power of output is exceptionally strong and well-suited for the most demanding applications that require a high level of power. Thus, the measured output of the designed earphone was greater than 250 milliwatts.	7
Range of Frequency Response	Limited Range of Frequency Response	This refers to a situation where the range of frequency response of a device or system is restricted or limited, which may result in a narrow or suboptimal audio quality. As a result, the measured range of frequency response of the designed earphone was less than 610 Hz to 10 kHz.	1
	Narrow Range of Frequency Response	At this level, the range of frequency response of a device or system is restricted but may still provide acceptable audio quality for some applications. Thus, the measured range of frequency response of the designed earphone was approximately 610 Hz to 10 kHz.	2
	Below-average Range of Frequency Response	This level of range of frequency response is slightly lower than average and may not provide optimal audio quality for some applications. Thus, the measured range of frequency response of the designed earphone was narrower than the typical range (310 Hz to 12 kHz).	3
	Moderate Range of Frequency Response	This level of range of frequency response is average or typical for similar devices or systems. It is sufficient for most applications but may not be optimal for high-quality audio. As a result, the measured range of frequency response of the designed earphone was approximately the typical range.	4
	Above-average Range of Frequency Response	At this level, the range of frequency response of a device or system is higher than average, making it suitable for more demanding applications that require higher audio quality. Thus, the measured range of frequency response of the designed earphone was wider than the typical range.	5
	Wide Range of Frequency Response	This refers to a situation where the range of frequency response of a device or system is broad or wide, providing optimal audio quality for a range of applications. Therefore, the measured range of frequency response of the designed earphone was approximately 20 Hz to 20 kHz.	6
	Full Range of Frequency Response	At this level, the range of frequency response of a device or system covers the entire audible range of human hearing, providing the highest-quality audio performance. Thus, the measured range of frequency response of the designed earphone was greater than 20 Hz to 20 kHz.	7

Table 2. *Cont.*

Sound Quality Performance	Performance Range	Remark	Assigned Values
SNR	Extremely Low SNR	This level of SNR is extremely low, indicating a significant amount of noise in the audio signal that may interfere with the desired audio content. Therefore, the measured SNR of the designed earphone was less than 60 decibels.	1
	Low SNR	At this level, the SNR is low, indicating the presence of some noise in the audio signal. Thus, the measured SNR of the designed earphone was approximately 60 decibels.	2
	Below-average SNR	This level of SNR is slightly lower than average and may affect the overall audio quality. As a result, the measured SNR of the designed earphone was approximately 80 decibels.	3
	Moderate SNR	This level of SNR is average or typical for similar devices or systems. It is sufficient for most applications, but may not be optimal for high-quality audio. Thus, the measured SNR of the designed earphone was approximately 10 decibels.	4
	Above-average SNR	At this level, the SNR is higher than average, indicating a lower level of noise in the audio signal. Therefore, the measured SNR of the designed earphone was approximately 120 decibels.	5
	Large SNR	This level of SNR is high, indicating a significant reduction in noise in the audio signal. Thus, the measured SNR of the designed earphone was approximately 160 decibels.	6
	Extremely Large SNR	This level of SNR is exceptionally high, indicating an extremely low level of noise in the audio signal. Therefore, the measured SNR of the designed earphone was greater than 200 decibels.	7
The Impedance of the Speaker	Extremely High Impedance of the Speaker	This level of impedance of the speaker is exceptionally high, indicating a high resistance to the flow of electrical current through the speaker. As a result, the measured impedance of the speaker of the designed earphone was greater than 40 ohms.	1
	High Impedance of the Speaker	At this level, the impedance of the speaker is high, indicating a relatively high resistance to the flow of electrical current through the speaker. As a result, the measured impedance of the speaker of the designed earphone was approximately 32 ohms.	2
	Above-average Impedance of the Speaker	This level of impedance of the speaker is slightly higher than average and may affect the overall audio quality. As a result, the measured impedance of the speaker of the designed earphone was approximately 24 ohms.	3
	Moderate Impedance of the Speaker	This level of impedance of the speaker is average or typical for similar devices or systems. It is sufficient for most applications, but may not be optimal for high-quality audio. As a result, the measured impedance of the speaker of the designed earphone was approximately 22 ohms.	4
	Below-average Impedance of the Speaker	This level of impedance of the speaker is slightly lower than average and may affect the overall audio quality. Thus, the measured impedance of the speaker of the designed earphone was approximately 18 ohms.	5
	Low Impedance of the Speaker	At this level, the impedance of the speaker is relatively low, indicating a lower resistance to the flow of electrical current through the speaker. As a result, the measured impedance of the speaker of the designed earphone was approximately 12 ohms.	6

Table 2. *Cont.*

Sound Quality Performance	Performance Range	Remark	Assigned Values
	Extremely Low Impedance of the Speaker	This level of impedance of the speaker is exceptionally low, indicating a very low resistance to the flow of electrical current through the speaker. As a result, the measured impedance of the speaker of the designed earphone was less than 12 ohms.	7
Headroom	No Effect on Headroom:	This level of headroom indicates that the device or system has no effect on the maximum level of audio output that can be achieved. For evaluative purposes, a feedback form was created, and human testers were engaged in the testing process.	1
	Low Headroom:	At this level, the headroom of the device or system is relatively low, indicating a limited maximum level of audio output that can be achieved. The evaluative process involved the creation of a feedback form, and human testers were utilized to conduct the testing.	2
	Below-average Headroom	This level of headroom is slightly lower than average and may limit the maximum level of audio output that can be achieved. A feedback form was developed for the purpose of evaluation, and human testers were employed to participate in the testing process.	3
	Moderate Headroom	This level of headroom is average or typical for similar devices or systems, providing a sufficient maximum level of audio output for most applications. In order to evaluate the product, a feedback form was designed, and human testers were enlisted to carry out the testing.	4
	Above-average Headroom	At this level, the headroom of the device or system is higher than average, providing a greater maximum level of audio output that can be achieved. The testing process involved the use of a feedback form for evaluation, with human testers playing a crucial role in the process.	5
	Significant Headroom	This level of headroom is high and provides a significant maximum level of audio output that can be achieved. For the purpose of conducting the evaluation, a feedback form was specifically designed, and human testers were involved in the testing phase.	6
	Extremely Large Headroom	This level of headroom is exceptionally high and provides an extremely large maximum level of audio output that can be achieved. With the aim of evaluation in mind, a feedback form was created, and human testers were brought in to conduct the testing.	7

Along with the assigned values, the average score of the designs for the modelling can be computed, and the six average scores of the sound quality performance of the studied earphone design of the training dataset were 3.9175, 3.8660, 3.8918, 3.9459, 4.0052, and 4.0335, respectively (Figure 3). They have a descending ordered sequence: headroom (average = 4.0335) > impedance of the speaker (average = 4.0052) > SNR (average = 3.9459) > THD (average = 3.9175) > range of frequency response (average = 3.8918) > power of output (average = 3.8660), while the best- and worst-performing indicators were headroom and power of output, respectively. Although there were differences among the performance indicators, their performance scores were similar, indicating the dataset's suitability for modelling.

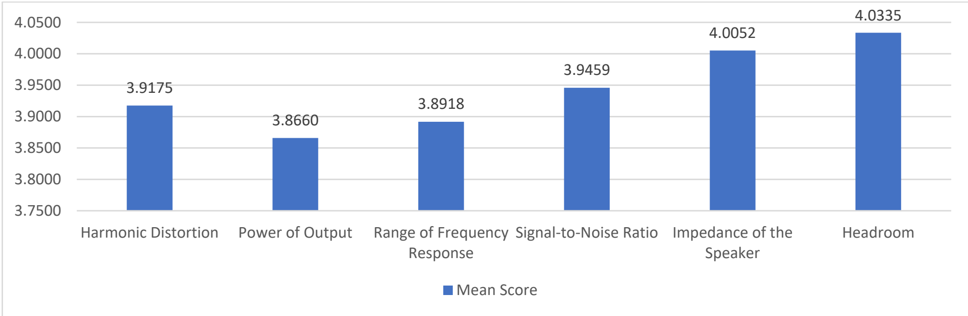

Figure 3. Average scores of the sound quality performance of the studied earphone designs of the training dataset.

Therefore, with respect to the relativity of the scores, the ranks of the performance identified among the training dataset can be deduced, and the result can be seen in Table 3.

Table 3. Sound quality performance of the studied earphone design of the training dataset based on the average performance scores.

Rank	Sound Quality Indicator
1	Headroom
2	Speaker Impedance
3	SNR
4	THD
5	Range of Frequency Response
6	Power of Output

The dataset for modelling, including the eight design parameters with finite options and the six sound performance indicators ranging from 1 to 7, was prepared, which would be applied to formulate the regression model. Before the adoption of the data in the modelling process, a correlative check was conducted, and the results can be seen in Table 4. A close connection between the earphone design parameters and outcomes of the sound quality can be observed, which indicates that meaningful linkages exist between the independent and dependent variables. As a result, it was worthy of data analysis and modelling.

Table 4. Pearson correlation values of the modelling data between the eight design parameters and six sound quality performances.

Design Parameter	THD	Power of Output	Range of Frequency Response	SNR	The impedance of the Speaker	Headroom
Type (Primary Unit)	0.520 **	0.473 **	0.436 **	0.466 **	0.427 **	0.432 **
Magnet Type (Primary Unit)	0.475 **	0.457 **	0.397 **	0.389 **	0.419 **	0.431 **
Voice Coils (Primary Unit)	0.384 **	0.420 **	0.408 **	0.391 **	0.353 **	0.440 **
Diaphragm (Primary Unit)	0.510 **	0.511 **	0.458 **	0.444 **	0.430 **	0.512 **
Type (Secondary Unit)	0.453 **	0.487 **	0.447 **	0.477 **	0.442 **	0.465 **
Magnet Type (Secondary Unit)	0.453 **	0.511 **	0.445 **	0.522 **	0.441 **	0.492 **
Voice Coils (Secondary Unit)	0.506 **	0.545 **	0.479 **	0.500 **	0.493 **	0.512 **
Diaphragm (Secondary Unit)	0.508 **	0.542 **	0.476 **	0.496 **	0.460 **	0.505 **

**. Correlation is significant at the 0.01 level (2-tailed).

2.4. Development of the Predictive Models

After defining the dataset for the modelling process, a predictive model is essential for analyzing the performance of the proposed approaches. Linear regression, a statistical technique applied to model relationships between variables, is used to create a basic linear model. It can handle both simple and multiple regression analyses, making it suitable for developing a predictive model for earphone design parameters and sound quality outcomes. Linear regression is widely used in data analysis and machine learning for supervised and unsupervised learning. It works by fitting a linear equation to data points, with the goal of finding the best-fitting line that minimizes the squared differences between predicted and actual values. However, it is important to check the assumptions of linearity, homoscedasticity, normality of residuals, and independence of errors for reliable and valid results. Despite its limitations, linear regression serves as a baseline method for evaluation, with applications in prediction, trend analysis, hypothesis testing, and outlier detection. It can model relationships between variables, predict future values, analyze trends over time, and identify outliers. While it is crucial to ensure that the variables' relationship can be described by a linear equation, linear regression remains a powerful tool for data analysis and machine learning. The formulation of the parameters and sound quality performance is shown in the following. The formulation revealed that the type of secondary driver has minimal impact on sound quality performance, so it was excluded in practical applications.

$$
\begin{aligned}
&\begin{bmatrix} \text{THD} \\ \text{Power of Output} \\ \text{Range of Frequency Response} \\ \text{SNR} \\ \text{The Impedance of the Speaker} \\ \text{Headroom} \end{bmatrix} \\
&= \begin{bmatrix} 0.676 & 0.367 & 0 & 0.412 & 0 & 0 & 0 & 0.355 \\ 0.420 & 0.294 & 0 & 0.375 & 0 & 0 & 0.336 & 0.323 \\ 0.425 & 0.228 & 0.351 & 0.325 & 0 & 0 & 0 & 0.351 \\ 0.733 & 0 & 0 & 0 & 0 & 0.585 & 0 & 0 \\ 0.436 & 0.337 & 0 & 0.282 & 0 & 0 & 0.539 & 0 \\ 0.261 & 0.246 & 0.366 & 0.393 & 0 & 0 & 0.279 & 0.250 \end{bmatrix} \\
&\times \begin{bmatrix} \text{Type (Primary Unit)} \\ \text{Magnet Type (Primary Unit)} \\ \text{Voice Coils (Primary Unit)} \\ \text{Diaphragm (Primary Unit)} \\ \text{Type (Secondary Unit)} \\ \text{Magnet Type (Secondary Unit)} \\ \text{Voice Coils (Secondary Unit)} \\ \text{Diaphragm (Secondary Unit)} \end{bmatrix} + \begin{bmatrix} 0.314 \\ 0.515 \\ 0.578 \\ 0.539 \\ 0.043 \\ 0.565 \end{bmatrix} \\
&= \begin{bmatrix} 0.676 & 0.367 & 0 & 0.412 & 0 & 0 & 0.355 \\ 0.420 & 0.294 & 0 & 0.375 & 0 & 0.336 & 0.323 \\ 0.425 & 0.228 & 0.351 & 0.325 & 0 & 0 & 0.351 \\ 0.733 & 0 & 0 & 0 & 0.585 & 0 & 0 \\ 0.436 & 0.337 & 0 & 0.282 & 0 & 0.539 & 0 \\ 0.261 & 0.246 & 0.366 & 0.393 & 0 & 0.279 & 0.250 \end{bmatrix} \\
&\times \begin{bmatrix} \text{Type (Primary Unit)} \\ \text{Magnet Type (Primary Unit)} \\ \text{Voice Coils (Primary Unit)} \\ \text{Diaphragm (Primary Unit)} \\ \text{Magnet Type (Secondary Unit)} \\ \text{Voice Coils (Secondary Unit)} \\ \text{Diaphragm (Secondary Unit)} \end{bmatrix} + \begin{bmatrix} 0.314 \\ 0.515 \\ 0.578 \\ 0.539 \\ 0.043 \\ 0.565 \end{bmatrix} \cdots
\end{aligned} \tag{1}
$$

A principal component analysis (PCA)-based formulation was also derived. PCA is a statistical technique that reduces a dataset's dimensionality while preserving as much variation as possible, making it widely used in data analysis and machine learning. PCA transforms potentially correlated variables into linearly uncorrelated variables called principal components. These components account for the maximum amount of variation in the data and are chosen to be orthogonal to previous components. PCA has various applications, such as data visualization, data compression, feature selection, noise reduction, and clustering. Overall, PCA is a powerful technique for reducing dataset dimensionality while retaining important features. By transforming large and complex datasets into linearly uncorrelated variables, PCA simplifies the analysis process and helps researchers draw meaningful insights from the data.

In summary, principal component analysis (PCA) offers the significant advantage of reducing dataset dimensionality while preserving essential information, benefiting machine learning and data analysis tasks that often involve numerous variables. This reduction aids in visualization and analysis, enabling more efficient training of machine learning algorithms. PCA has been particularly influential in earphone design research. However, PCA has limitations, including the assumption of normal distribution and linear correlation in data, which may not hold true in practice. Moreover, interpreting principal components can be challenging, especially with many variables, as seen in earphone design problems.

All in all, principal component analysis (PCA) is an effective method in data analysis and machine learning for simplifying intricate datasets and discovering underlying patterns. In a specific computation, the first four components accounted for 82.78% of the explanatory power, leading to their use in modelling. Consequently, a formulation was established to connect these components with the eight design parameters.

$$
\begin{bmatrix} \text{Component 1} \\ \text{Component 2} \\ \text{Component 3} \\ \text{Component 4} \end{bmatrix}
= \begin{bmatrix}
0.306971 & 0.297114 & 0.296176 & 0.33795 & 0.387704 & 0.400377 & 0.395214 & 0.385826 \\
0.445829 & 0.441501 & 0.381985 & 0.288923 & -0.33654 & -0.26187 & -0.28892 & -0.33437 \\
-0.07285 & -0.64326 & 0.759317 & 0.034571 & 0.028397 & -0.02469 & -0.03704 & -0.02593 \\
-0.82963 & 0.368576 & 0.215333 & 0.335549 & -0.03038 & 0.071337 & -0.09644 & -0.02774
\end{bmatrix}
\times \begin{bmatrix} \text{Type (Primary Unit)} \\ \text{Magnet Type (Primary Unit)} \\ \text{Voice Coils(Primary Unit)} \\ \text{Diaphragm (Primary Unit)} \\ \text{Type (Secondary Unit)} \\ \text{Magnet Type (Secondary Unit)} \\ \text{Voice Coils (Secondary Unit)} \\ \text{Diaphragm (Secondary Unit)} \end{bmatrix}
$$

In essence, the formulation reveals that the eight design parameters can be condensed into four components, which reduces storage and computational demands. With the utilization of these four components, a regression model can be created. It is important to note that the PCA-based model outputs z-scores and additional conversion is needed for comparison studies. However, z-scores are adequate for performance estimation in practice since only a relative benchmark is needed as long as component values can be generated from the existing dataset.

$$
\begin{bmatrix} \text{Z} - \text{score of THD} \\ \text{Z} - \text{score of Power of Output} \\ \text{Z} - \text{score of Range of Frequency Response} \\ \text{Z} - \text{score of SNR} \\ \text{Z} - \text{score of Impedance of the Speaker} \\ \text{Z} - \text{score of Headroom} \end{bmatrix}
= \begin{bmatrix}
0.334 & -0.362 & -0.356 & 0 \\
0.332 & -0.182 & 0.270 & -0.526 \\
0.276 & 0 & 0 & 0 \\
0.288 & 0 & 0 & 0 \\
0.270 & 0 & 0 & 0 \\
0.295 & 0 & 0 & 0
\end{bmatrix}
\times \begin{bmatrix} \text{Component 1} \\ \text{Component 2} \\ \text{Component 3} \\ \text{Component 4} \end{bmatrix}
+ \begin{bmatrix} 0.048 \times 10^{-7} \\ -1.716 \times 10^{-6} \\ 0.338 \times 10^{-6} \\ -8.618 \times 10^{-7} \\ 0.600 \times 10^{-7} \\ 0.066 \times 10^{-6} \end{bmatrix}
$$

Overall, it can be seen that along with the training dataset, both traditional and principal component analysis-based regression formulations were deduced. Performance analysis is conducted in the next section.

3. Results

Further to the derivation of the formulations, a comparative study of the two models is conducted in order to contrast the predictive accuracy. The current section starts with a depiction of the characteristics of the adopted testing data so as to give an overview of them along with the contrast with the training dataset. Then, due to the misalignment of the inputs and outputs of the principal component analysis-based formulation with the traditional regression model, the conversion is conducted in order to underpin the performance evaluation. Finally, the performance is compared, while the root-mean-square error values of the six sound quality indicators are reported to contrast the performance.

3.1. Descriptive Analysis of the Testing Data

As the performance comparison relied on the testing dataset, it is important to conduct a descriptive analysis of the adopted data to gain an overview and contrast with the modelling data. Similar to the training data, each earphone design in the testing dataset was characterized by eight variables. The corresponding options and their distribution in the testing dataset can be seen in Table 5. With the intention of facilitating the comparison with the modelling dataset, the distribution of the modelling dataset was also included. From the inspection of the percentage values, although differences can be found among the categories, even distribution and full coverage of each class can be observed in the testing set, which is similar to the training data. Therefore, the testing set was eligible for the evaluation of the performance due to the shared characteristics. Conducting descriptive analysis of the testing dataset allows us to gain a better understanding of the distribution of the data and how it compares to the modelling data. By ensuring that the testing dataset has similar characteristics to the modelling dataset, we can have more confidence in the performance evaluation of the proposed approaches. This is important for ensuring that the evaluation is fair and accurate. On the whole, by conducting a descriptive analysis of the testing dataset, we can gain insights into the distribution of the data and ensure that it is eligible for the evaluation of the performance. This helps to ensure that the results of the evaluation are reliable and valid.

Table 5. Distribution of the cases involved in the testing of the developed predictive models with respect to the eight design parameters and the associated options. Apart from the statistics of the testing dataset, the distribution of the training dataset are included for comparison.

Parameters of the Design	**Possible Options**	**Testing Data**		**Training Data**	
		N (Total = 168)	**% (Total = 100%)**	**N (Total = 388)**	**% (Total = 100%)**
Type (Primary Unit)	Dynamic Unit/Moving Coil	58	34.52%	196	50.52%
	Balanced Armature Unit	50	29.76%	90	23.20%
	Planar Magnetic Unit	60	35.71%	102	26.29%
Magnet Type (Primary Unit)	N35 Grade	48	28.57%	119	30.67%
	N40 Grade	41	24.40%	114	29.38%
	N45 Grade	45	26.79%	85	21.91%
	N45 Grade	34	20.24%	70	18.04%
Voice Coils (Primary Unit)	Copper Wire	60	35.71%	161	41.49%
	Aluminum Wire with Copper Covered	56	33.33%	106	27.32%
	Silver Wire	52	30.95%	121	31.19%

Table 5. *Cont.*

Parameters of the Design	Possible Options	Testing Data N (Total = 168)	Testing Data % (Total = 100%)	Training Data N (Total = 388)	Training Data % (Total = 100%)
Diaphragm (Primary Unit)	Polyethylene Terephthalate	50	29.76%	141	36.34%
	Polyethene Naphtholate	43	25.60%	98	25.26%
	Polyetheretherketone (PEEK)	40	23.81%	77	19.85%
	PEEK + Polyurethane	35	20.83%	72	18.56%
Type (Secondary Unit)	No Secondary Unit Included	36	21.43%	86	22.16%
	Dynamic Unit/Moving Coil	48	28.57%	83	21.39%
	Balanced Armature Unit	48	28.57%	100	25.77%
	Planar Magnetic Unit	36	21.43%	119	30.67%
Magnet Type (Secondary Unit)	No Secondary Unit Included	36	21.43%	86	22.16%
	N35 Grade	34	20.24%	80	20.62%
	N40 Grade	35	20.83%	74	19.07%
	N45 Grade	30	17.86%	78	20.10%
	N45 Grade	33	19.64%	70	18.04%
Voice Coils (Secondary Unit)	No Secondary Unit Included	36	21.43%	86	22.16%
	Copper Wire	45	26.79%	127	32.73%
	Aluminum Wire with Copper Covered	41	24.40%	71	18.30%
	Silver Wire	46	27.38%	104	26.80%
Diaphragm (Secondary Unit)	No Secondary Unit Included	36	21.43%	86	22.16%
	Polyethylene Terephthalate	38	22.62%	83	21.39%
	Polyethene Naphtholate	48	28.57%	75	19.33%
	Polyetheretherketone (PEEK)	39	23.21%	75	19.33%
	PEEK + Polyurethane	31	18.45%	69	17.78%

The sound quality performance of the earphones in the training dataset are depicted, while the six average scores of the indicators were computed. Along with the average scores of the training data, the performance average of both training and testing sets can be seen in Table 6, along with the visualization in Figure 4.

Table 6. Average score of the sound quality performance of the studied earphone design of the testing dataset can be observed in the table. Average values of sound performance in training data are included as well to facilitate comparison.

Sound Quality Indicator	Average Score (Testing Data)	Average Score (Training Data)
THD	4.2024	3.9175
Power of Output	4.1845	3.8660
Range of Frequency Response	4.1488	3.8918
SNR	4.1905	3.9459
Impedance of the Speaker	4.1369	4.0052
Headroom	4.3155	4.0335

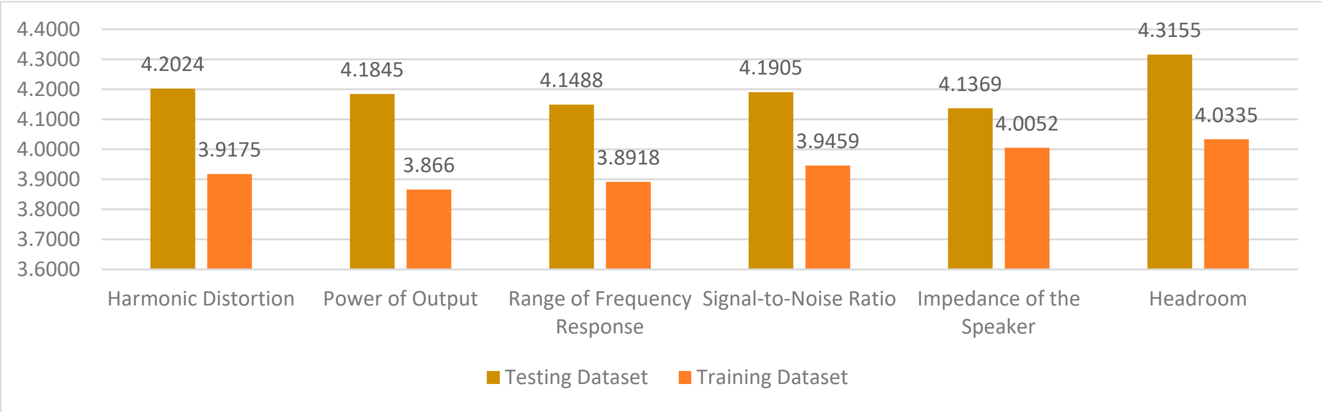

Figure 4. Visualization of the average score of the six sound quality performances of the studied earphone designs of the testing dataset and average values of the training dataset are included as well for ease of referencing.

From the visualization, the relativity of the six indicators of the testing set had a descending ordered sequence, which was headroom (mean = 4.3155) > THD (mean = 4.2024) > signal-to-noise ratio (mean = 4.1905) > power of output (mean = 4.1845) > range of frequency response (mean = 4.1488) > impedance of the speaker (mean = 4.1369), while the best- and worst-performing indicators were headroom and impedance of the speaker, respectively. In essence, the best-performing indicator is shared with the training set, which reflects the alignment of the dataset. Although differences can be observed in the performance scores of the two sets of data, little variation can be observed in the six performance indicators. Therefore, adopting the data in the performance evaluation was reasonable.

Hence, with respect to the relativity of the scores, performance ranking among the testing dataset can be deduced (Table 7), while similarity to ranks of the training set can be observed as well.

Table 7. Rank of the sound quality performance of the studied earphone design of the testing dataset based on the six average performance scores. The ranks for the training dataset are also included.

Rank	Sound Quality Indicator (Testing Dataset)	Sound Quality Indicator (Training Dataset)
1	Headroom	Headroom
2	THD	Speaker Impedance
3	SNR	SNR
4	Power of Output	THD
5	Range of Frequency Response	Range of Frequency Response
6	Speaker Impedance	Power of Output

Similar to the analysis of the training data, a correlation analysis between the design parameters and sound quality outcomes was performed in order to inspect the connection among the variables (Table 8). A close connection between the design parameters and sound quality outcomes can be observed, which indicates that meaningful linkages exist between the independent and dependent variables. Therefore, the data were sharing the same properties as the training data and thus suitable for the evaluation of the predictive performance of the developed formulations.

Table 8. Pearson correlation values of the testing data between the eight design parameters and the six sound quality performances.

Design Parameter	THD	Power of Output	Range of Frequency Response	SNR	Impedance of the Speaker	Headroom
Type of the Primary Driver	0.338 **	0.392 **	0.514 **	0.480 **	0.439 **	0.266 **
Magnet of the Primary Driver	0.448 **	0.464 **	0.229 **	0.203 **	0.192*	0.349 **
Voice Coils of the Primary Driver	0.179 *	0.155 *	0.148	0.300 **	0.145	0.120
The Diaphragm of the Primary Driver	0.452 **	0.398 **	0.599 **	0.215 **	0.206 **	0.491 **
Type of the Secondary Driver	0.475 **	0.488 **	0.324 **	0.579 **	0.495 **	0.522 **
Magnet of the Secondary Driver	0.352 **	0.424 **	0.266 **	0.498 **	0.493 **	0.495 **
Voice Coils of the Secondary Driver	0.625 **	0.631 **	0.592 **	0.692 **	0.714 **	0.597 **
Diaphragm of the Secondary Driver	0.619 **	0.608 **	0.238 **	0.582 **	0.761 **	0.700 **

*. Correlation is significant at the 0.0 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).

3.2. Alignment of the Model Based on Principal Component Analysis

Prior to the comparison of the predictive performance of the two models, the formulations should be aligned in order to facilitate the contrast. Thus, the principal component analysis-based formula is transformed to the standard form in order to support the performance evaluation. The principal component analysis-based method adopted the four components and z-scores of the sound quality indicators as inputs and outputs, respectively. The z-scores of the sound quality indicators and their numerical values in seven levels can be connected by the standard derivation of mean values. Thus, the z-scores and scores in seven levels can be linked with the following formula.

$$\begin{bmatrix} \text{Z} - \text{score of THD} \\ \text{Z} - \text{score of Power of Output} \\ \text{Z} - \text{score of Range of Frequency Response} \\ \text{Z} - \text{score of SNR} \\ \text{Z} - \text{score of Impedance of the Speaker} \\ \text{Z} - \text{score of Headroom} \end{bmatrix} = \begin{bmatrix} 1/2.227 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/2.213 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1/2.200 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/2.112 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/2.205 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1/2.197 \end{bmatrix} \times \left(\begin{bmatrix} \text{THD} \\ \text{Power of Output} \\ \text{Range of Frequency Response} \\ \text{SNR} \\ \text{The Impedance of the Speaker} \\ \text{Headroom} \end{bmatrix} - \begin{bmatrix} 3.92 \\ 3.87 \\ 3.89 \\ 3.95 \\ 4.01 \\ 4.03 \end{bmatrix} \right)$$

Hence, with respect to the inverse of the functions, the conversion from z-scores to the seven-level values can be accomplished, which is expressed as follows.

$$
\begin{bmatrix} \text{THD} \\ \text{Power of Output} \\ \text{Range of Frequency Response} \\ \text{SNR} \\ \text{TheImpe dance of the Speaker} \\ \text{Headroom} \end{bmatrix}
= \begin{bmatrix} 2.227 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2.213 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2.200 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2.112 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2.205 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2.197 \end{bmatrix}
\times \begin{bmatrix} \text{Z} - \text{score of THD} \\ \text{Z} - \text{score of Power of Output} \\ \text{Z} - \text{score of Range of Frequency Response} \\ \text{Z} - \text{score of SNR} \\ \text{Z} - \text{score of Impedance of the Speaker} \\ \text{Z} - \text{score of Headroom} \end{bmatrix}
+ \begin{bmatrix} 3.92 \\ 3.87 \\ 3.89 \\ 3.95 \\ 4.01 \\ 4.03 \end{bmatrix}
$$

On the other hand, the connection between the design parameters and the four components can be expressed by:

$$
\begin{bmatrix} \text{Component 1} \\ \text{Component 2} \\ \text{Component 3} \\ \text{Component 4} \end{bmatrix}
= \begin{bmatrix} 0.306971 & 0.297114 & 0.296176 & 0.33795 & 0.387704 & 0.400377 & 0.395214 & 0.385826 \\ 0.445829 & 0.441501 & 0.381985 & 0.288923 & -0.33654 & -0.26187 & -0.28892 & -0.33437 \\ -0.07285 & -0.64326 & 0.759317 & 0.034571 & 0.028397 & -0.02469 & -0.03704 & -0.02593 \\ -0.82963 & 0.368576 & 0.215333 & 0.335549 & -0.03038 & 0.071337 & -0.09644 & -0.02774 \end{bmatrix}
\times \begin{bmatrix} \text{Type (Primary Unit)} \\ \text{Magnet Type (Primary Unit)} \\ \text{Voice Coils (Primary Unit)} \\ \text{Diaphragm (Primary Unit)} \\ \text{Type (Secondary Unit)} \\ \text{Magnet Type (Secondary Unit)} \\ \text{Voice Coils (Secondary Unit)} \\ \text{Diaphragm (Secondary Unit)} \end{bmatrix}
$$

As a result, by substituting the dependent and independent variables of the principal component analysis-based formulation, the expression in matrix form can be obtained.

$$
\begin{bmatrix} \text{Z} - \text{score of THD} \\ \text{Z} - \text{score of Power of Output} \\ \text{Z} - \text{score of Range of Frequency Response} \\ \text{Z} - \text{score of SNR} \\ \text{Z} - \text{score of Impedance of the Speaker} \\ \text{Z} - \text{score of Headroom} \end{bmatrix}
= \begin{bmatrix} 0.334 & -0.362 & -0.356 & 0 \\ 0.332 & -0.182 & 0.270 & -0.526 \\ 0.276 & 0 & 0 & 0 \\ 0.288 & 0 & 0 & 0 \\ 0.270 & 0 & 0 & 0 \\ 0.295 & 0 & 0 & 0 \end{bmatrix}
\times \begin{bmatrix} \text{Component 1} \\ \text{Component 2} \\ \text{Component 3} \\ \text{Component 4} \end{bmatrix}
+ \begin{bmatrix} 0.048 \times 10^{-7} \\ -1.716 \times 10^{-6} \\ 0.338 \times 10^{-6} \\ -8.618 \times 10^{-7} \\ 0.600 \times 10^{-7} \\ 0.066 \times 10^{-6} \end{bmatrix}
$$

$$
\begin{aligned}
\begin{bmatrix} \text{THD} \\ \text{Power of Output} \\ \text{Range of Frequency Response} \\ \text{SNR} \\ \text{The impedance of the Speaker} \\ \text{Headroom} \end{bmatrix}
&= \begin{bmatrix} 2.227 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2.213 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2.200 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2.112 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2.205 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2.197 \end{bmatrix} \\
&\times \left(\begin{bmatrix} 0.334 & -0.362 & -0.356 & 0 \\ 0.332 & -0.182 & 0.270 & -0.526 \\ 0.276 & 0 & 0 & 0 \\ 0.288 & 0 & 0 & 0 \\ 0.270 & 0 & 0 & 0 \\ 0.295 & 0 & 0 & 0 \end{bmatrix} \right. \\
&\times \begin{bmatrix} 0.306971 & 0.297114 & 0.296176 & 0.33795 & 0.387704 & 0.400377 & 0.395214 & 0.385826 \\ 0.445829 & 0.441501 & 0.381985 & 0.288923 & -0.33654 & -0.26187 & -0.28892 & -0.33437 \\ -0.07285 & -0.64326 & 0.759317 & 0.034571 & 0.028397 & -0.02469 & -0.03704 & -0.02593 \\ -0.82963 & 0.368576 & 0.215333 & 0.335549 & -0.03038 & 0.071337 & -0.09644 & -0.02774 \end{bmatrix} \\
&\times \left. \begin{bmatrix} \text{Type (Primary Unit)} \\ \text{Magnet Type (Primary Unit)} \\ \text{Voice Coils (Primary Unit)} \\ \text{Diaphragm (Primary Unit)} \\ \text{Type (Secondary Unit)} \\ \text{Magnet Type (Secondary Unit)} \\ \text{Voice Coils (Secondary Unit)} \\ \text{Diaphragm (Secondary Unit)} \end{bmatrix}
+ \begin{bmatrix} 0.048 \times 10^{-7} \\ -1.716 \times 10^{-6} \\ 0.338 \times 10^{-6} \\ -8.618 \times 10^{-7} \\ 0.600 \times 10^{-7} \\ 0.066 \times 10^{-6} \end{bmatrix} \right)
+ \begin{bmatrix} 3.92 \\ 3.87 \\ 3.89 \\ 3.95 \\ 4.01 \\ 4.03 \end{bmatrix}
\end{aligned}
$$

Along with the simplification, the formula in standard regression form can result, as follows.

$$\begin{bmatrix} \text{THD} \\ \text{Power of Output} \\ \text{Range of Frequency Response} \\ \text{SNR} \\ \text{The impedance of the Speaker} \\ \text{Headroom} \end{bmatrix} = \begin{bmatrix} -0.0733 & 0.3751 & -0.6896 & -0.0090 & 0.5372 & 0.5285 & 0.5563 & 0.5771 \\ 0.9682 & -0.7729 & 0.2668 & -0.2380 & 0.4727 & 0.3018 & 0.4969 & 0.4349 \\ 0.1864 & 0.1804 & 0.1798 & 0.2052 & 0.2354 & 0.2431 & 0.2400 & 0.2343 \\ 0.1867 & 00.1807 & 0.1802 & 0.2056 & 0.2358 & 0.2435 & 0.2404 & 00.2347 \\ 0.1828 & 0.1769 & 0.1763 & 0.2012 & 0.2308 & 0.2384 & 0.2353 & 0.2297 \\ 0.1990 & 0.1926 & 0.1920 & 0.2190 & 0.2513 & 0.2595 & 0.2561 & 0.2501 \end{bmatrix} \times \begin{bmatrix} \text{Type (Primary Unit)} \\ \text{Magnet Type (Primary Unit)} \\ \text{Voice Coils (Primary Unit)} \\ \text{Diaphragm (Primary Unit)} \\ \text{Type (Secondary Unit)} \\ \text{Magnet Type (Secondary Unit)} \\ \text{Voice Coils (Secondary Unit)} \\ \text{Diaphragm (Secondary Unit)} \end{bmatrix} + \begin{bmatrix} 3.92 \\ 3.87 \\ 3.89 \\ 3.95 \\ 4.01 \\ 4.03 \end{bmatrix}$$

In essence, the formulation contrasted with the form obtained by the traditional regression approach shown in (1).

3.3. Comparison of the Predictive Performance

Further to the formulation of the models based on different approaches, the predictive performance is compared in order to evaluate the superiority. Prior to the computation of the performance benchmarks of the two models, it was known the models could be characterized with (8 + 1) × 6 = 54 loadings. The loadings of the traditional regression model and the principal component analysis-based model can be observed in Tables 9 and 10, correspondingly. Hence, the diversity of the two models can be revealed along with the inspection of the loadings.

Table 9. Loading values of the traditional regression model between the eight design parameters, along with bias and the six sound quality performances.

Design Parameter	THD	Power of Output	Range of Frequency Response	SNR	Impedance of the Speaker	Headroom
Type of the Primary Driver	0.676	0.420	0.425	0.733	0.436	0.261
Magnet of the Primary Driver	0.367	0.294	0.228	0.000	0.337	0.246
Voice Coils of the Primary Driver	0.000	0.000	0.351	0.000	0.000	0.366
Diaphragm of the Primary Driver	0.412	0.375	0.325	0.000	0.282	0.393
Type of the Secondary Driver	0.000	0.000	0.000	0.000	0.000	0.000
Magnet of the Secondary Driver	0.000	0.000	0.000	0.585	0.000	0.000
Voice Coils of the Secondary Driver	0.000	0.336	0.000	0.000	0.539	0.279
Diaphragm of the Secondary Driver	0.355	0.323	0.351	0.000	0.000	0.250
Bias	0.314	0.515	0.578	0.539	0.043	0.565

Table 10. Loading values of the principal component analysis-based model between the eight design parameters, along with bias and the six sound quality performances.

Design Parameter	THD	Power of Output	Range of Frequency Response	SNR	Impedance of the Speaker	Headroom
Type of the Primary Driver	−0.073	0.968	0.186	0.187	0.183	0.199
Magnet of the Primary Driver	0.375	−0.773	0.180	0.181	0.177	0.193
Voice Coils of the Primary Driver	−0.690	0.267	0.180	0.180	0.176	0.192
Diaphragm of the Primary Driver	−0.009	−0.238	0.205	0.206	0.201	0.219
Type of the Secondary Driver	0.537	0.473	0.235	0.236	0.231	0.251
Magnet of the Secondary Driver	0.529	0.302	0.243	0.244	0.238	0.260
Voice Coils of the Secondary Driver	0.556	0.497	0.240	0.240	0.235	0.256
Diaphragm of the Secondary Driver	0.577	0.435	0.234	0.235	0.230	0.250
Bias	3.920	3.870	3.890	3.950	4.010	4.030

Finally, with the application of the testing data and the deduced formulations, the performance of the six sound quality indicators in terms of root-mean-square error was computed (Table 11). It can be observed that the traditional regression approach demonstrated superior accuracy of the estimation in comparison with the principal component analysis-based counterpart. Thus, although the principal component analysis-based method can reduce the number of design parameters, suboptimal accuracy results.

Table 11. Results of the predictive performance of the six sound quality indicators in terms of the root-mean-square error for the traditional regression model and the principal component analysis-based model.

Root-Mean-Square Error	THD	Power of Output	Range of Frequency Response	SNR	Impedance of the Speaker	Headroom
Regression Analysis	1.577	1.574	1.459	1.872	1.748	1.507
Principal Component Analysis	2.738	2.610	2.843	2.802	2.863	2.738

4. Discussion

Subsequent to the presentation of the results, a discussion of the analytic findings of the study is provided in order to interpret them from the perspective of previous studies and of the working hypotheses. Thus, three points of discussion should be highlighted. First, it can be observed that the suboptimal accuracy was coming from the principal component analysis-based model, while the reduced dimensions of inputs facilitated the alleviation of the computational load. Additionally, preprocessing of the data for the conversion of the eight design parameters to the four components can be adopted so as to reduce the storage of the data. Hence, the proposed algorithm provided a computationally economical option for the users in modelling the earphone design. Secondly, with reference to the deduced loadings of the models, the relative importance of the parameters to the outcomes can be inspected in order to gain insights into the earphone design. For instance, the traditional model deduced the ineffectiveness of the type of secondary driver in affecting the sound quality outcomes, which can be observed from the fact that the loadings of the type of the secondary driver were all zero, whereas the principal component-based model suggested the importance of the type of the primary driver to the power of output from the loadings, with a value of 0.968 in comparison with the rest of the loadings in the same row. Hence, the knowledge can be expressed with the consolidated loading tables with different models. Finally, along with the newly implemented design, the new parameters and outcomes can be imported to update the loading table in order to generate new models with enhanced accuracy. Thus, knowledge inside an organization can accumulate even with a turnover of senior staff. Hence, this is good practice in terms of knowledge management [26].

In terms of future directions of research, new approaches, such as neural networks [27], support vector machines [28], genetic algorithms [29], etc., can be applied to reveal the connection between design parameters and sound quality outcomes. It was expected that the estimation accuracy could be improved considering the nonlinearity between the independent and dependent variables. Apart from the defined eight design parameters along with the associated options assumed in the current work, expansion in numbers of both design parameters and the corresponding options can be conducted in order to yield an enhanced characterization of the earphone design. Finally, similar to the extension of the sets of design parameters, the outcomes can be expanded as well so that enhanced coverage of sound quality performance can be accomplished.

5. Conclusions

The tested approaches for modelling the earphone sound performance have been evaluated, and conclusions can be drawn based on the results. There are three key aspects to consider. Firstly, principal component analysis (PCA) was used to reduce the number of variables in the formulation and simplify the formulation. However, the results showed that the performance of the PCA model was suboptimal. Therefore, it is important for the user to select the appropriate model based on the specific application and requirements. Secondly, with the development of the model and the consolidation of knowledge, enhanced knowledge management can be achieved [30]. This can be gained by documenting the knowledge gained during the modelling process, which can then be used for future projects and studies. This can help in improving the design process and reducing the time and resources required for future projects. Finally, further investigation into the loading matrix of the models can reveal the design implications. This can help the engineer to generalize the design principles and improve the overall design process based on the results of previously conducted projects. By understanding the design implications, the engineer can make informed decisions and optimize the design for better performance. In conclusion, it is important to carefully consider the various modelling approaches available and select the appropriate one based on the specific application and requirements. Additionally, documenting the knowledge gained during the modelling process can help in achieving enhanced knowledge management, and investigating the loading matrix of the models can reveal valuable design implications for future projects.

Author Contributions: Conceptualization, L.K.H.L.; methodology, L.K.H.L.; software, L.K.H.L.; validation, L.K.H.L. and C.K.M.L.; formal analysis, L.K.H.L.; investigation, L.K.H.L.; resources, L.K.H.L.; data curation, L.K.H.L.; writing—original draft preparation, L.K.H.L.; writing—review and editing, L.K.H.L. and C.K.M.L.; visualization, L.K.H.L.; supervision, L.K.H.L.; project administration, L.K.H.L.; funding acquisition, L.K.H.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data are currently unavailable due to privacy and ethical restrictions, as well as the terms of cooperation that were agreed upon with the information provider. No data were generated as a result of this cooperation and agreement.

Acknowledgments: We would like to take the opportunity to express our thankfulness to the earphone design company for providing the required earphone data for the data analysis. We would like to acknowledge Research Institute for Advanced Manufacturing (Project code 1-CD4E).

Conflicts of Interest: There is no conflict of interest declared by the authors.

References

1. Patel, V.; Cheer, J.; Fontana, S. Design and Implementation of an Active Noise Control Headphone with Directional Hear-through Capability. *IEEE Trans. Consum. Electron.* **2020**, *66*, 32–40. [CrossRef]
2. Widén, S.E.; Möller, C.; Kähäri, K. Headphone Listening Habits, Hearing Thresholds and Listening Levels in Swedish Adolescents with Severe to Profound HL and Adolescents with Normal Hearing. *Int. J. Audiol.* **2018**, *57*, 730–736. [CrossRef]
3. Xiao, F.; Chan, P.K. A Performance-aware Low-quiescent Headphone Amplifier in 65-nm CMOS. *IEEE J. Solid-State Circuits* **2017**, *52*, 505–516. [CrossRef]
4. Lui, K.H.; Lee, K.M. An Investigation of the Earphone Design with Regression Analysis. In Proceedings of the First Australian International Conference on Industrial Engineering and Operations Management, Sydney, Australia, 20–22 December 2022.
5. Beattie, J.R.; Esmonde-White, F.L. Exploration of Principal Component Analysis: Deriving Principal Component Analysis Visually Using Spectra. *Appl. Spectrosc.* **2021**, *75*, 361–375. [CrossRef] [PubMed]
6. Klich, R. Amplifying Sensory Spaces: The In- and Out-puts of Headphone Theatre. *Contemp. Theatre Rev.* **2017**, *27*, 366–378. [CrossRef]
7. Overberg, J. 'Skipping the Quality Abracadabra': Academic Resistance to Quality Management in Finnish Higher Education Institutions and Quality Managers' Strategies to Handle It. *Qual. High. Educ.* **2019**, *25*, 227–244. [CrossRef]
8. Diy-Audio-Heaven, "Headphone Driver Types | Diy-Audio-Heaven". Available online: https://diyaudioheaven.wordpress.com/headphones/headphone-driver-types/ (accessed on 7 July 2023).
9. Denk, F.; Hiipakka, M.; Kollmeier, B.; Ernst, S.A. An Individualised Acoustically Transparent Earpiece for Hearing Devices. *Int. J. Audiol.* **2018**, *57* (Suppl. S3), 5–25. [CrossRef]
10. McCracken, T.R.; Fabie, J.E.; Burton, J.A.; Munawar, S.; Holcomb, M.A.; Dubno, J.R. Earphone and Aided Word Recognition Differences in Cochlear Implant Candidates. *Otol. Neurotol.* **2018**, *39*, 6–15. [CrossRef] [PubMed]
11. Smull, C.C.; Madsen, B.; Margolis, R.H. Evaluation of Two Circumaural Earphones for Audiometry. *Ear Hear.* **2019**, *40*, 177–183. [CrossRef]
12. Bi, H.; Sun, Y.; Liu, J.; Cao, L. Smartear: Rhythm-based Tap Authentication Using Earphone in Information-centric Wireless Sensor Network. *IEEE Internet Things J.* **2022**, *9*, 885–896. [CrossRef]
13. Ramatsoma, H.; Koekemoer, D.; Clark, J.L.; Malan, K. One-eartip Solution for Pure-tone Audiometry and Acoustic Immittance Measurements: Using Insert Earphone with an Immittance Probe Ear Tip. *Int. J. Audiol.* **2021**, *61*, 251–257. [CrossRef] [PubMed]
14. Alaei, A.; Saghaeian Nejad, S.M.; Gieras, J.F.; Lee, D.-H.; Ahn, J.-W. Reduction of High-Frequency Injection Losses, Acoustic Noise and Total Harmonic Distortion in IPMSM Sensorless Drives. *IET Power Electron.* **2019**, *12*, 3197–3207. [CrossRef]
15. Hang, L.; Subramaniam, U.; Bayrak, G.; Moayedi, H.; Ghaderi, D.; Minaz, M.R. Influence of a Proposed Switching Method on Reliability and Total Harmonic Distortion of the Quasi Z-source Inverters. *IEEE Access* **2020**, *8*, 33088–33100. [CrossRef]
16. Sánchez, A.R.; Moreno, R.L.; Ferreira, L.H.; Crepaldi, P.C. Biasing Technique to Improve Total Harmonic Distortion in an Ultra-low-power Operational Transconductance Amplifier. *Iet Circuits Devices Syst.* **2019**, *13*, 920–927. [CrossRef]
17. Martin, D.W.; Anderson, L.J. Headphone Measurements and Their Interpretation. *J. Acoust. Soc. Am.* **1947**, *19*, 63–70. [CrossRef]
18. Liu, Y.; You, S.; Tan, J.; Zhang, Y.; Liu, Y. Assessment and Enhancement of the U.S. Power Grids toward Extra-high Photovoltaic Generation Penetrations-An Industry Perspective. *IEEE Trans. Power Syst.* **2018**, *33*, 3438–3449. [CrossRef]
19. Hiipakka, M.; Tikander, M.; Karjalainen, M. Modeling the External Ear Acoustics for Insert Headphone Usage. *J. Audio Eng. Soc.* **2010**, *58*, 269–281.
20. Christensen, A.T.; Hess, W.; Silzle, A.; Hammershøi, D. Magnitude and Phase Response Measurement of Headphones at the Eardrum. In Proceedings of the 51st International Conference: Loudspeakers and Headphones, Helsinki, Finland, 22–24 August 2013; Volume 3, pp. 1–10.
21. Olive, S.; Welti, T.; Mcmullin, E. Listener preference for different headphone target response curves. In Proceedings of the 134th International Convention, Rome, Italy, 4–7 May 2013; p. 8867.
22. Struck, C.J. Refinements in the Electroacoustic Testing of Headphones. In Proceedings of the 2016 AES Conference on Headphone Technology, Aalborg, Denmark, 24–26 August 2016; p. 1.
23. Christer, P.V.; Mathieu, L.; Søren, B.; Flemming, C. Identifying the Dominating Perceptual Differences in Headphone Reproduction. *J. Acoust. Soc. Am.* **2016**, *140*, 3664–3674.
24. Kandukuri, J.; Yu, S.; Yao, T.; Yuan, B. Modulation of Ultrasound-switchable Fluorescence for Improving Signal-to-noise Ratio. *J. Biomed. Opt.* **2017**, *22*, 076021. [CrossRef]
25. Martinez-Luengo, M.; Shafiee, M.; Kolios, A. Data Management for Structural Integrity Assessment of Offshore Wind Turbine Support Structures: Data Cleansing and Missing Data Imputation. *Clinical* **2019**, *173*, 867–883. [CrossRef]
26. Santoro, G.; Vrontis, D.; Thrassou, A.; Dezi, L. The Internet of Things: Building a Knowledge Management System for Open Innovation and Knowledge Management Capacity. *Technol. Forecast. Soc. Chang.* **2018**, *136*, 347–354. [CrossRef]
27. Li, X.-M.; Zhang, B.; Li, P.; Zhou, Q.; Lu, R. Finite-horizon H State Estimation for Periodic Neural Networks Over Fading Channels. *IEEE Trans. Neural Netw. Learn. Syst.* **2020**, *31*, 1450–1460. [CrossRef] [PubMed]
28. Guo, C.-Y.; Chou, Y.-C.; Stoean, R. A Novel Machine Learning Strategy for Model Selections—Stepwise Support Vector Machine (Stepsvm). *PLoS ONE* **2020**, *15*, e0238384. [CrossRef] [PubMed]

29. Liu, Y.; Ji, S.; Su, Z.; Guo, D.; Wang, Y. Multi-objective AGV Scheduling in an Automatic Sorting System of an Unmanned (Intelligent) Warehouse By Using Two Adaptive Genetic Algorithms and a Multi-adaptive Genetic Algorithm. *PLoS ONE* **2019**, *14*, e0226161. [CrossRef] [PubMed]
30. Razzaq, S.; Shujahat, M.; Hussain, S.; Nawaz, F.; Wang, M.; Ali, M.; Tehseen, S. Knowledge Management, Organizational Commitment and Knowledge-worker Performance: The Neglected Role of Knowledge Management in the Public Sector. *Bus. Process Manag. J.* **2019**, *25*, 923–947. [CrossRef]