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Review Article

An Artificial Intelligence Approach to Evaluating the Sound Absorption Performance of Materials: A Systematic Review

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ABSTRACT

In recent years, the rapidly increasing use of artificial intelligence has begun to be incorporated into many fields in academia and the market. This study investigates the extent to which artificial intelligence is used in determining the sound absorption performance of materials, which have practical implications in improving indoor acoustic conditions. To this end, studies conducted over the past ten years based on three specified keywords were examined. Various constraints were applied during the review process. First, titles and keywords were scrutinized to filter the studies. Then, research articles were selected, while other studies were eliminated. Secondary keywords used in the studies were identified, and a field assessment was conducted using an analysis program. The results were evaluated by grouping them under different subheadings. The evaluation included the year the studies were conducted, the artificial intelligence methods used, and any additional inferences, if available. In the evaluation section, comments were made on the usability of artificial intelligence in sound-absorbing materials, and the shortcomings in the field were addressed. Suggestions for future studies were also presented. The review study is intended to serve as a guide, particularly for new studies in this field.

Keywords: *artificial intelligence, sound absorption, sound absorption material, systematic review*

Malzemelerin Ses Yutma Performansının Değerlendirilmesinde Yapay Zeka Yaklaşımı: Sistematik İnceleme

Öz

Son yıllarda, yapay zekanın hızla artan kullanımı akademi ve piyasa dahil olmak üzere birçok alanda kendine yer bulmaya başlamıştır. Bu çalışma, malzemelerin ses yutma katsaysının belirlenmesinde yapay zeka kullanımının yerini araştırmaktadır. Bu amaçla, belirlenen üç anahtar kelime doğrultusunda son on yılda yapılan çalışmalar incelenmiştir. İnceleme sürecinde çeşitli kısıtlamalar uygulanmıştır. İlk olarak, çalışmaların başlıkları ve anahtar kelimeleri incelenerek bir ön eleme yapılmıştır. Daha sonra, yalnızca araştırma makaleleri seçilmiş ve diğer türdeki çalışmalar elenmiştir. Çalışmalarda kullanılan ikincil anahtar kelimeler belirlenmiş ve bir analiz programı kullanılarak alan değerlendirmesi yapılmıştır. Elde edilen sonuçlar farklı alt başlıklar altında gruplandırılarak değerlendirilmiştir. Değerlendirme, çalışmaların yapıldığı yılları, kullanılan yapay zeka yöntemlerini ve varsa ek çıkarımları içermektedir. Değerlendirme bölümünde, yapay zekanın ses yutucu malzemelerdeki kullanılabilirliği üzerine yorumlar yapılmış ve alandaki eksiklikler tartışılmıştır. Gelecek çalışmalara yönelik öneriler de sunulmuştur. Derleme çalışması, özellikle bu alanda yapılacak yeni araştırmalara yol gösterici olmayı amaçlamaktadır.

Anahtar Kelimeler: *yapay zeka, ses yutma, ses yutucu malzeme, sistematik inceleme*

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I. INTRODUCTION

Noise is generally defined as unwanted sounds that negatively affect people's daily activities and health. According to the World Health Organization (WHO) [1], noise was initially considered a minor threat to people's physical and psychological health. However, with the evolving and changing environmental conditions, it has become one of the primary disturbances threatening human health today. Daily, people are exposed to different types of noise, indoors and outdoors. In particular, in developed and some developing nations, noise limits are established by regulations and are strictly enforced. Noise can be prevented in various ways, either at the source, along the transmission path, or at the receiver. In enclosed spaces, while multiple methods exist for controlling noise, the most commonly preferred approach, and one frequently encountered in studies, is the improvement of indoor acoustic conditions using finishing materials.

Studies on using materials for sound control can be traced back to ancient times. When examining the ruins of spaces such as theaters in Hellenistic and Roman cities, it is believed that the materials used in the construction and their geometric forms were chosen with an awareness of sound control. Additionally, various studies have shown that animal wool was used in different areas for sound control. With the advent of the Industrial Revolution and the emergence of factory buildings, the need for noise control increased, while technological advancements in materials were also made. However, the concept of "acoustic materials" emerged in the 19th century through various studies. Particularly with changes in building technology, using materials like steel and concrete in larger spaces led to issues with reverberation, increasing the demand for acoustic materials [2]. Over time, the use of plant and animal fibers was followed by Helmholtz resonators, plastic-based foams and materials, and, more recently, the growing popularity of metamaterials. However, with the depletion of natural resources and the increasing emphasis on sustainability, natural materials have again become the focus of research and are being reconsidered under advanced technological conditions. In the future, materials that are smart and capable of self-adaptation to environmental conditions are expected to enter the market.

In enclosed spaces, the surface area of finishing materials, their sound absorption coefficient, the material's placement within the space, and the space's volume are effective parameters in controlling acoustic conditions. In particular, the first intervention for ensuring acoustic comfort in an existing area is the selection of appropriate materials based on their sound absorption performance characteristics.

A portion of the sound waves reaching the material is converted into thermal energy and dampened as they pass through the material. The remaining sound waves either continue through the material to the other surface or are reflected from the material's surface (Figure 1). The sound absorption coefficient (SAC) of a material is defined as the ratio of the energy absorbed by the material to the energy incident on the material, representing the material's sound absorption capacity. The SAC of materials ranges between 0 and 1. The closer the coefficient (α) is to 1, the more absorptive the material is.

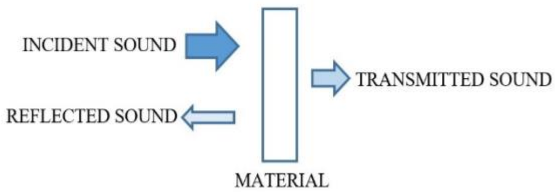

Figure 1. *Schematic explanation of the principle of sound absorption.*

The impedance tube and reverberation room methods are the most commonly preferred methods used to determine the SAC of materials. The impedance tube measurement method frequently employs international standards such as ISO 10534-2:2023 [3] or ASTM E1050-12 [4]. The basic principle of the impedance tube method involves two microphones, usually one at the source and one at the sample side, within the tube. Sound waves are transmitted from the source to the sample. Information about the material's sound absorption capacity is obtained by examining the reflected and absorbed energy when the sound waves hit the surface. The reflection coefficient (R), SAC (α), and acoustic impedance (Z) are calculated using the amplitude and phase information of the reflected and incident waves. This method is particularly favored in academic research due to the small sample sizes required. Additionally, measurements can be conducted in a controlled environment and at different frequencies. However, despite these advantages, there are some drawbacks. Since the samples are not in actual size, the results may differ in practical applications. Variations in edge constraints in different impedance tubes can affect measurement results. Furthermore, different frequency ranges are recommended in various standards, which can lead to variations in the results. The physical conditions of the measurement environment also inevitably affect the results. Therefore, while the impedance tube method is a valuable tool for studying the acoustic performance of materials, especially in academic research, the results' accuracy and reliability depend on the equipment's quality and experimental conditions.

Standards such as ISO 354:2003 [5] or ASTM C423-17 [6] are commonly used in the reverberation room method. This method provides more accurate results because the sample sizes are realistic, and sound waves from the source are diffuse, unlike the perpendicular waves used in the impedance tube. The design of the reverberation room is crucial to ensure balanced sound distribution within the space. Hasan and Hodgson found that a 150 m^3 room yielded better results than other room sizes [7]. Tang and Chuang indicated that the room size should not be smaller than 150 m^3 in reverberation room measurements due to the critical frequency. They also noted that if the room size exceeds 500 m^3, the results might be inaccurate due to the absorption of sound by the air [8]. While the reverberation room method may be preferred for its more realistic results, the impedance tube method is more frequently used, particularly in academic studies requiring practical results. Typically, preliminary studies are conducted using the impedance tube, followed by additional tests in a reverberation room during industrial material production. In such studies, an equation can convert SAC from the impedance tube into results from the reverberation room measurements. London proposed equation 1 below to convert direct sound wave absorption coefficient data from the impedance tube into diffuse sound wave data from reverberation room measurements. He conducted numerous experimental studies to derive this formula and stated that it is the most accurate with minimal error. The ASTM C384 – 04 [9] standard also references London's research. This conversion process is crucial for ensuring consistency and comparability of results across different measurement methods.

$$\alpha_e = 4 * \left|\frac{1-(1-\alpha_0)^{\frac{1}{2}}}{1+(1-\alpha_0)^{\frac{1}{2}}}\right| \left\{\ln 2 - \frac{1}{2} - \ln\left[1-(1-\alpha_0)^{\frac{1}{2}}\right] - \frac{(1-\alpha_0)^{\frac{1}{2}}}{2}\right\} \tag{1}$$

In equation:

α_e: the SAC for diffuse sound waves (random incidence)

α_0: the SAC for direct sound waves (normal incidence)

The concept of 'artificial intelligence' (AI), which began to be used in engineering, mathematics, and physics, has expanded to many different disciplines. It was first introduced by John McCarthy in 1956 [10]. McCarthy stated that AI is similar to understanding human intelligence through computers, but AI does not have to be restricted by biological methods [11]. One of the fields where AI has been increasingly utilized, especially in recent times, is materials science engineering. Experiments and density functional theory (DFT) based calculations have been primary methods for learning and under-standing materials' chemical and physical properties. Experimental processes are exceptionally costly and time-consuming. Although DFT calculations are more cost-effective, they can lead to significant differences in results due to the experimental setup's physical conditions [12]. With the wealth of data ac-cumulated from experimental work, the trial-and-error method, and subsequent DFT-based research, AI has started to play a role in designing data-driven approaches in materials science. Recently, the use of AI and machine learning to gain deeper insights into materials through increasing experimental and simulation-based data sets has become common [13]. With the growing popularity of AI research, a new field known as 'materials informatics' has emerged, integrating all three traditional paradigms of materials science: theory, experimentation, and computation/simulation [14]. The key reason for AI's suitability in material design is its ability to handle large data volumes and high-dimensional analyses [15]. A literature review shows that AI usage in materials science engineering spans a broad range, from chemical studies of materials to examining their physical properties.

A review of research on the use of artificial intelligence in architectural acoustics indicates that it has become a popular and widely used technique, particularly in the past decade. Studies have explored AI approaches in various areas, including soundscape design [16; 17; 18; 19; 20], building acoustics [21; 22], noise prediction [23; 24; 25], interior acoustic design [26; 27], and the prediction of acoustic materials' sound insulation and absorption [28; 29; 30]. Numerous examples of research exist in these areas, with only a few references provided here as examples. It is evident from these studies that the use of artificial intelligence in architectural acoustics is an undeniable reality, offering innovative alternatives in the field.

Experimental studies on sound absorption in materials are time-consuming and costly, leading to the suggestion of alternative models such as empirical models proposed by Delany and Bazley (1970), Miki (1990), Mechel (1976), and Garai and Pompoli (2005), and phenomenological models proposed by Allard and Champoux (1992), Kino and Ueno (2008), and Attenborough (1983). Although these models provide accuracy on various parameters, their evaluation is a complex process. Therefore, in the past 20 years, significant attention has been given to studies involving artificial neural networks (ANNs) and fuzzy logic (FL) [31].

The research question of this study is: "How widely is artificial intelligence used in determining the SAC of materials, and can it serve as an alternative method?" In this context, the research methodology involves identifying critical terms in the field and conducting a general literature review on the relevance of these terms. The findings include publication years, researchers' countries, material properties, material parameters beyond SAC, measurement methods, and the compatibility of artificial intelligence algorithms. The evaluation section discusses the findings and the applicability of artificial intelligence.

II. METHODOLOGY

A.1 Literature Search Strategy and Inclusion/Exclusion Criteria

A systematic literature review is a research method designed to answer specific research questions using a systematic and transparent approach, enabling the identification of results from studies included in the research and providing a critical evaluation [32]. In systematic research, since all studies addressing a particular question are examined, an impartial summary of the conducted research is presented [33]. The transparency of this process ensures the integrity of the study.

This study meticulously employed a systematic research method to answer the research questions. The main categories examined and the progression of the research process are presented in Figure 2. The literature searches were conducted with utmost care, and keywords were identified. A comprehensive field search was first carried out to determine the keywords. For this purpose, a preliminary search was conducted on Google Scholar using the keywords "Artificial Intelligence," "Architectural Acoustics," "Sound Absorbing Materials," and "Sound Absorption Coefficient." A total of 26 publications were reviewed, and the research study's keywords were finalized as "Artificial Intelligence," "Sound Absorption," and "Material.

After the keywords were established, the publishers and databases included in the research were carefully selected based on the results from Google Scholar. Accordingly, articles published in ScienceDirect, Taylor and Francis (TandF), MDPI, Springer, and Sage, which are widely recognized for their academic rigor, were included in the scope of the study. In the initial phase, the keyword-based search yielded 1835 publications on TandF, 126 on MDPI, 115 on ScienceDirect, 63 on Springer, and 7 on Sage.

Due to the increasing significance of research involving artificial intelligence in recent years, the study period was set to ten years between 2014 and 2024. Only articles published in English were selected for review. Accordingly, the number of studies identified was updated to 542 in TandF, 126 in MDPI, 96 in ScienceDirect, 63 in Springer, and 7 in Sage.

In this study, which aims to examine the usage rate of artificial intelligence in determining the SAC of materials, search criteria were restricted to include only 'research articles' among the obtained publications. As a result of this limitation, the number of articles identified was 359 in TandF, 56 in ScienceDirect, 20 in Springer, and 6 in Sage. A specific issue was identified with MDPI. A limited number of publications were found when conducting AI-related searches directly on MDPI's site, with other research articles showing keywords like "machine learning" instead. Therefore, the search for MDPI research articles was conducted through Google Scholar. Consequently, MDPI was excluded from subsequent restrictions, and all 126 articles were screened manually.

Following the article type limitation, a subject-specific restriction was applied to ensure that the studies were directly related to the determination of sound absorption coefficients. Given that each publisher's site offered different options, field limitations were applied under the engineering category using "Materials Science," "Computer Science," and "Environmental Science" as the selected fields. After this restriction, 51 articles were identified in ScienceDirect, 46 in TandF, 15 in Springer, and 6 in Sage.

In the final stage, all articles' titles, keywords, and abstracts were reviewed, and those directly related to the topic were selected for further analysis. As a result, 27 articles were examined in this study: 15 from ScienceDirect, 7 from MDPI, 2 from TandF, 2 from Springer, and 1 from Sage.

Figure 2. *Flowchart of literature review steps.*

A. 2. Data Synthesis and Analysis

The "Quantitative and Comparative Synthesis with Graphical Analysis" method was employed in the literature review. This approach involves collecting and organizing quantitative data, visualizing results using graphical tools, and comparing different variables to gain insights. A comparative synthesis is an approach that examines similarities and differences by making comparisons between different datasets, methods, or results. Quantitative synthesis is carried out transparently and consistently, with clear methodology statements, providing scientifically summarized information [34]. In comparative synthesis, instead of asking "Is something good?" the question "Is something better than another?" is addressed [35]. The graphical analysis method examines and presents datasets using visual tools. This method involves creating graphs, charts, and diagrams to identify data trends, relationships, and patterns.

After establishing the necessary limitations within the scope of the study, the first step was data collection, and the collected data were organized by creating Excel tables. The headings under which the data were grouped are listed below:

- Year of publication
- Research keywords and other keywords used in the articles
- Publisher/database where the research was published
- Country where the research was conducted
- Material examined/produced within the research
- Material parameters included in the research
- Method used to determine the SAC in the study
- AI method examined in the research
- Analysis of the correlation between the model and measurement results

After grouping the data under the main headings and creating tables, visualizations were made to observe trends and outcomes. Subsequently, a comparative analysis was conducted among the results, and the findings/conclusions were summarized.

III. FINDINGS

After applying all the restrictions, 245 research articles were initially identified. Following a review of the titles, keywords, and abstracts, 27 of these articles were relevant to investigating the applicability of artificial intelligence methods in determining the SAC of materials. The studies were organized according to the nine categories outlined in Section A.2.

Figure 3 presents the distribution of studies conducted in this field over the past ten years (2014-2024).

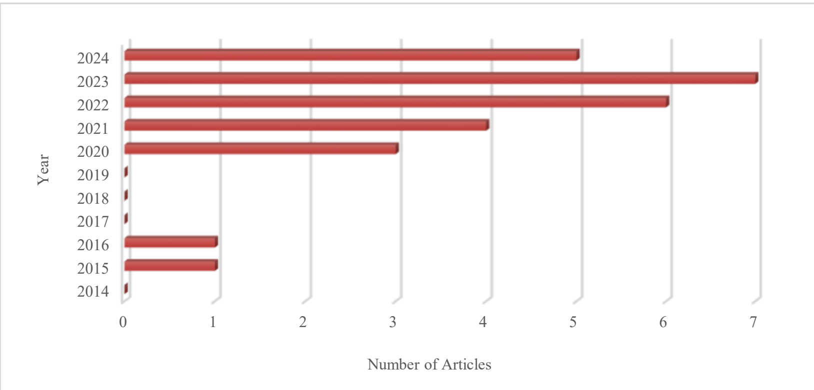

Figure 3*. Graph of the distribution of academic studies on determining the sound absorption co-efficient using artificial intelligence from 2014 to 2024 by year.*

Accordingly, research on predicting the SAC using artificial intelligence has notably increased over the past five years. This finding reflects the impact of advancing technology and the increasing accessibility of artificial intelligence tools.

Figure 4 presents the number of publishers/databases where the studies were published. The graph shows that most studies in this field were published in ScienceDirect and MDPI.

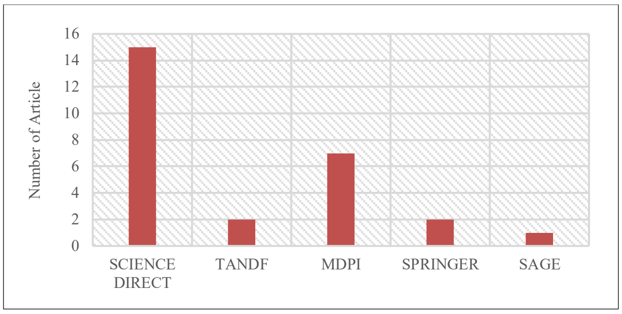

Figure 4. *Number of publications in the last ten years (2014-2024) by publisher/database.*

Figure 5 shows the distribution of studies on artificial intelligence models for SAC prediction by country across the identified publishers/databases. As illustrated in the figure, China encompasses the majority of researchers. China's larger population influences this compared to other countries, but it also reflects China's perspective on technological advancements and innovative approaches. Following China, Italy is identified as another significant country where innovative research on determining the SAC of materials is predominantly conducted.

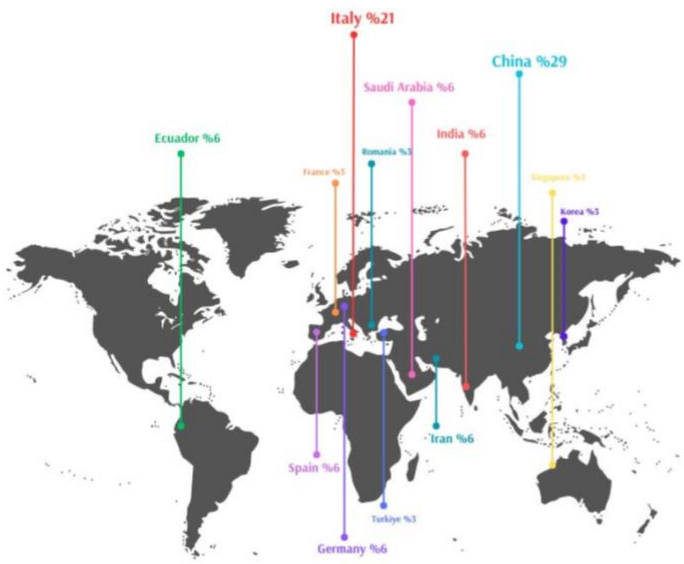

Figure 5. *Percentage distribution of studies on artificial intelligence models for predicting SAC by country in the last ten years .*

Figure 6 presents the keywords "Artificial Intelligence," "Sound Absorption," and "Material" used in the research process according to their usage proportions in the articles. The proportions are predominantly distributed across 'Artificial Intelligence' and 'Sound Absorption,' in line with the research title. Keywords used in the examined studies beyond the main keywords have been synthesized to provide insights for future research and are grouped under the main keyword headings, as shown in Figures 7, 8, and 9.

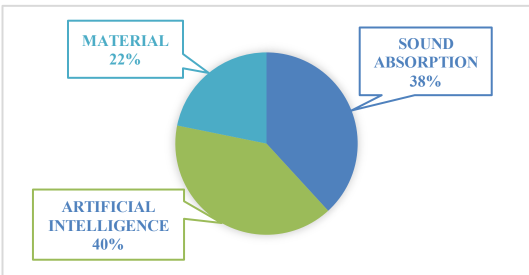

Figure 6. *Percentage usage of keywords examined in the research across studies.*

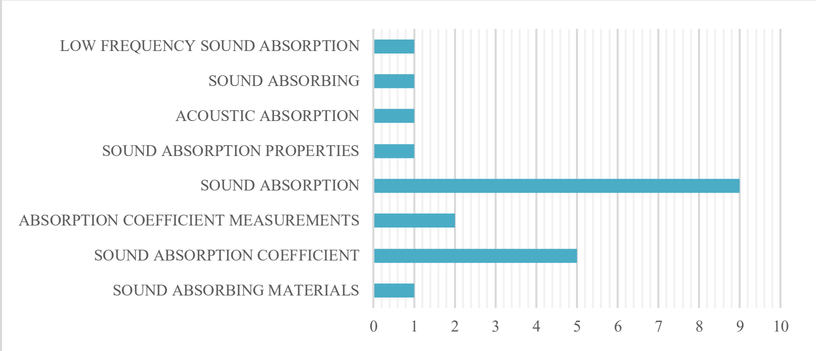

Figure 7*. Additional keywords used in studies under the primary heading of sound absorption.*

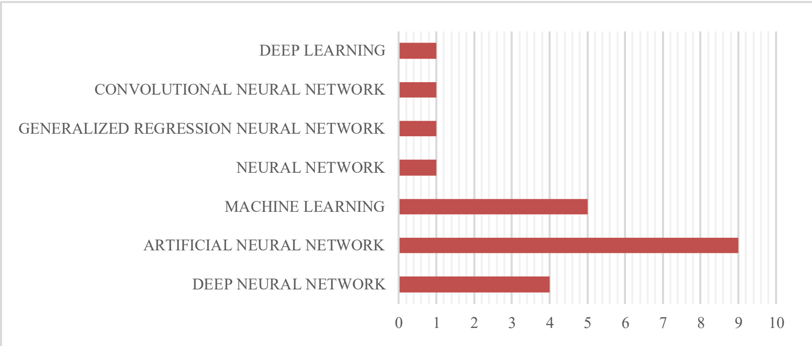

Figure 8*. Additional keywords used in studies under the primary heading of artificial intelligence.*

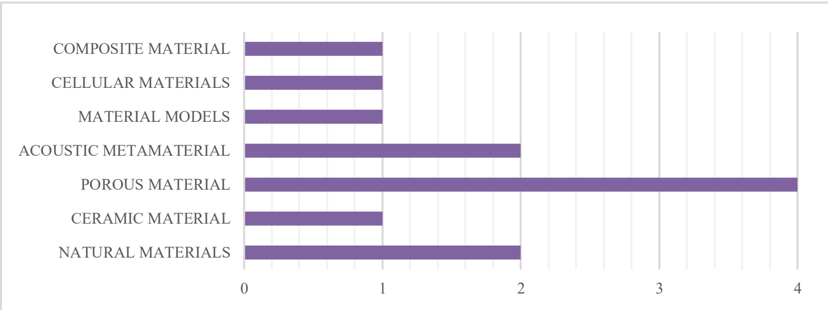

Figure 9*. Additional keywords used in studies under the primary heading of materials.*

Upon reviewing the results, it is observed that while "sound absorption" is predominantly used as a main heading, the method for "Artificial Intelligence" is directly included in the keywords. Similarly, for the "materials" group, the specific material is often included as a keyword. Detailed keyword usage for specific studies is considered a positive approach.

Another key heading in the study is the material parameters examined in the research. Various physical parameters affecting the SAC in materials have been considered to analyze the factors influencing sound absorption. As shown in Figure 10, material thickness is frequently investigated as a parameter affecting sound absorption in materials. Material thickness is particularly effective at low frequencies, so assessing thickness is beneficial when proposing innovative materials. Another significant parameter is the pore width in porous materials. The width of the pores affects the amount of friction as sound waves travel through the material, making it a crucial parameter to investigate in porous and fibrous materials. Beyond these two parameters, studies have also explored the effects of fiber physical properties (such as fiber diameter, fiber size, and fiber arrangement), material density, the number of layers in layered materials, and air gaps in Helmholtz resonators and layered structures on sound absorption. These material parameters are used as inputs in AI models, highlighting their importance in detailing model design.

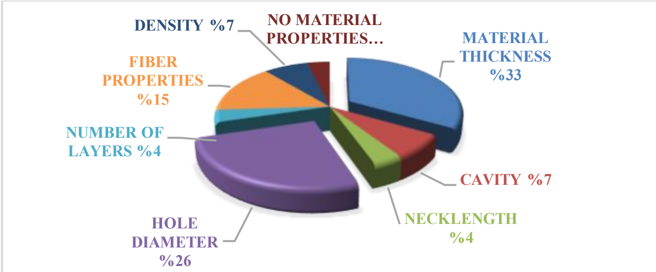

Figure 10*. Material parameters examined in studies that affect sound absorption.*

The methods used in the articles to determine the SAC in materials were examined in the next phase of the study. As shown in Figure 11, it is evident that, as mentioned in the introduction, the impedance tube method is the most commonly preferred method for determining the SAC in academic studies. The second most preferred method for SAC determination is COMSOL Multiphysics. In COMSOL, after defining the material properties and sound source, the necessary algorithms are created according to the acoustic defects. The sound absorption coefficient is determined based on the ratio between the incoming sound energy and the absorbed energy. Although practical for reaching results, there can be issues with the accuracy of the results due to environmental conditions in measurements like impedance tubes or reverberation rooms. Calculations have also emerged as another preferred method in the studies. Other methods have been used in various studies as well. Nevertheless, in studies using methods such as simulations, it is recommended to use the impedance tube method comparatively for reliability.

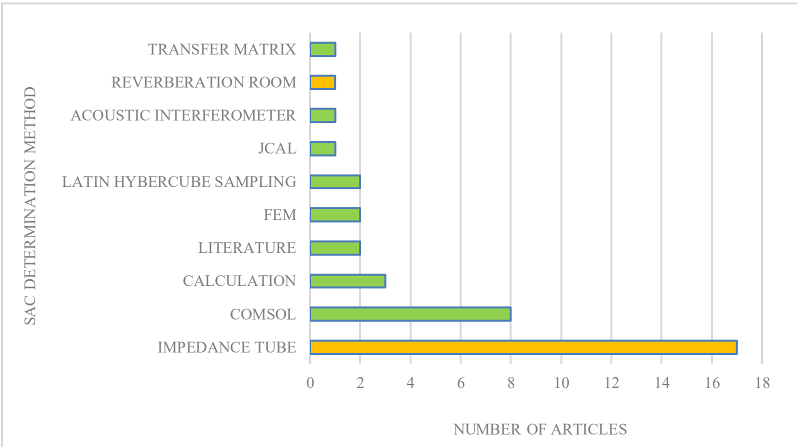

Figure 11*. Number of measurement/calculation methods used in academic studies for determining SAC.*

In the final stage of the findings, the AI programs used for SAC prediction in the articles were examined, and the results are presented in Figure 12. The AI models and techniques were categorized into five groups. Table 1 presents the methods within these five groups and provides a reference table for the research articles examined in the systematic review that utilized these techniques.

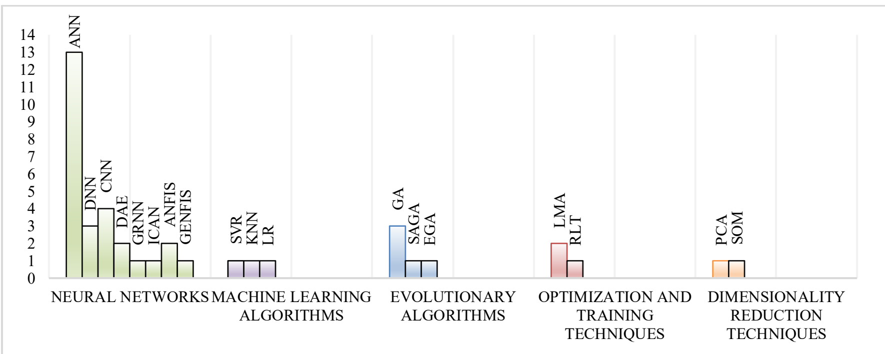

Figure 12*. AI Techniques and Models Used in Studies for Predicting SAC.*

Table 1. Categorized AI models and techniques.

AI Main Category	AI Secondary Category	References
Neural Networks	ANN (Artificial Neural Networks)	[36]; [37]; [38]; [39]; [40]; [31]; [41]; [42]; [43]; [44]; [45]; [46]; [47]
	DNN (Deep Neural Networks)	[48]; [49]; [50]
	CNN (Convolutional Neural Networks)	[51]; [52]; [53]; [54]
	DAE (Denoising Autoencoder)	[55]; [48]
	GRNN (General Regression Neural Networks)	[56]
	ICAN (Independent Component Analysis Network)	[50]
	ANFIS (Adaptive Neuro-Fuzzy Inference System)	[36]; [31]
	GENFIS (Genetic Fuzzy Inference System)	[36]
Machine Learning Algorithms	SVR (Support Vector Regression)	[57]
	KNN (K-Nearest Neighbors)	[40]
	LR (Linear Regression)	[37]
Evolutionary Algorithms	GA (Genetic Algorithm)	[31]; [54]; [58]
	SAGA (Self-Adaptive Genetic Algorithm)	[54]
	EGA (Evolutionary Genetic Algorithm)	[54]
Optimization And Training Techniques	LMA (Levenberg-Marquardt Algorithm)	[38]; [45]
	RLT (Reinforcement Learning Techniques)	[15]; [60]
Dimensionality Reduction Techniques	PCA (Principal Component Analysis)	[59]

In the studies, approximately 35% of the different AI models were used together, and comparisons were made between measurement results and AI models. In some studies, regression results (R2) were provided, while in others, it was stated that there was a high correlation with the measurement results, but no numerical value was given. In some cases, the absolute error margin (MSE) was reported. Indicators of the agreement between AI models and measurement results are presented in Table 2.

Table 2. AI Model-calculation/measurement compatibility.

AI Model	Compatibility	References
Neural Networks / **ANN**	$\mathbf{R^2}$ = 0.95	[44]
	$\mathbf{R^2}$ = 0.8	[45]
	$\mathbf{R^2}$ = 0.93	[42]
	$\mathbf{R^2}$ = 0.99	[46]
	$\mathbf{R^2}$ = 0.986	[39]
	$\mathbf{R^2}$ = 0.894	[41]
	Comment: High	[43]; [47]
Neural Networks / **DAE** and **DNN**	**MSE** = 0.00487 **Comment:** DNN > DAE	[48]
Neural Networks / **DAE**	**MSE** = 0.0122 (DNN)	[55]
Neural Networks / **CNN**	**MSE** = 0.028	[52]
	$\mathbf{R^2}$ = 0.98	[53]
	Comment: High	[51]
Neural Networks / **GRNN**	**MSE** = 0.017	[56]
Neural Networks / **ICAN**	**MSE** = 0.04	[50]
Machine Learning Algorithms / **SVR**	**MSE** = 0.98149	[57]
Evolutionary Algorithms / **GA** and **SAGA** and **EGA**	**Comment:** High	[54]

Optimization And Training Techniques / **RLT**	**Comment:** High	[60]
Neural Networks / **ANN** and Evolutionary Algorithms / **GA**	**MSE** = 0.11	[31]
Neural Networks / **ANFIS** and Evolutionary Algorithms / **GA**	**MSE** = 0.17	[31]

AI Model	Compatibility	References
Neural Networks / **ANN** and **ANFIS** and **GENFIS**	**Comment:** ANFIS has a higher correlation	[36]
Neural Networks / **ANN** and Machine Learning Algorithms / **LR**	**R^2** = 0.989 (ANN) **R^2** = 0.571 (LR)	[37]
Neural Networks / **ANN** and Optimization And Training Techniques / **LMA**	**R^2** = 0.9	[38]
Neural Networks / **ANN** and Machine Learning Algorithms / **KNN**	**Comment:** High	[40]
Dimensionality Reduction Techniques / **PCA**	**Comment:** Higher correlation but needs more research	[59]

IV. DISCUSSION

This study reviews the literature on using artificial intelligence (AI) models for determining sound absorption coefficients. 2,146 articles were retrieved from Science Direct, Taylor and Francis, MDPI, Springer, and Sage databases. After applying filters based on year, article type, research area, title, and abstract, 27 articles were selected for in-depth analysis. These articles were categorized and evaluated based on publication year, keywords, publisher, country, material properties examined, SAC determination methods, and AI model performance. The following summary highlights the observed trends in existing research within the literature:

- In recent years, the application of Artificial Intelligence (AI) techniques in predicting the sound absorption coefficient (SAC) has increased significantly, primarily due to the high costs and time demands of experimental processes. China has emerged as the leading country in this field, with approximately 80% of studies utilizing experimental measurements conducted through impedance tubes, followed by optimization studies employing AI. By substituting experimental measurements with AI models, these studies aim to achieve significant savings in both time and cost.

- The fact that studies have been conducted in both developed countries, such as Italy, and developing countries, such as Ecuador, indicates an interest in sustainability across nations with varying economic and geographic conditions, as reflected in the preference for natural fibrous materials. The evaluation of natural materials using artificial intelligence models for determining sound absorption coefficients in these studies represents a significant step toward promoting alternative materials aligned with environmental sustainability goals.

- The analysis reveals that neural network-based techniques are the most commonly used methods, with Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Deep Neural Networks (DNN) standing out among these models. This preference can be attributed to these models' strong learning capacities and ability to effectively process complex data relationships in predicting sound absorption coefficients. Specifically, ANN is valued for its broad applicability, CNN for its high accuracy with visual and spatial data, and DNN for handling more complex prediction tasks due to its deep-layered structure. In particular, ANN is a cost-effective and fast option for smaller datasets. Given its over 90% correlation with measurement results, ANN is expected to see increased application in this field.

- Less commonly used models, such as General Regression Neural Network (GRNN) and Denoising Autoencoders (DAE), may be less favored due to their limitations in handling a smaller range of materials and parameters. Although one study [56] using the GRNN model reported a low mean absolute error of 0.017, it would be premature to make general conclusions based on the limited number of studies available. Similarly, another study [59] employing the less frequently used Self-Organizing Maps (SOM) and Principal Component Analysis (PCA) suggested that PCA could potentially be used for predicting sound absorption coefficients. However, it also highlighted the need for further research with a larger sample size.

- The impact of hybrid model usage on correlation was also examined in the studies. In one study [31], which combined ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) models with Genetic Algorithms (GA), the integration of ANN with GA enabled the model to reach optimal results more quickly; however, such algorithms require high computational power and, consequently, adequate hardware. In another study [54], which utilized GA, Self-Adaptive Genetic Algorithm (SAGA), and CNN, the combined method known as the Elitist Genetic Algorithm (EGA) appeared advantageous for solving complex problems. Still, they were not ideally suited for predicting sound absorption coefficients due to the extensive data requirements.

- As seen in Table 1, AI models are suitable as an alternative method for determining the sound absorption coefficient of materials. Over time, training AI models with more materials and parameters can increase their applicability. Creating a comprehensive material database will provide a significant foundation for improving the reliability of these models.

As the next step in this research, a comprehensive study on the physical and sound absorption properties of sound-absorbing materials is planned to make AI models usable within this framework.

V. CONCLUSION

This literature review examines existing studies in artificial intelligence approaches for determining the sound absorption performance of materials, highlighting key trends and gaps in the literature. Within the scope of this study, five keywords were identified, and publications from five different publishers/databases were reviewed, with restrictions based on publication year, article type, and research field. Publications obtained under these restrictions were further filtered by closely examining titles, abstracts, and, where necessary, content details to exclude works that, despite keyword alignment, did not align with the study's content focus. The findings reveal prominent topics such as the applicability and advantages of using AI in determining sound absorption coefficients for materials while identifying underexplored or overlooked areas in the literature. In particular, environmental factors like temperature and humidity significantly impact the sound absorption performance of materials; however, such data are often overlooked in computer-based studies, underscoring the need for further research in this area. Future studies incorporating environmental conditions as inputs for AI predictions are expected to enhance the knowledge base in this field. In conclusion, this study provides a framework that emphasizes the applicability of AI methods in assessing the acoustic performance of sound-absorbing materials, offering a time- and cost-effective approach that can guide future research in this domain.

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