Original Article

Harnessing Data-mining Algorithms to Model and Evaluate Factors Influencing Distortion Product Otoacoustic Emission Variations in a Mining Industry

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Abstract

Aim: The aim of this study was to gauge the condition of otoacoustic emissions (OAEs) in workers, followed by modeling and estimating the weight of factors affecting changes in their emissions. **Methods:** The present study comprises two main phases. In the first phase, the OAEs were assessed using the distortion product OAEs (DPOAEs) test. Furthermore, the occupational factors influencing fluctuations in OAEs, including sound exposure, frequency, age, work experience, and exposure time, were measured. In the second phase, the weight of the factors affecting OAEs was investigated using deep learning (DL) and support vector machine (SVM) algorithms. **Results:** The results of both algorithms showed that sound exposure had the greatest effect (weighting between 36% and 45%) on the changes in OAEs. Frequency, with a weight ranging from 19% to 25%, was recognized as the second factor impacting the changes in DPOAEs. Conversely, age had the slightest effect on OAEs (weighing between 6% and 11%). The results also showed that the DL algorithm had higher accuracy compared to the SVM algorithm. **Conclusions:** As a result of determining the weight of factors causing variations in OAEs, the allocation of resources for control measures and effective reduction will be accomplished more efficiently and accurately.

Keywords: Modeling, otoacoustic emissions, signal-to-noise ratio

Introduction

Noise is one of the most common occupational and environmental risk factors and is known as a major cause of injuries to the auditory system of exposed individuals.[1] Exposure to dangerous noise is one of the greatest occupational risks worldwide. It has been reported that about 25% of workers in the United States, 15% of workers in Canada, 20% of workers in Australia, and 28% of workers in the European Union are exposed to noise above the allowed limit in the range of 85 dB –90 dB(A).[2,3] Furthermore, according to the statistics of the Center for Environmental and Occupational Health of the Ministry of Health of Iran, 2 million workers are exposed to noise above the occupational level.[4] Continuous exposure to noise levels higher than the occupational Threshold Limit Value leads to occupational hearing loss and auditory consequences such as difficulty recognizing speech and background sound, tinnitus, and inability to identify the location of sound sources.[5] Noise-induced hearing loss (NIHL) is the most common noise-induced complication in the workplace and occurs mainly in the workforce when exposed to noise above 85 dB (A). According to the World Health Organization, 466 million people across the world have hearing loss, and occupational risks cause 16% of all adult hearing loss.[4] Furthermore, simultaneous exposure to the factors such as sound and heat leads to stress and the secretion of stress-related hormones in workers.[6-8]

Access this article online

Quick Response Code:

Website: https://journals.lww.com/IJEH

DOI: 10.4103/ijehe.ijehe_20_24

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How to cite this article: Zare S, Esmaeili R, Nakhaei pour M. Harnessing data-mining algorithms to model and evaluate factors influencing distortion product otoacoustic emission variations in a mining industry. Int J Env Health Eng 2024;13:27.

Received: 18-04-2024, **Revised:** 07-07-2024,
Accepted: 08-07-2024, **Published:** 31-12-2024

One of the most challenging issues in occupational health of the industry is the review and management of NIHL condition in different countries. Indeed, identifying this condition at the early stages of industry is very important. Although pure-tone audiometry (PTA) is a very important method of assessing hearing system in the industry and determines the type and degree of hearing loss, it is a subjective assessment method and directly depends on individuals' responses, which are in turn influenced by the factors such as fatigue, stress, and inattention.[9] Other disadvantages of PTA include low sensitivity in diagnosing defects, lack of accurate information about changes caused by noise exposure in the auditory system, inability to detect changes in otoacoustic emissions (OAEs), and inability to detect hearing injuries at early stages.[10] In contrast, distortion product OAEs (DPOAEs) can detect very subtle changes before they are observed in conventional audiogram.[11] Moreover, DPOAEs are quite reliable given that changes are ascertained before serious harms to the ear.[12] As a result, DPOAEs have been recently adopted as a high-performance tool and as a supplement to PTA to detect and monitor NIHL in industrial workplaces.[13,14] DPOAEs comprise a noninvasive and objective tool used to gain a better understanding of auditory mechanisms of the inner ear and assess the condition of the outer cochlear hair cells to identify possible injuries to them.[15]

DPOAE is the response of the inner ear to two pure-tone stimuli (the primaries f1 and f2), which cause a set of distortion products that are common at the frequency 2f1−f2. Throughout, according to the two-source model, it is believed that DPOAE is generated by at least two sources. The two components of DPOAE are (1) the distortion component generated at the f2 place and (2) the reflection component produced at the 2f1–f2 place. In DPOAE measuring, the emissions formed and amplified in the cochlea by certain frequencies of f1 and f2 are recorded.[16]

This test is sensitive to the presence of various lesions and injuries in the cochlea and has the ability to detect transient and sensorineural hearing loss at early stages. In humans, 2f1–f2 DPOAEs were found to reduce due to any type and any levels of sound trauma, with the reduction often occurring at primary frequencies.[17] In addition, the DPOAE test has been very important in research due to its multiple advantages such as simplicity of measurement method, high test speed, and reliable and repeatable results.[18] It has recently been used for evaluating the effects of sound exposure on the hearing system.[2,19]

Data mining, often referred to as "knowledge discovery in the database," is a new subfield of computer science that aims to automate the interpretation of large sets to discover unknown patterns and structures, and extract their accurate, reliable, and practical knowledge and information.[20,21] Data mining assesses the data set at three main stages of exploration, pattern identification, and deployment. At the exploration stage, the data are cleared and then transformed to determine the important variables and the nature of the data according to the needs of the problem. Then, the process of modifying and redefining the variables is completed. At the pattern identification stage, the patterns that make the best predictions will be identified and selected. Finally, at the deployment stage, the selected patterns are used to achieve the desired result.[22] Data mining has recently been widely used in health-related systems[23,24] such as predicting hearing system-related problems.[25,26] Various types of data mining techniques such as neural networks, support vector machines (SVMs), decision trees, random forests, and deep learning (DL) are currently utilized to assess data.[27]

One of the methods that has recently been used to assess data related to the auditory system is SVM algorithm.[28] The SVM algorithm searches for the optimal hyperplane (optimal predictor pattern) so that it can separate the backup vector of each data set in the best possible way and finally predict the final weight of each data set on the main variable. The SVM algorithm is very useful when it is necessary to identify patterns and/or classify objects in specific classes with different weights.[29]

Another data mining algorithm used for assessing health-related data is the DL algorithm, which exploits different layers and levels to develop computational models of high-level abstract data.[30] In DL, computer learning is based on experience and the computer understands problems and concepts hierarchically. The strength of this algorithm is that there is no need for human operators to specify all the knowledge required by the computer. In fact, understanding the hierarchy of concepts allows the algorithm to infer more complex concepts than the existing complex concepts.[31]

Workers in the mining industry face significant challenges due to noise-induced problems such as hearing loss, yet few studies have utilized data mining algorithms to model factors affecting signal-to-noise ratio (SNR). This study aims to achieve several objectives: first, to evaluate the early-stage condition of workers' auditory systems through SNR measurements using the DPOAE test; second, to employ DL and SVM algorithms for modeling SNR-influencing factors and assessing their respective impacts; and finally, to determine the most effective algorithm for evaluating SNR-related data.

Materials and Methods

Participants

The participants included male workers in a mining industry in southeastern Iran. Besides that, changes occurring in the DPOAE SNR were measured after 3-h and 8-h exposure to the noise at the workplace in both study groups. Before entering the study, the health condition of the participants' auditory system was explored by reviewing the medical records and those who had no hearing health problems (e.g. hearing loss, otitis, etc.,) were selected for the study. The participants in the case group were chronically exposed to sound. On the other hand, the participants did not experience any heat stress and were not in contact with any major vibration source. SNR measurements were conducted in both ears of the participants.

Sample size

In a 2022 study by Zare *et al*.,[28] the average standard deviation (SD) equivalent sound pressure level (SPL) (Leq) of the subjects was reported as 89.7.[3] Using this data, the sample size for the current study was calculated with a SD of 3, a 95% confidence level, and error level of 0.25 SD:

$$N = \frac{\left(Z_{1-\frac{\alpha}{2}}\right)^2 \times \delta^2}{d^2}$$

Where $Z_{1-\frac{\alpha}{2}}$ is a constant value that is equal to 1.96 for 95% confidence level, δ is SD, and d is error level.

Consequently, the minimum required sample size was determined to be 71 participants for each group, accounting for a potential 10% dropout rate. Therefore, 150 workers were divided into two groups, with the case group (n = 75) being exposed to SPLs between 85 dB(A) and 95 dB(A) and the control group (n = 75) working in the administrative department exposed to SPLs ranging from 65 dB to 75 dB(A).

Study design

The present study, which was carried out in 2020, was a case–control study aiming to model changes in SNR of OAEs in workers exposed to different levels of sound pressure using DL and SVM algorithms. Two general phases were pursued in this research. In the first phase, the data related to factors affecting OAEs (including exposure to different levels of sound pressure, different frequencies of sound, age, work experience, and time of noise exposure) were gleaned for all participants. Otoacoustic emission values were then measured as an SNR in all participants. In the second phase, the results of the first phase were modeled using data mining algorithms (SVM and DL algorithms). In this phase, the weight of each factor was determined as an indicator of its impact on SNR changes, and finally, the accuracy index was used to determine the accuracy and precision of the models' predictions to determine the weight of the factors.

Measurement of changes in otoacoustic emissions of workers exposed to different levels of sound pressure

In this study, the participants were exposed to different levels of workplace sound pressure in several different days. The participants' response to OAEs was investigated in frequencies of 2000, 3000, 4000, and 6000 by DPOAEs at the beginning of the shift, 3 h later, and at the end of the shift in both the case and control groups.[16] Before starting the measurement, the following steps were taken:

(a) Based on PTA results in medical records, only healthy individuals without hearing loss (with hearing thresholds under 25 dB) were selected for this study; (b) there should be no obstruction of the external ear; (c) one should position the probe suitably in the ear canal; (d) the probe should be thoroughly covered by the ear canal; (e) no middle ear pathology should be observed; and (f) during the test, the participant should be silent and positioned sedentarily.

Signal-to-noise ratio rate measurement

The DPOAE test device (Vivosonic 2.5.2; Vivosonic, Toronto, Canada) was used to measure SNRs at the frequencies of 1000, 2000, 3000, 4000, and 6000 Hz. The DPOAE test was choose as the arbitrary test because it has a frequency-selective nature. All the participants were placed in sedentary positions during the test. The f2/f1 was selected as 1.22 and the levels of the signals were L1 = 65 dB and L2 = 55 dB SPL, respectively. Small probes were utilized to send the outer ear canal audio frequencies to the tympanic membrane; the probes received the reflected sounds that were a little delayed by a microphone that was set in the probe. A silent room was utilized to perform the test procedures and recordings. In the present study, the SNR in 2f1−f2 was considered and measured as a response to DPOAEs at 1000, 2000, 3000, 4000, and 6000 Hz in the participants' right and left ears, separately. The authors choose this range of frequencies because within this range ears are prone to hearing loss. Distortion-product otoacoustic emission noise floor was also used to estimate SNRs for the three groups. The SNR of 6 dB or higher was considered the inclusion criterion.[16]

Weighing factors affecting signal-to-noise ratios using deep learning and support vector machine algorithms

Modeling the SNR values was done by feeding all data related to the SPL (sound exposure), frequency, age, work experience, and exposure time to IBM SPSS modeler V.18 (made by SPSS Inc. in USA). The data were first classified and then analyzed with a ratio of 70–30 (70% of the data was spent on algorithm training and 30% on testing) and repetition over 200 times. In data mining, usually 70% of data are used to train the developed model and 30% of them are used to test the developed model (sometimes this ratio is also 90–10). Two hundred repetitions mean the number of repetitions by software (in the training data step) to find the optimal point of the model in predicting and weighting the data. Number of repetitions automatically is determined by the software.[32,33] Finally, factor gain ratios were calculated as weight.

Determining accuracy and error rate of each model

Categorization algorithms are utilized to classify discrete output variables. In such algorithms, assessment is accomplished through a set of criteria such as accuracy, confusion matrix, sensitivity, and features. Out of these criteria, accuracy and confusion were used in the current study. The confusion matrix, which is a square matrix, has equal dimensions in terms of output category predictions.[34] The purpose of presenting the accuracy index in this study is to evaluate the accuracy of the studied models in predicting the effect of SPL (sound exposure), frequency, exposure time, work experience, and age on SNR changes. Based on this index, the efficiency of each model in evaluating and weighing data can be measured.

Data analysis and processing

The mean and SD of the age, work experience, and SNR were analyzed by the use of Statistical Package for the Social Sciences (SPSS) V. 22. An independent samples t-test was used to compare quantitative variables between the two groups, with the significance level being set at 0.05 ($P \leq 0.05$). Weighing and modeling the factors affecting SNR was performed by IBM SPSS Modeler V. 18.0.

Results

Demographic information

The demographic information of the study participants is displayed in Table 1. This table provides information on the mean and SD of age, work experience, and equivalent SPL in the both control and case groups.

Results of signal-to-noise ratios

The mean and SD of SNR measured by DPOAEs in frequencies of 2000, 3000, 4000, and 6000 Hz at the beginning, middle, and end of the shift work in both case and control groups are illustrated in Table 2. Accordingly, in the course of time during the shift, the SNR value reduced slightly in both control and case groups. Therefore, it can be stated that the passage of time affects SNR value to some extent. Furthermore, increasing frequency in the control group led to the reduced value of SNR. In contrast, in the case group, no sizeable relationship was detected between changes in frequency and SNR rate.

Modeling signal-to-noise ratio changes using deep learning and support vector machine algorithms

At this stage, the experimental results obtained from the previous stages were modeled based on the hypothesis that "different variables affect SNR changes." Table 3 demonstrates the results of modeling SNR changes using DL algorithms during three periods, i.e., at the beginning, in the middle, and at the end of the work shift. According to the results, the accuracy rates of the models of the DL algorithm are 92%, 97%, and 95%. The weights of factors affecting SNR value are also presented in Table 3. The accuracy rates of the resulting models of the SVM algorithm are 84%, 92%, and 83%. The weights of the factors affecting the model on SNR value are also displayed in Table 3.

As mentioned above, the accuracy rates of the models obtained from the SVM algorithm varied between 83% and 91% and the ones gleaned from the DL algorithm varied between 92% and 97%. Therefore, it is concluded that the DL algorithm performs the modeling process and investigates the effects of predictor variables on SNR values with higher accuracy.

In Figure 1, the weights of the factors affecting SNR changes at three different measurement times are compared based on the outputs of DL and SVM algorithms. According to this figure, changes in the sound exposure have the greatest effect on SNR value, followed by frequency and exposure time in that order. On the contrary, the age has the smallest effect on SNR value.

Discussion

The present study was conducted on 150 male workers ($n = 75$ in the control group and $n = 75$ in the case group) in a mining company in Kerman, Iran. Two main phases were pursued in this research. In the first phase, the mean SNR obtained from two ears in workers was measured using the DPOAE test. In the second one, the results of the first phase were modeled by DL and SVM algorithms, and the weight of factors affecting SNR value was estimated.

Table 1: Demographic information of study participants including case group and control

Variables	Group		P*
	Control (n=75) (65 dB[A] <SPL<75 dB[A]), mean±SD	Case (n=75) (85 dB[A]< SPL<95 dB[A]), mean±SD	
Age (years)	40.32±5.41	39.54±7.43	0.064
Work experience (years)	13.3±6.2	10.45±4.22	0.031
SPL (dB[A])	65	91.2±2.22	<0.0001

*Significance level was considered P<0.05. SPL: Sound pressure level, SD: Standard deviation

Table 2: Mean±standard deviation of signal-to-noise ratios at different frequencies and different times of study

Measurement time	Group	Frequency (Hz)			
		2000	3000	4000	6000
7/30–8 am	Control group (65 dB[A] <SPL <75 dB[A])	27.32±2.79	24.68±1.92	22.49±4.82	22.30±3.22
	Case group (80 dB[A] <SPL <95 dB[A])	21.90±0.49	22.35±0.35	20.50±0.84	20.00±1.97
	P*	<0.0001	<0.0001	<0.0001	<0.0001
10/30–11 am	Control group (65 dB[A] <SPL <75 dB[A])	26.94±1.83	23.86±2.03	22.35±5.11	21.97±3.07
	Case group (80 dB[A] <SPL <95 dB[A])	20.40±0.56	21.15±2.33	19.15±0.494	20.40±0.49
	P*	<0.0001	<0.0001	<0.0001	0.024
13/30–14 pm	Control group (65 dB[A] <SPL <75 dB[A])	26.34±2.12	23.54±1.84	21.79±4.68	21.54±5.06
	Case group (80 dB[A] <SPL <95 dB[A])	19.25±0.07	19.85±1.34	19.10±0.84	21.00±1.41
	P*	<0.0001	<0.0001	<0.0001	0.047

*Significance level was considered P<0.05. SPL: Sound pressure level

Table 3: Modeling results using deep learning and support vector machine algorithms

Variables	SNR 1		SNR 2		SNR 3	
	Weight (%)	Accuracy DL (%)	Weight (%)	Accuracy DL (%)	Weight (%)	Accuracy DL (%)
L_{eq}	38	92	42	97	45	95
Frequency	24		19		20	
Experience	15		14		12	
Age	11		9		6	
Exposure time	12		16		17	
Variables	**SNR 1**		**SNR 2**		**SNR 3**	
	Weight (%)	**Accuracy SVM (%)**	**Weight (%)**	**Accuracy SVM (%)**	**Weight (%)**	**Accuracy SVM (%)**
L_{eq}	36	84	44	91	39	83
Frequency	25		21		23	
Experience	18		12		12	
Age	10		9		11	
Exposure time	11		14		15	

SNR 1: SNR value at the beginning of the shift (7:30–8 am), SNR 2: SNR value in the middle of the work shift (10:30–11 am), SNR 3: SNR value at the end of the work shift (13:30–14 pm), L_{eq}: Equivalent sound pressure level, SNR: Signal-to-noise ratio, SVM: Support vector machine, DL: Deep learning

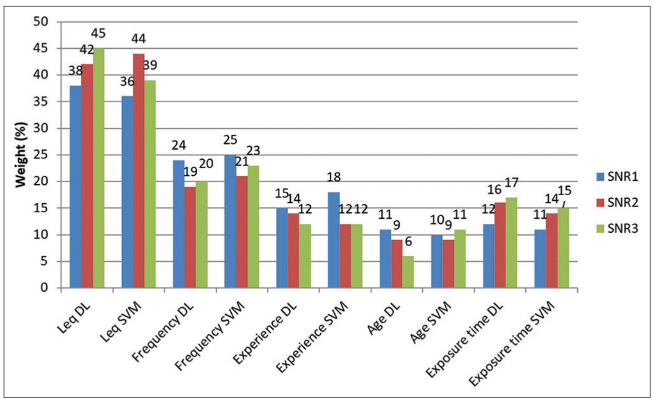

Figure 1: Comparison of factors affecting the value of signal-to-noise ratio at three different measurement times using deep learning and support vector machine algorithms

The results of the present study showed that exposure to loud noise leads to a reduction in SNR values obtained from DPOAEs [Table 2]. It seems that an increase in sound exposure leads to a reduction in the response of the cochlear receptors of the ear to ambient sound. In a study conducted by Moepeng *et al*., a difference was unveiled between SNR of the control and case groups and the results confirmed the effect of sound exposure on SNR value.[35] Other studies have emphasized the effectiveness of exposure to excessive noise in reducing the response level of the DPOAE test.[36,37] Furthermore, according to the modeling results of the two algorithms, the L_{eq} had the highest weight and the greatest effect on SNR value. In a study by Shera and Guinan *et al*., sound exposure had a significant effect on the value of SNR and[16] also Lake and Stuart discovered a significant relationship between sound exposure and DPOAE test output.[38] Kujawa and Liberman also demonstrated a statistically measurable association between DPOAEs and reduced function of cochlear hair cells in the ear, eventually leading to a reduction of ear reaction.[39]

In this study, the results of modeling by the SVM algorithm showed that the frequency was identified as the second effective factor (with weights of 25%, 21%, and 23% measured at different times) affecting SNR value [Figure 1]. Furthermore, following the output results of DL modeling, frequency at all three times of measurement was recognized as the second factor affecting SNR (with weights of 24%, 19%, and 20%) [Figure 1]. In a similar vein, Mhatre *et al*.[40] and Lake and Stuart[38] demonstrated significant relationships between DPOAE test output and exposure frequency.

In the current research, the passage of time and thus an increase in exposure time to sound led to a decreasing trend in SNR values [Table 3]. Therefore, it can be stated that increasing the time of exposure to sound leads to a reduction in the reactivity of cochlear receptors to the sound. Mhatre *et al*., studying transgenic mice, showed that time exposure influences the output of the DPOAE test.[40] Furthermore, in a study by Nadon *et al*., the passage of exposure time led to a reduction in the value of DPOAE.[41] Furthermore, the present research showed that increasing exposure time leads to a reduction in the function of cochlear receptors in the ear. Similarly, Soylemez and Mujdeci reported that the value of DOPAEs was more affected by workers working in metal industries with longer working hours.[42] However, in the models obtained from the SVM algorithm, the weight of exposure time was lower compared to other effective factors, which may be due to the lower accuracy of the model in measuring weights compared to the DL model.

This study also explored age as a factor affecting the SNR value of the DPOAE test. According to the results of models from both DL and SVM algorithms, age had the lowest weights, hence the least effect on changes in SNR [Figure 1]. In a study by Laffoon *et al*., it was stated that DPOAE test output is lower in older people compared to younger people. However, this study showed that the relationship between age and SNR value is not very significant.[14] However, in a study by Roggia *et al*., the relationship between age and DPOAE test output was significant.[43] This discrepancy may be attributed to the difference in the age range of the participants in the two studies. In this study, the participants were over 30 years old, whereas the age range of the participants in Roggia *et al*. was 19–67 years.

In our study, both DL and SVM algorithms were used to model the weight of factors affecting the SNR value of the DPOAE test. Accordingly, the accuracy rates of SNR 1, SNR 2, and SNR 3 models for the DL algorithm were 92%, 97%, and 95%, whereas those for the SVM algorithm were 84%, 91%, and 83%, respectively. Thus, it is argued that the use of DL algorithms to model the factors affecting DPOAEs will provide more accurate results compared to SVM algorithms.

In a study by Elahi Shirvan *et al*., which aimed to weigh and prioritize factors affecting hearing loss using the SVM algorithm, the accuracy of the developed models varied from 94% to 100%.[28] However, as mentioned above, the accuracy of the models used in the SVM algorithm in the present study varied between 83% and 91%. This difference seems to be due to the better use of SVM models for modeling audiometric-related data.

The primary advantage of this study lies in utilizing data mining algorithms to evaluate the factors influencing the SNR values obtained from DPOAE tests. The findings enable the calculation of the impact of various factors on test outputs, facilitating the development of proportionate control measures for existing harmful factors and their effectiveness. Given the high accuracy of these models, their application can significantly enhance resource allocation processes, allowing managers to address existing issues precisely. A notable limitation of this study was the small sample size, constrained by the limited population in the studied industry. Future research should aim to include larger sample sizes from multiple industries to enhance the generalizability of the findings.

Conclusions

This study aimed to evaluate the factors affecting OAEs through data mining techniques, specifically utilizing DL and SVM algorithms for modeling. Results indicated that sound exposure and its variations were the most significant factors influencing OAEs, followed by frequency, exposure duration, and work experience. In contrast, age had the minimal impact. These findings underscore the critical role of sound exposure in SNR changes and subsequent ear damage, highlighting the necessity of implementing sound control measures in workplaces to mitigate noise exposure. Furthermore, the study found that while both algorithms demonstrated high accuracy, DL algorithms outperformed SVM in predicting otoacoustic emission changes. The accuracy of data mining algorithms in assessing OAEs was notably high, ranging from 83% to 98%, demonstrating their superiority over traditional statistical methods.

Acknowledgment

We are deeply grateful for the support provided by this center and the Research Deputy of Kerman University of Medical Sciences, Kerman, Iran.

Financial support and sponsorship

This study is the output of a research project (code number: 98001062) in the Health Modeling Research Center at Kerman University of Medical Sciences.

Ethics code

This study was approved as a research project in the ethics committee of Kerman University of Medical Sciences with code number IR. KMU. REC.1398.665. In the present study, all participants were above 18 years old and signed an informed consent form before taking part in the study.

Conflicts of interest

There are no conflicts of interest.

Authors' contributions

Sajad Zare: Conceptualization, Methodology, Project administration, Validation, Writing – review and editing; Reza Esmaeili: Conceptualization, Formal analysis, Methodology, Supervision, Writing – original draft, Writing – review and editing; Mojtaba Nakheipour: Data curation, Formal analysis, Investigation, Visualization, Writing – review and editing;

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