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Automatic thermoacoustic monitoring for animal production facilities using a low-cost device

Jhoan Nicolas Ramos Niño
Magister Scientiae

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Dissertation submitted to the Agricultural Engineering Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Magister Scientiae*.

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ABSTRACT

NIÑO, Jhoan Nicolas Ramos, M.Sc., Universidade Federal de Viçosa, July, 2025. **Automatic thermoacoustic monitoring for animal production facilities using a low-cost device**. Adviser: Fernanda Campos de Sousa. Co-advisers: Robinson Osorio Hernández and Andre Luiz de Freitas Coelho.

The assessment of thermal and acoustic conditions in intensive animal production facilities is essential to promote animal welfare and increase productive efficiency. In this context, the general objective of this dissertation was to conduct a systematic review focusing on the acoustic environment in intensive animal production facilities and to develop a low-cost, automatic, and continuous monitoring system for evaluating the thermal and acoustic conditions in dairy cattle housing. This dissertation is composed of two articles that address the topic from complementary theoretical and technological perspectives. The first article presents a systematic review focused on the use of environmental sound and animal vocalizations in cattle (beef and dairy), poultry, and swine production systems. Following the PRISMA protocol and the PICO framework, 36 experimental studies were selected based on inclusion criteria such as publication in English, use of objective and quantifiable acoustic measurements, and clear technical descriptions of the procedures used. The studies were categorized into four thematic approaches: (i) the use of vocalizations as indicators of animal welfare; (ii) the characterization of environmental sound sources; (iii) the combined analysis of sound sources and vocalizations; and (iv) the evaluation of behavioral and physiological responses to acoustic stimuli. The second article comprises the development and validation of a low-cost prototype based on an ESP32 microcontroller, integrating thermal and acoustic sensors with automatic data storage on a microSD card. The thermal and acoustic environment of an intensive dairy cattle production facility was monitored, characterizing the air temperature, relative humidity, animal thermal comfort indices, such as the Temperature and Humidity Index (THI) and the Globe Temperature Humidity Index (BGHI) and specific enthalpy of air (h), and the noise levels and peaks in the different animal facilities of the system. Laboratory calibration indicated good general performance of most sensors used in the device, although limitations were observed in the accuracy of relative humidity measurements and the acoustic sensor's sensitivity at low sound levels. Field tests showed consistent responsiveness in identifying periods of higher thermal load and elevated noise exposure, confirming the device's applicability for environmental monitoring in intensive livestock facilities. These findings provide a robust theoretical and technological foundation for advancing environmental monitoring in animal production. Future work should aim to improve device components, particularly the acoustic sensor and sampling strategy. Furthermore, the findings of the systematic review highlights the need for more accessible, replicable, and robust technological solutions in order to explore the potential of sound as a real-time monitoring tool in commercial production environments.

Keywords: animal welfare ; bioacoustics; noise; sensors; sound measurement

RESUMO

NIÑO, Jhoan Nicolas Ramos, M.Sc., Universidade Federal de Viçosa, julho de 2025. **Monitoramento termoacústico automático para instalações de produção animal utilizando dispositivo de baixo custo**. Orientadora: Fernanda Campos de Sousa. Coorientadores: Robinson Osorio Hernández e Andre Luiz de Freitas Coelho.

A avaliação das condições térmicas e acústicas em instalações de produção animal intensiva é essencial para promover o bem-estar dos animais e aumentar a eficiência produtiva. Nesse contexto, o objetivo geral desta dissertação foi realizar uma revisão sistemática com foco no ambiente acústico em instalações de produção animal intensiva e desenvolver um sistema de monitoramento automático, contínuo e de baixo custo para avaliar as condições térmicas e acústicas em instalações para bovinos leiteiros. Esta dissertação é composta por dois artigos que abordam o tema sob perspectivas teóricas e tecnológicas complementares. O primeiro artigo apresenta uma revisão sistemática focada no uso do som ambiental e das vocalizações de animais em sistemas de produção de bovinos (de corte e leiteiros), aves e suínos. Seguindo o protocolo PRISMA e a estrutura PICO, 36 estudos experimentais foram selecionados com base em critérios de inclusão, tais como publicação em inglês, uso de medições acústicas objetivas e quantificáveis, e descrição técnica clara dos procedimentos utilizados. Os estudos foram categorizados em quatro abordagens temáticas: (i) o uso das vocalizações como indicadores de bem-estar animal; (ii) a caracterização das fontes sonoras ambientais; (iii) a análise combinada de fontes sonoras e vocalizações; e (iv) a avaliação das respostas comportamentais e fisiológicas a estímulos acústicos. O segundo artigo compreende o desenvolvimento e a validação de um protótipo de baixo custo baseado no microcontrolador ESP32, integrando sensores térmicos e acústicos com armazenamento automático de dados em um cartão microSD. O ambiente térmico e acústico de uma instalação intensiva de bovinos leiteiros foi monitorado, caracterizando a temperatura do ar, a umidade relativa, os índices de conforto térmico animal, como o Índice de Temperatura e Umidade (THI), o Índice de Temperatura de Globo e Umidade (BGHI) e a entalpia específica do ar (h), além dos níveis de ruído e picos sonoros nos diferentes setores da instalação. A calibração em laboratório indicou um bom desempenho geral da maioria dos sensores utilizados no dispositivo, apesar de terem sido observadas limitações na precisão das medições de umidade relativa e na sensibilidade do sensor acústico em baixos níveis sonoros. Os testes de campo demonstraram uma resposta consistente na identificação de períodos com maior carga térmica e maior exposição ao ruído, confirmando a aplicabilidade do dispositivo para o monitoramento ambiental em instalações pecuárias intensivas. Esses resultados fornecem uma base teórica e tecnológica sólida para o avanço do monitoramento ambiental na produção animal. Estudos futuros devem buscar aprimorar os componentes do dispositivo, especialmente o sensor acústico e a estratégia de amostragem. Além disso, os achados da revisão sistemática destacam a necessidade de soluções tecnológicas mais acessíveis, replicáveis e robustas, a fim de explorar o potencial do som como ferramenta de monitoramento em tempo real em ambientes de produção comercial.

Palavras-chave: bem-estar animal; bioacústica; ruído; sensores; medição sonora

SUMMARY

GENERAL INTRODUCTION

Demographic projections indicate that the global population could exceed 10.3 billion people by 2080 (United Nations Department of Economic and Social Affairs, 2024), generating new demands for agri-food systems, particularly in the production of animal-based foods. Over the past decade, the dairy sector has adopted a variety of technologies to raise efficiency while maintaining sustainability and animal health and welfare (Ali et al., 2020; Dayoub et al., 2024).

Dairy production has become increasingly intensive, leading farmers to adopt facilities for housing animals such as Compost Barn and Free Stall. At the same time, they have incorporated technologies that stabilize the thermal and environmental conditions of the facilities, automate day-to-day tasks and improve thermal comfort and animal well-being (Caldato et al., 2020). As a result, continuous monitoring of environmental variables has become essential, with special attention to air temperature, relative humidity, air velocity, solar radiation, light intensity and environmental noise (Baêta and Souza, 2012).

Thermal comfort is commonly evaluated with two classic indicators. The Temperature Humidity Index, introduced by Thom (1959), combines air temperature and relative humidity and is now widely used to characterize barn conditions. The Black Globe Humidity Index, formulated by Buffington et al. (1981), incorporates radiant heat. Both indices can be related to respiratory rate, milk production and reproductive efficiency. Some studies record THI and BGHI several times a day because readings that move outside recommended thresholds can reduce productivity and compromise animal comfort (Buffington et al., 1981; Giannone et al., 2023; Oliveira et al., 2025). In this context, air enthalpy has also been proposed as a complementary environmental descriptor, as it integrates temperature and humidity into a single measure of the thermal energy content of the air within animal facilities (Rodrigues et al., 2011).

Sound is another key environmental factor in animal production. Sustained exposure to high noise levels has been shown to undermine animal welfare. Reported effects include physiological and behavioral changes (Olczak et al., 2023) and disruptions to endocrine and reproductive function (Kight and Swaddle, 2011; Li et al., 2023), which conflict with the welfare principles defined by the Farm Animal Welfare Council (2009). Field investigations show that common farm machinery can generate sound levels that compromise cattle welfare. Broucek et al. (1983) measured tractor engines at 97dB and linked this exposure to higher blood glucose, increased leukocyte counts and lower hemoglobin in cattle. Ghaderi et al. (2019) recorded more than 100 dB from an MF285 tractor running at two thousand revolutions per minute. Willson et al. (2021) reported greater animal resistance during handling when a loud truck stood nearby. Mihina et al. (2018) measured sound pressure levels in several milking parlors and occasionally recorded values close to 110 dB.

Research in bioacoustics shows that livestock vocalizations mirror physiological and behavioral status. Specific call patterns have been linked to heat stress, feeding behavior, and other conditions (Aydin and Berckmans, 2016; Huang et al., 2021; McGrath et al., 2017; Wegner et al., 2019). Despite this progress, on-farm adoption remains limited because high-quality microphones are costly and the sector lacks agreed protocols for recording and processing large audio data sets (Oestreich et al., 2024; Roch et al., 2024).

These constraints are highly relevant to precision livestock farming, which depends on reliable, real-time information about environmental and physiological conditions to guide management (Lovarelli et al., 2023; Yin et al., 2023). Advancing this field will require accurate, robust and affordable tools that monitor thermal and acoustic variables simultaneously. Devices built with low-cost commercial sensors provide a practical route for automating such data collection. In light of this, the present dissertation is structured around two complementary chapters that address, from different yet interconnected perspectives, the integration of acoustic and thermal variables in animal production.

The first chapter reports a systematic review that examines how sound is considered in livestock production systems involving pigs, poultry and cattle. It analyses the use of acoustic data in intensive settings, outlining current applications, the research methods applied, and the species most frequently investigated. The review also flags several unanswered questions and practical challenges that that continue to hold back adoption on commercial farms. By charting these gaps, it offers clear guidance for future studies and highlights how acoustic tools can support day-to-day welfare monitoring.

The second chapter describes the design, construction and validation of a low-cost device able to track thermal and acoustic conditions around the clock in intensive dairy barns. Built with freely available hardware and software, the unit logs temperature, humidity and sound pressure at the same time and turns those readings into comfort indices such as THI and BGHI. Accuracy was assessed first in the laboratory and later in the field, where results were compared with certified instruments. The outcome is a practical, dependable and affordable tool that can fit seamlessly into commercial herds or research projects that seek to combine productivity with high welfare standards.

Together, these studies provide scientific and technological evidence on the relevance of thermal-acoustic environments in animal production and propose practical monitoring solutions that contribute to the advancement of more sustainable, automated, and welfare-centered production systems.

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CHAPTER I - SYSTEMATIC REVIEW OF ACOUSTIC MONITORING IN LIVESTOCK FARMING: VOCALIZATION PATTERNS AND SOUND SOURCE ANALYSIS

applied sciences

MDPI

Systematic Review

Systematic Review of Acoustic Monitoring in Livestock Farming: Vocalization Patterns and Sound Source Analysis

Jhoan Nicolas Ramos Niño [1], Fernanda Campos de Sousa [1,*], Carlos Eduardo Alves Oliveira [1,2], André Luiz de Freitas Coelho [1], Robinson Osorio Hernandez [3] and Matteo Barbari [4]

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Featured Application

An evidence map for study design in acoustic welfare monitoring. By synthesizing 36 experimental studies across cattle, poultry, and swine, this review collates recording setups, SPL scales, and frequency-based descriptors, and identifies gaps in calibration and reporting. These summaries support metric and device selection, data-acquisition planning, and interpretation of vocalization/noise under farm conditions, enabling comparable designs and gradual integration into precision-livestock workflows.

Abstract

Environmental sound and animal vocalizations provide non-invasive information for welfare assessment in livestock systems. This systematic review surveys their application in beef and dairy cattle, poultry, and swine, with a focus on environmental noise, vocalizations and the characterization of acoustic sources. Searches in Scopus and Web of Science followed PRISMA guidance and the PICO framework. After applying strict criteria that required peer-reviewed experimental studies in English, quantifiable acoustic data, and clear descriptions of measurement procedures, the review included 36 studies. Four approaches recur: vocalizations as welfare indicators; characterization of acoustic sources; combined analyses of vocalizations and sources; and evaluation of animal responses to acoustic stimuli. Recent work reports advances in recording equipment, signal processing, and precision livestock tools. Important challenges remain, including heterogeneous acoustic metrics, limited physiological validation, and difficulties applying models under commercial conditions. Overall, the evidence supports sound as a candidate for real-time monitoring and highlights the need for accessible, standardized methods. The findings provide a basis for future research and practical applications in welfare assessment.

Keywords: bioacoustics; animal environment; animal facilities; environmental noise; sound monitoring

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1. Introduction

Estimates suggest that by the year 2080, the global population is projected to reach 10.3 billion people [1], which will result in a substantial increase in the demand for animal-based food products. In this context, it is essential to intensify production systems while ensuring productive efficiency and addressing sustainability challenges. The adoption of innovative technologies plays a fundamental role in optimizing productivity, preserving natural resources, and improving animal welfare conditions [2,3].

Several aspects that promote animal welfare are closely linked to recent technological developments. As highlighted by [4], non-invasive monitoring technologies are becoming increasingly important in ensuring appropriate welfare standards. Real-time data collection systems have proven valuable in supporting decision-making processes in production settings by providing measurable indicators related to productivity, efficiency, and welfare [5]. An example of this is the development of precision livestock farming (PLF) tools that integrate environmental and physiological variables. In swine farming, for instance, such technologies have demonstrated great potential for supporting the development of future comfort and welfare indices [6].

The variables of interest in production facilities, which are mentioned by Baêta and Souza [7], include air temperature, relative humidity, air velocity, radiation, light intensity and noise. The latter has been pointed out by [8] as an emerging factor in the evaluation of thermal comfort and animal behavior. Its influence on animals' emotional state and health can ultimately compromise their welfare [9].

Recent studies have shown that environmental stimuli, including acoustic stimuli, influence physiological and behavioral well-being. Noise is considered a relevant stressor that can impair neuroendocrine, cardiovascular, and reproductive functions [10,11]. The advancement of monitoring technologies has also improved the precision with which these variables can be managed, reinforcing the importance of incorporating noise as a quantifiable parameter in environmental improvement programs [12].

Nevertheless, sound in animal production systems does not function exclusively as a stressor. Several studies have shown that sound can be a useful and non-invasive indicator of the physiological and emotional state of animals. Within the field of bioacoustics, vocalizations, acoustic signals, and environmental sound patterns have been analyzed as indicators of health, behavior, and thermal comfort.

In the case of swine production, prolonged vocalizations during the weaning phase were used to indicate the existence of stress [13]. Other studies have used acoustic analysis as a tool to evaluate welfare and thermal comfort in slaughterhouses and pig farms [14,15]. Likewise, poultry production systems have used vocal analysis, as demonstrated in [16], which found relationships between sound signals of laying hens with their welfare in enriched environments. Similarly, ref. [17] found acoustic patterns related to the feeding behaviors of broilers, generating a relevant contribution to the management and welfare in the facility.

Despite the growing interest in using bioacoustics as a control tool in animal production systems, its implementation still encounters some methodological challenges that have been pointed out in research papers and literature reviews. These include the lack of technical standardization for the use and analysis of acoustic variables [18], logistical barriers that limit access to specialized equipment [19], the absence of methodological standardization and variability in relating acoustic parameters to other parameters of interest in animals such as age, body size, and health status [20].

Although interest in acoustic monitoring within livestock production has increased in recent years, the available literature is still rather fragmented. Coutant et al. [20] reviewed advances in bioacoustics, with an emphasis on animal welfare indicators across different species, whereas [21] concentrated on specific applications such as the study of pig vocalizations. These reviews, however, stop short of offering a systematic comparison of methodologies, acoustic parameters, and outcomes across production systems. A further challenge that has been repeatedly highlighted is the absence of standardized protocols for sound recording, analysis, and interpretation [20], which complicates reproducibility and limits cross-study comparisons. Meanwhile, Precision Livestock Farming (PLF) has emerged as an important approach to promote the sustainable intensification of livestock production [22]. Berckmans [23] pointed out that acoustic information can serve as a valuable resource for tracking animal health and welfare in real time. Even so, its incorporation into PLF systems is still in its early stages.

Thus, the aim of the systematic review was to provide a comprehensive overview of studies that have evaluated sound in animal production systems, particularly in swine farming, poultry farming (broilers and laying hens) and cattle farming (dairy and beef). This review seeks to identify current trends, methodologies, and challenges, and to propose recommendations to guide future research and the technological application of acoustic monitoring for animal welfare assessment in intensive production systems.

2. Materials and Methods

2.1. Search Strategy

This systematic review was conducted exclusively using electronic formats from two databases: Web of Science and Scopus, selected for their broad coverage and scientific relevance. Grey literature sources, industry reports, and other academic databases were not included in the search strategy, which represents a limitation of the review but ensures methodological consistency and comparability of the selected studies. Data collection followed the PICO framework (Population, Intervention, Comparison, and Outcome), in accordance with the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [24]. This systematic review was registered in the Open Science Framework (OSF) under the identifier https://osf.io/e5ybj (accessed on 7 September 2025). Based on these criteria, key terms were defined and organized according to the acronyms presented in Table 1.

Table 1. Keywords used to search for papers in the Web of Science and Scopus databases, based on the PICO structure (Population, Intervention, Comparison and Outcome).

Acronym	Palabras Clave
Population	(((cattle OR cow* OR calves OR calf OR heifer*) AND (dairy OR lactating OR milking OR beef)) OR (chicken* OR "laying hen*" OR broiler* OR poultry) OR (pig* OR swine* OR sow* OR piglet* OR pork* OR "domestic pig*"))
Intervention	(facility OR facilities OR installation* OR farm* OR livestock OR "animal husbandry" OR "Precision Livestock Farming" OR "precision animal production" OR confinement* OR handling OR parlor* OR slaughter* OR nursing)
Comparison	((noise OR sound* OR acoustic* OR vocal* OR audio*) AND (sensor* OR sensing OR measurement OR quantification OR monitoring))
Outcome	("acoustic characteristics" OR dB OR decibel* OR Hz OR frequency OR "sound intensity" OR "sound level*" OR "sound pressure" OR "sound analysis")

*—employed to include alternative spellings of the words and/or expressions of interest, such as variations between US English and British English. Source: Authors.

2.2. Study Selection

Studies indexed in both databases from the first record in 1965 up to the most recent available date in October 2024 were included. However, the earliest article meeting the eligibility requirements was published in 1989, so the effective coverage of the final sample spans 1989–2024. In the preliminary stage, results from both sources were merged, and duplicate entries were removed using the R software environment [25] and the RStudio interface, version 4.4.2 [26]. However, due to inconsistencies in title formatting, a manual review was necessary to identify duplicate references not detected by the software. At this stage, J.N.R.N. (Author 1) and C.E.A.O. (Author 3) conducted the initial screening of records, followed by verification of categorization by J.N.R.N. (Author 1) and F.C.S. (Author 2). Any discrepancies were discussed collectively and resolved by consensus among all authors, who also contributed to finalizing the classification into thematic categories.

As an initial filter, only articles written in English were accepted. Non-experimental publications, such as literature reviews, theses, conference abstracts, and book chapters, were excluded. Subsequently, only studies meeting the following criteria, formulated as guiding questions, were selected:

- Was noise and/or sound measured in facilities housing dairy cattle, beef cattle, laying hens, broiler chicken, or swine?
- Were the measurements conducted within animal production facilities, slaughter-houses, or controlled research environments?
- Was the methodology and the equipment used for sound measurement in animal production described in detail?
- Were quantitative criteria applied to assess sound within animal production systems?

It is important to highlight that the last question served as a key inclusion criterion for filtering out articles that, although meeting the previous parameters, focused primarily on variables other than sound. This included studies that used sound data as input for machine learning (ML) models without providing a detailed description or evaluation of the sound measurement itself. The sequence of search and selection of studies is presented in flowchart format (Figure 1).

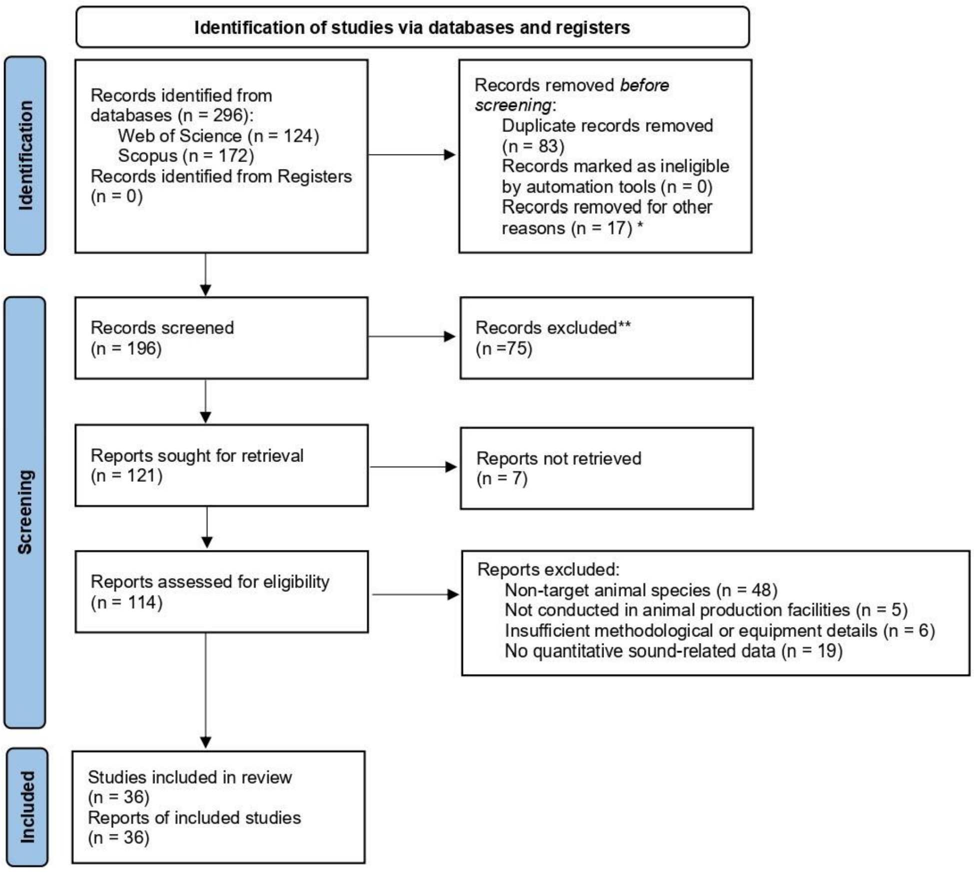


Figure 1. Flowchart indicating the sequence of search and selection of studies. * The language used is different from English. ** Non-experimental articles were excluded, and no automatic exclusion tools were used. Source: Adapted from [24].

2.3. Data Extraction and Data Processing

As a final step, relevant information was extracted from the 36 selected papers with the aim of addressing the research question posed in this systematic review. During this process, several aspects were analyzed, including general information for each article (such as title and objectives), characteristics of the animals studied (species or production category, age, weight, and so forth), and details regarding the location where the study was conducted (type of facility, country, and specific setting).

In addition, methodological aspects directly related to sound evaluation were reviewed, including the type of equipment used, the positioning of the devices, and the techniques applied. The most relevant findings reported by the authors were identified, distinguishing between variables directly related to sound and those that were non-acoustic, as well as the conclusions and future research perspectives indicated in each study.

Each article was then classified into one of the following thematic categories: (1) vocalizations as indicators of animal welfare, (2) characterization of sound sources, (3) combined analysis of sound sources and vocalizations, or (4) animal responses to acoustic stimuli. In cases where a study addressed more than one theme, classification was based on the predominant research aim described by the authors.

For example, Andrade et al. [27], who analyzed the amount of noise and gas concentrations within swine housing systems, were placed under (2) "characterization of sound sources". Similarly, Ferrari et al. [28], who analyzed the potential for characterizing sounds of cough from sounds of the background, were placed under (1) "vocalizations as welfare indicators for animals". Another example is Ferrari et al. [29], who presented acoustic features of sounds of cough based on pulmonary infection and compared them with coughs caused by citric acid, placed into (3) "combined analysis of sound sources and vocalizations". Finally, Lemcke et al. [30], who analyzed the effect of some genres of music on dairy cows that are milked from automatic systems, were placed under (4) "animal responses to acoustic stimuli".

The variables identified were categorized as acoustic (Table 2) and non-acoustic (Table 3). These tables include both the purposes or definitions of each category and specific examples extracted directly from the 36 papers analyzed in this study.

Table 2. Classification of sound-related (acoustic) variables.

Acoustic Category	Direct Examples	Purpose in the Studies
Sound-pressure level (SPL)	LAeq, Lmax, L10–L90 percentiles, dB (Lin), dB(A), dB(C), etc.	Quantify overall noise load.
Duration/time	Call duration, inter-call interval.	Analyze emission rhythms and temporal patterns.
Vocalization type/emission	Alarm, contact, estrus sounds, tractor noise.	Link the sound to its function or technical source.
Waveform/acoustic contour	Amplitude variation in the time domain, temporal envelope, number of pulses.	Segment signals; detect artefacts.
Overall acoustic profile	Spectro-temporal characteristics: timbre, entropy, roughness, global power spectrum.	Summarize the global sonic signature of a habitat or species.
Frequency	Fundamental f_0, formants, main resonance f*.	Used in the detection of sounds and stressful situations or animal health

Note: The asterisk (*) indicates the main resonance frequency (f*). Source: Authors.

Table 3. Classification of non-acoustic variables.

Category	What It Groups	Typical Examples Found in the Papers
Environmental conditions	Physical factors of the housing environment.	Relative humidity, air velocity, CO_2 or NH_3 concentration, wet bulb temperature, dust, etc.
Animal behavior	Observable actions or postures that signal welfare or stress.	Wing flapping in poultry, tail biting in piglets, pain related vocalizations, lying/standing time, cubicle occupancy.
Weight/development	Growth and body condition metrics.	Live weight, average daily gain, feed conversion ratio, heart girth circumference, body condition score.
Stress/physiology/health	Biochemical or physiological indicators of the internal state.	Salivary or serum cortisol, heart rate, respiration rate, plasma lactate, rectal temperature, lesion scoring.
Phenotype/classification	Genetic or morphological traits that differentiate groups.	Breed, genetic line.
Management/routine	Human imposed housing or experimental practices.	Number of milkings per day, feeding regime, fan/sprinkler cycles.

Source: Authors.

To facilitate the analysis and interpretation of the results, graphical resources and visual representations were employed in this review. Initially, a word cloud was generated using the R Bibliometrix package, version 0.3.0 [31], based on the metadata (titles, abstracts, and keywords) of the 36 articles selected after the full screening process. This approach enabled the identification of the most frequently occurring terms in the final sample, offering an overview of the main thematic trends addressed in the reviewed literature. The collected data were analyzed to identify temporal and thematic patterns across studies, as well as associations between animal categories, production phases, and acoustic variables. Additionally, co-occurrence analysis was performed to explore the relationships between acoustic and non-acoustic parameters.

As part of the data extraction process, information regarding the production stage of the animals studied was standardized. In the case of swine, terms used across studies varied, requiring harmonization to ensure consistent analysis. The review keeps terminology consistent by assigning each swine category to one production stage, guided by physiological traits and production goals. This approach recognizes four stages: nursery, growing, finishing, farrowing, and breeding and gestation. For instance, the terms “nursery pigs” and “nursery-to-finishing pigs” were placed under the nursery phase, while reproductive categories such as “sows,” “gilts,” and “gestating or breeding sows” were included in the breeding and gestation phase. This standardized approach facilitated more accurate comparisons across production contexts and research settings.

Risk of bias was evaluated using the Joanna Briggs Institute (JBI) eight-item checklist for analytical cross-sectional designs [32,33]. Two independent reviewers (J.N.R.N. and C.E.A.O.) performed the appraisal and reconciled discrepancies through consensus. The overall risk was categorized as low when ≥70% of applicable items were marked “Yes”; high when <70% were “Yes” and the share of “Unclear” judgments was ≤50%; and unclear when “Unclear” predominated (≥50% of applicable items or a tie). Plots and summary tables were created in RStudio interface, version 4.2.2 [26].

The statistical analyses and graphical outputs were performed using the following packages in the R statistical software: bibliometrix [31], tidyverse [34], readxl [35], dplyr [36], tidyr [37], ggplot2 [38], forcats [39], writexl [40], scales [41], RColorBrewer [42], stringr [43], terra [44], sf [45], ggrepel [46], viridis [47], ComplexUpset [48], igraph [49] and ggraph [50].

3. Results

As a first step, the metadata of the 36 articles (abstracts, titles and keywords) were used to generate a word cloud (Figure 2), which represented the most frequently occurring terms and provided an overview of the predominant themes in the literature review.

Figure 2. Word cloud generated from the metadata (titles, abstracts, and keywords) of the 36 selected articles. Note: A synonym dictionary was applied to unify terms during word extraction. The term "vocalisation" was standardized across spelling variants (e.g., "vocalization") and therefore appears as the consolidated form. Despite the use of American English throughout the manuscript, the unified term reflects the standardization applied during metadata processing. Source: Authors.

3.1. General Overview of Studies

The 36 studies included in Table 4 encompass a diverse range of research on the use of acoustics in animal production systems. Each study was classified under one of four thematic axes defined during the methodological phase: (1) vocalizations as indicators of animal welfare, (2) characterization of sound sources, (3) combined analysis of sound sources and vocalizations, or (4) animal responses to acoustic stimuli. This classification, indicated in the last column of Table 4, provides a structured basis for the subsequent analysis.

Table 4. Summary of the objectives of the 36 papers selected for this study.

Paper	Summary of Objectives	Thematic Axis *
[27]	Analyze noise levels and gas concentrations in swine housing systems.	(II)
[51]	Assess gas concentrations and sound pressure levels across three types of facilities for swine growing and finishing phases.	(II)
[52]	Assess the impact of acute noise exposure on stress responses in broiler chicken.	(IV)
[53]	Extract and classify acoustic features to develop a model for the identification of vocalizations in laying hens.	(III)
[29]	Describe the acoustic features of cough sounds associated with pulmonary infection and compare them with coughing induced by citric acid inhalation.	(III)

Table 4. *Cont.*

Paper	Summary of Objectives	Thematic Axis *
[28]	Investigate the feasibility of distinguishing cough sounds from background noise within a livestock facility.	(I)
[54]	Investigate the relationship between animal vocalizations and body weight.	(I)
[55]	Analyze and characterize chick vocalizations in relation to social behaviors and age progression.	(I)
[56]	Identify and validate a model linking broiler growth rate with peak vocalization frequencies.	(I)
[57]	Explore how vocalizations and phonatory behaviors of Holstein-Friesian cows during peripartum events (e.g., dystocia and calf separation) convey contextual and sensory information relevant to animal welfare assessment.	(I)
[58]	Determine whether individual swine can be identified through scream analysis in audio recordings.	(I)
[59]	Evaluate whether swine vocalizations are useful indicators of thermal adaptability.	(I)
[60]	Measure noise levels in three slaughterhouses (bovine and swine) using a smartphone application.	(II)
[61]	Update current knowledge regarding noise levels in swine farms in Germany.	(II)
[62]	Propose a robust system for behavioral characterization of laying hens to enhance monitoring efficiency.	(I)
[30]	Explore the effects of selected music genres on dairy cows milked by automated milking systems (AMS).	(IV)
[63]	Evaluate the immediate physiological and behavioral responses of piglets subjected to ear notching, ear tagging, and intraperitoneal transponder injection.	(I)
[64]	Investigate the relationship between vocal behavior and other behavioral traits in cattle.	(I)
[65]	Analyze the relationship between sneeze frequency and various strains of influenza virus in domestic swine.	(I)
[66]	Develop software to monitor piglet vocalizations based on stress-related sound patterns.	(I)
[67]	Identify and analyze the vocal responses of sows and piglets following short-term separation and assess the potential of such calls to indicate levels of arousal.	(I)
[68]	Identify changes in swine vocalizations during different stages of the castration process.	(I)
[69]	Evaluate the impact of multiple daily feedings on body weight, backfat thickness, aggressiveness, and locomotor issues in sows.	(I)
[70]	Determine whether the energy envelope dynamics of swine coughing sounds are associated with respiratory pathologies.	(I)
[71]	Test the hypothesis that noise levels in swine housing vary with time of day and season.	(II)
[72]	Evaluate the potential impact of sound measurements in swine facilities based on distance, time of day, building orientation, and season.	(II)
[73]	Examine the effects of two injection methods and two local anesthetics on piglet escape behaviors, including vocalizations and resistance movements, as well as procedure duration.	(I)

Table 4. *Cont.*

Paper	Summary of Objectives	Thematic Axis *
[74]	Investigate the effects of tartaric acid nebulization in swine finishing units.	(II)
[75]	Characterize the types of sounds swine are exposed to during housing, transport, and slaughter stages.	(II)
[76]	Assess the effectiveness of buprenorphine in mitigating pain during piglet castration using behavioral and vocalization indicators.	(I)
[77]	Understand vocal behavior in cattle under different stress conditions.	(I)
[78]	Conduct a situational analysis of noise levels in swine finishing farms and evaluate the adequacy of noise as a welfare indicator.	(II)
[79]	Assess the feasibility of segmenting animal vocalizations using electronic acoustic analysis tools.	(I)
[80]	Assess whether significant differences exist among acoustic characteristics of various vocal signals within a herd of crossbred cows.	(I)
[81]	Determine the frequency ranges of six common sounds in commercial broiler houses, including fans, heaters, feeding systems, vocalizations, wing flapping, and dust bathing.	(III)
[82]	Evaluate the effectiveness of low-cost, passive strategies for significant noise reduction.	(II)

* Each study was classified into one of the following thematic axes: (I) Vocalizations as indicators of animal welfare; (II) Characterization of sound sources; (III) Combined analysis of sound sources and vocalizations; (IV) Animal responses to acoustic stimuli. Source: Authors.

Figure 3 illustrates the distribution of studies across thematic categories. The most prominent theme is the use of vocalizations as indicators of animal welfare, representing 58% of the studies.

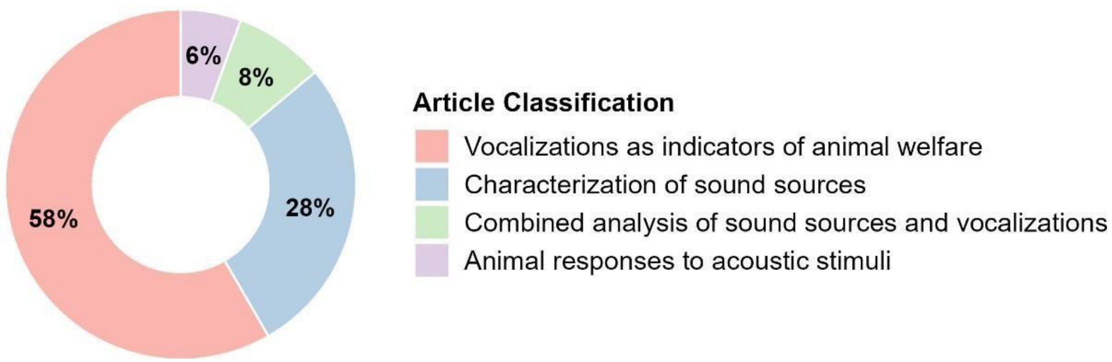


Figure 3. Graph showing the percentage distribution of papers among the thematic categories identified for the 36 selected papers. Source: Authors.

In this regard, several automated models have demonstrated the ability to detect specific vocal and behavioral patterns in laying hens, to detect behavioral patterns [53,62] to recognize individual swine screams [58], and to associate the peak frequency of broiler vocalizations with growth rate [56]. Studies found in swine production have used sneezing and coughing sounds as biomarkers of respiratory disease [29,65,70], and the intensity and duration of piglet squeals during procedures involving buprenorphine application as an indicator of pain [68,76].

Likewise, other research conducted on Holstein-Friesian cows has analyzed vocal modulation across peripartum phases [57] and as an individual personality trait [64]. Examples include the study by [54] that uses vocalizations in the estimation of body weight, and the study of sound emissions by [67], who evaluated the anxiety of gilts as a consequence of isolation.

The second most frequent category is the characterization of sound sources (28% of the studies). Some of these studies only measure sound intensities, as in the case of [61,78], who characterized the acoustic environment in commercial facilities in Germany. Others have presented other environmental variables as well as sound-related variables. This is the case of [27,51], who measured both sound intensity levels and concentrations of gases or dust. Other aspects related to the characteristics of the installations have also been studied, as in the case of [71,72] who analyzed the spatial and temporal variability of sound taking into consideration aspects such as distance to the source, orientation of the installation and seasonality. Ref. [82] also analyzed the effectiveness of low-cost barriers in reducing sound intensity. From the perspective of sound sources in facilities, ref. [81] identified, associated and mapped sound sources in broiler facilities, including fans, feeders and some animal behaviors such as wing flapping. Along the same lines, ref. [75] recorded and characterized the acoustic environment during the transport and slaughter of pigs.

A smaller part of the articles, corresponding to 8%, focus on a subject that combines the study of acoustic effects in animal production, both vocalizations and those generated by sound sources. The least represented theme (6%) includes studies on animal responses to acoustic stimuli, analyzing how different types of sound influence behavior and physiology. For example, acute noise exposure increases corticosterone levels and reduces weight gain in broiler chicken farming [52]. In dairy cattle, some studies have explored the impact of playing selected songs during automated milking routines [30].

Finally, Figure 4 provided a visualization of scientific production behavior over the years, highlighting that publication levels remained relatively stable until 2007, followed by a steady increase in research activity.

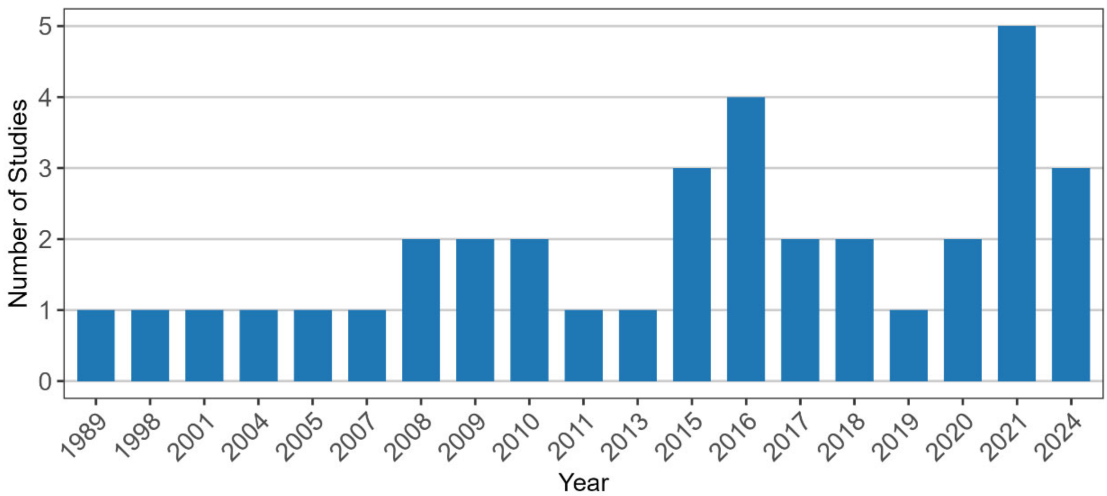


Figure 4. Number of annual publications on animal acoustics (1989–2024), of the 36 papers selected in this study. Source: Authors.

3.2. *Animal Production Context*

Figure 5 shows that 61% of the studies focus on swine. Research on dairy cattle and on broiler chickens each account for 14% of the total. The specific case of the multi-category study corresponds to the combination of swine and beef cattle in a slaughterhouse investigation conducted by [60]. Another relevant aspect is the type of facility where the studies were conducted. Figure 6 shows that the most balanced percentages are those corresponding to swine and poultry production studies.

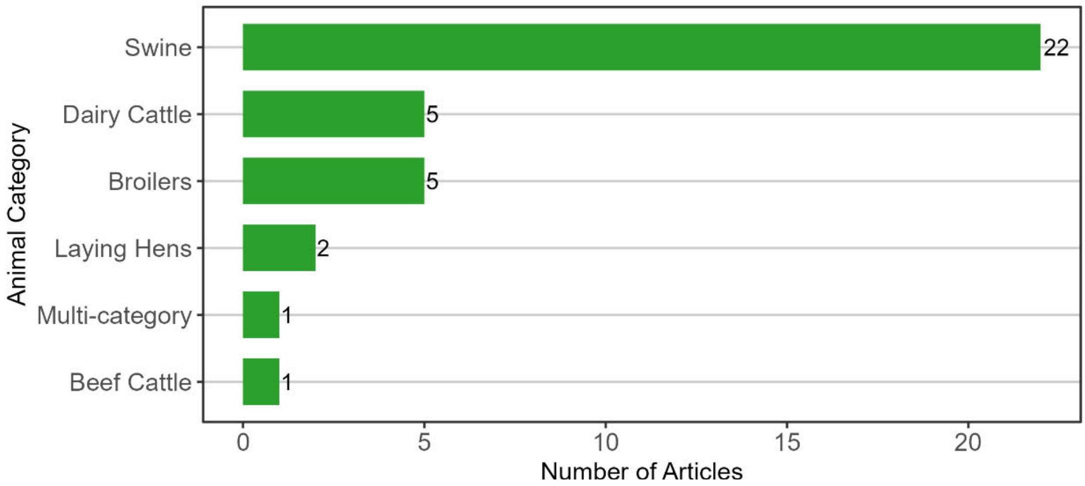


Figure 5. Number of publications by animal category, based on the 36 articles included in this review. Note: The multi-category study refers to the inclusion of both swine and beef cattle in a slaughterhouse investigation. Source: Authors.

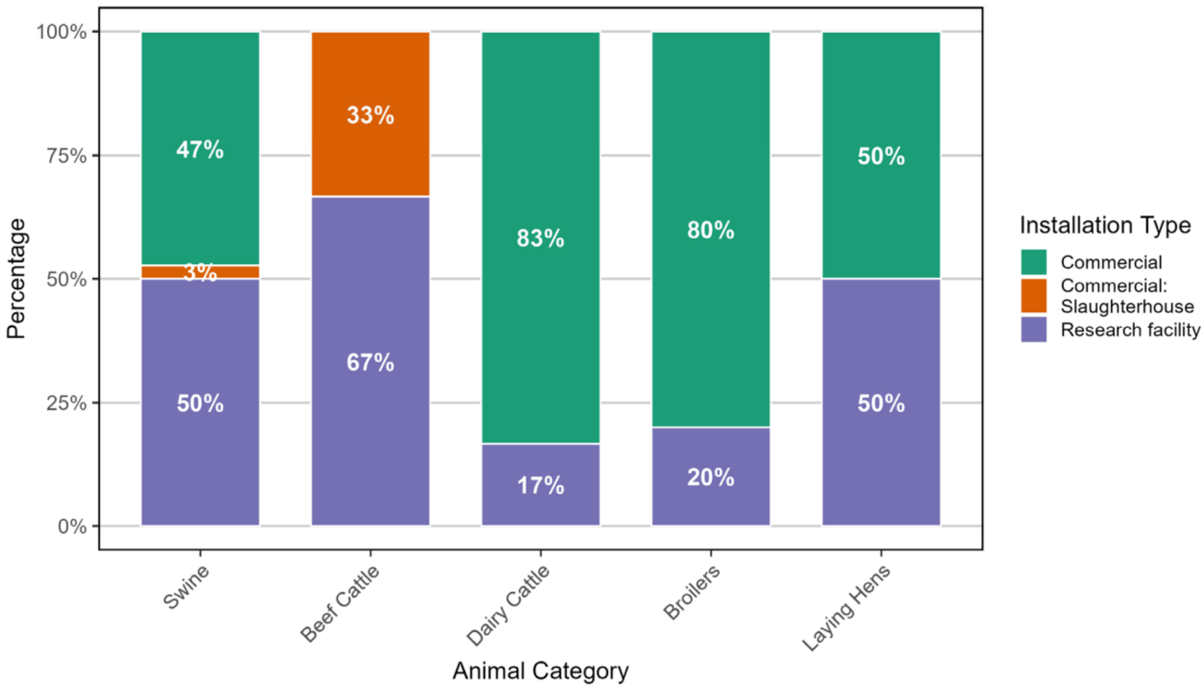


Figure 6. Percentage of studies by type of installation and animal species among the 36 articles included in the review. Source: Authors.

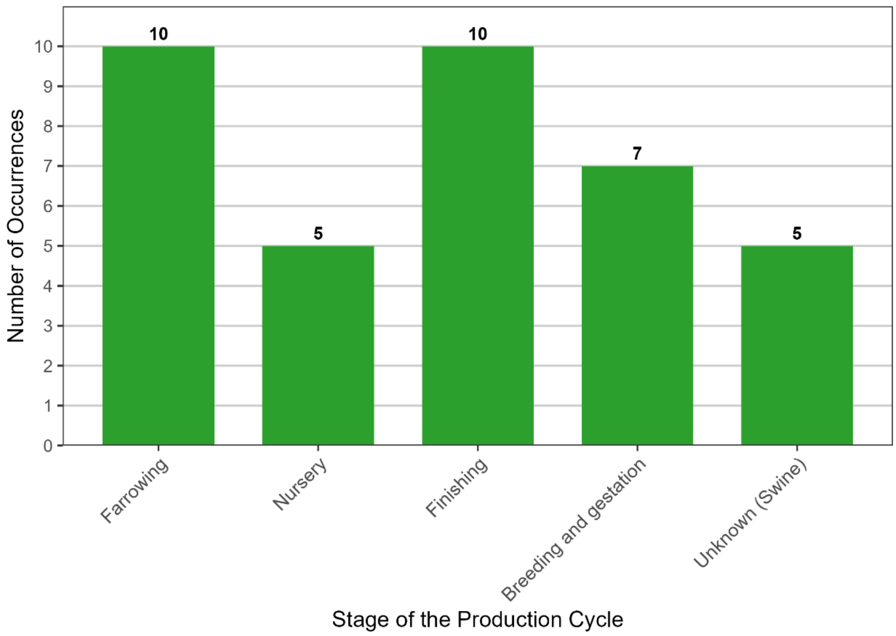
On the other hand, in broiler and dairy cattle, only between 17% and 20% of the studies were conducted in experimental facilities, which could limit the direct application of the results found. Also, in this review, only the study by [60] was found for commercial beef cattle facilities.

Figure 7A highlights a clear research focus on the farrowing and finishing stages of swine production, each covered by ten studies. Eight of the farrowing stage studies concentrate specifically on piglets. Breeding and gestation appeared in seven studies, whereas the nursery stage received the least attention, with only five studies.

In cattle (Figure 7B), the focus is divided between calves and lactating dairy cows, with three and four studies identified, respectively. Research has explored the role of vocalizations during critical events such as the peripartum period [57], responses to environmental noise under stress [77], and the positive influence of classical music in automated milking systems [30,83].

In poultry production (Figure 7C), acoustic research has primarily focused on the characterization of vocalizations and the identification of sound sources within housing environments. Notable among these is the work of [81], who identified frequency bands associated with various elements in broiler houses, including fans, heaters, feeding systems, vocalizations, wing flapping, and dust bathing. This characterization enabled the mapping of the internal sound environment and provided a basis for assessing environmental conditions from an acoustic perspective. Additionally, ref. [55] analyzed the progression of chick vocalizations throughout growth, linking them to social and developmental behaviors.

(**A**)



(**B**)

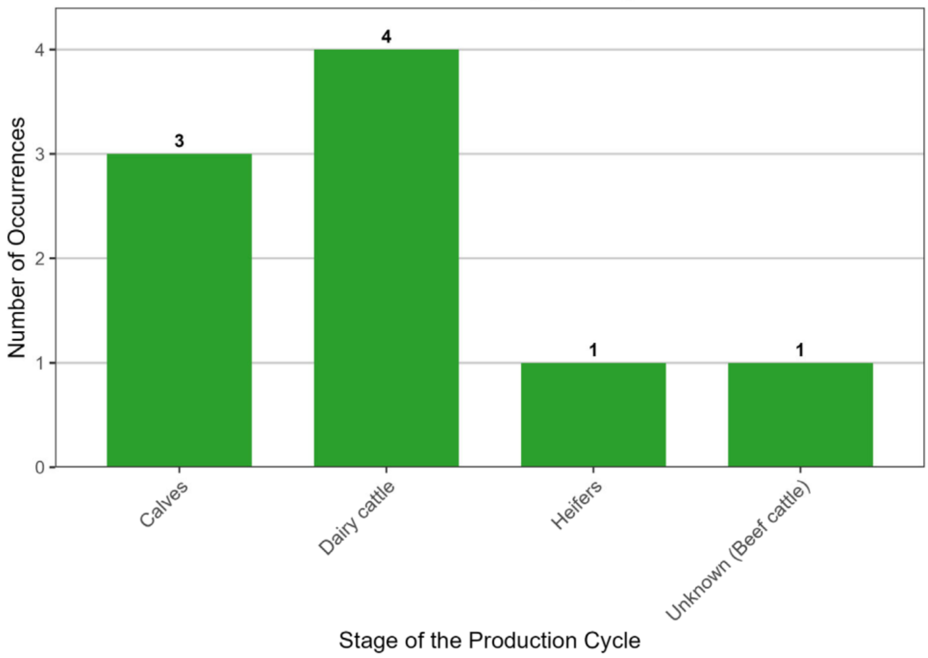


Figure 7. *Cont.*

(**C**)

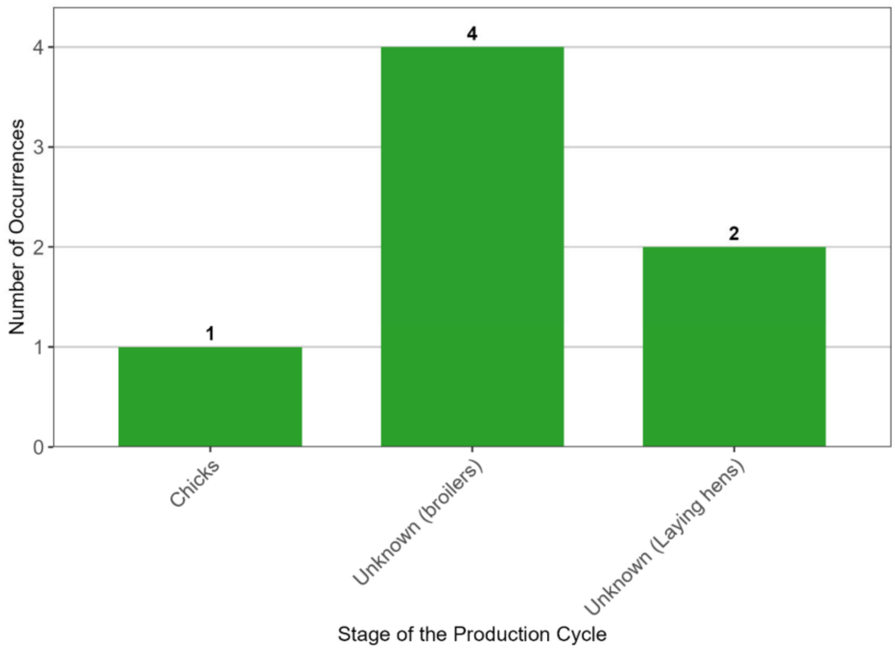


Figure 7. Number of occurrences of production phases in swine (**A**), cattle (**B**), and poultry (**C**) among the 36 articles included in this review. Note: Since some studies investigated more than one production phase, the number of occurrences exceeds the number of studies. An 'Unknown' category was included for swine, cattle, and poultry when the production phase could not be clearly identified from the study. Source: Authors.

However, the current landscape shows a predominance of studies on broilers without a defined growth phase (n = 4) and only one study focused on chicks, while two studies on laying hens did not specify the production stage.

3.3. Sound Capture Technologies

Early work in farm animal bioacoustics relied on straightforward studio microphones, for example, the Sennheiser MKH416 Tu3 and the Brüel & Kjær 4165, which researchers connected to portable tape recorders such as the Uher 4200 or the Racal Store 4DS [75,79].

Later work introduced high-sensitivity condenser microphones, including the Monacor ECM3005 and the Sennheiser ME67, which researchers plugged into laptops through sound cards such as the Realtek AC97 [28,29,57,70]. At the same time, projects that examined background noise in livestock buildings began to use hand-held sound-level meters like the Extech 407764 and the Voltcraft SL-300 [69,71,72,82].

Storage practices have evolved in step with recording hardware. In the late 1980s and 1990s, investigators preserved vocalizations on reel-to-reel or compact-cassette decks [75,77,79]. Most recent studies instead use solid-state recorders, for example, the Marantz PMD 661 MK II [56,57].

Similarly, several authors report using professional calibrators such as the Brüel & Kjær 4238 and the Norsonic AS 1251 to check levels before data collection [60,61,71,72,75,78,82]. However, many papers do not describe their calibration procedures. A detailed summary of the recording and calibration technologies reported in the reviewed studies, including representative brand/model examples and references, is presented in Table 5.

Table 5. Sound capture and calibration technologies reported in the reviewed studies.

Device Category	Representative Equipment (Brand/Model)	Typical Application	References
Early studio microphones	Sennheiser MKH416 Tu3; Brüel & Kjær 4165	Direct vocalization recording, often connected to analog tape recorders	[75,79]
Portable recorders (cassette/reel)	Uher 4200; Racal Store 4DS	Storage of vocalizations in early studies (1980s–1990s)	[75,77,79]
Condenser microphones	Monacor ECM3005; Sennheiser ME67	High-sensitivity recordings, often connected via laptop sound cards (e.g., Realtek AC97)	[28,29,57,70]
Sound level meters (SLM)	Extech 407764; Voltcraft SL 300	Background noise measurement in livestock housing	[69,71,72,82]
Solid-state recorders	Marantz PMD 661 MK II	Modern portable storage of acoustic data	[56,57]
Calibrators	Brüel & Kjær 4238; Norsonic AS 1251	Checking equipment levels before data collection	[60,61,71,72,75,78,82]
Video systems with external microphones	SOMO system (SoundTalks NV); other unspecified video + mic setups	Complement acoustic and visual data; automated detection	[56,62]
Multi-equipment setups	Microphone + SLM; microphone + video	Combine multiple data sources to enhance environmental and acoustic characterization	[57,64,65,73,81,82]

Note: The table summarizes the main sound capture and calibration technologies identified across the 36 studies included in this review. Not all articles specified equipment brands or models; therefore, the references listed correspond only to those studies that explicitly reported the use of the indicated devices. "SLM" refers to portable sound level meters used for measuring overall noise levels (e.g., dB(A), dB(C)). "Early studio microphones" refers to professional microphones (e.g., Sennheiser MKH416 Tu3, Brüel & Kjær 4165) employed in early farm animal bioacoustics studies, often connected to analog tape recorders.

In terms of device placement, two main strategies were observed. The first involved placing devices at a short distance from the animal, typically between 0.3 and 1.5 m. The second consisted of positioning the device slightly above the activity area, taking the ground level as a reference, particularly in broiler and swine housing environments [59,81].

Analysis of the proportion of technologies used by species reveals relevant differences (Figure 8). In laying hens, the use of video cameras was reported [62]. In broilers, a combination of microphones, sound level meters, and, to a lesser extent, specialized equipment such as the SOMO system by SoundTalks NV has been applied [56]. In swine and cattle, recording technologies are diversified and include condenser microphones, sound level meters, and video systems with external microphones.

An additional aspect highlighted in Figure 9 is the use of the term "multi-equipment", which refers to the simultaneous combination of more than one capture device within a single experiment. This strategy, documented in six of the reviewed articles [57,64,65,73,81,82], aims to complement acoustic information with visual data or environmental sound pressure levels.

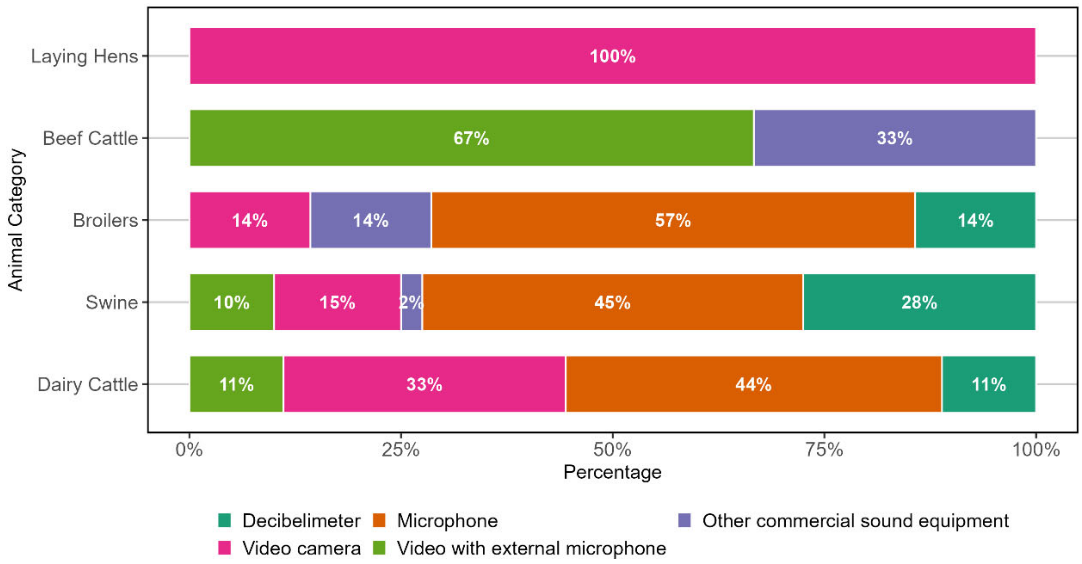


Figure 8. Proportion of recording technologies employed by species among the 36 studies included in the review. Source: Authors.

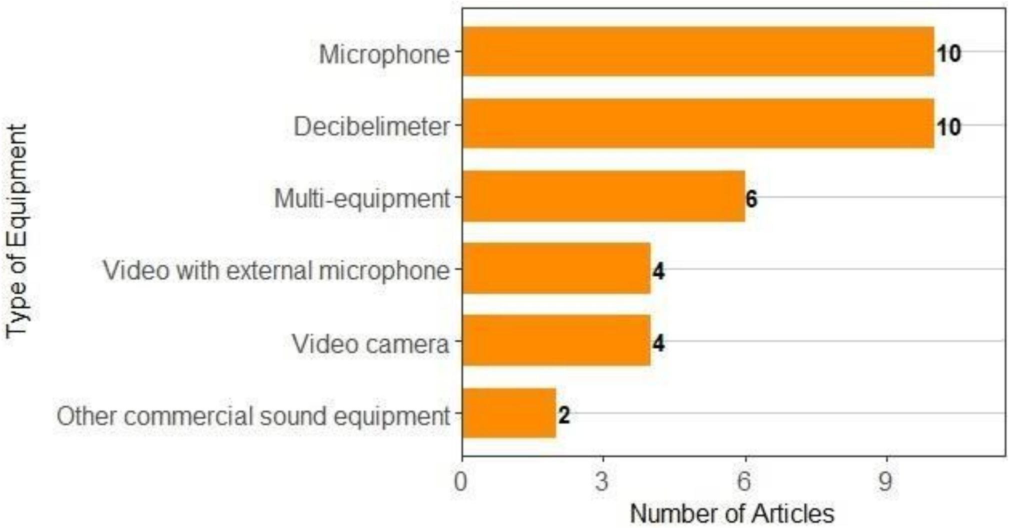


Figure 9. Number of studies by types of recording equipment used in the 36 selected studies. Note: The term "multi-equipment" refers to the simultaneous combination of more than one capture device within a single experiment. Source: Authors.

3.4. Variables and Parameters Assessed

Variables such as sound pressure level were expressed using different scales (dB, dB(A), dB(C)), while frequency-related parameters referred to various aspects of sound, such as fundamental frequency, mean frequency, and resonance frequency, despite sharing the same unit of measurement (Hz). In addition, several studies grouped multiple acoustic characteristics into general descriptions.

The analysis of variable co-occurrence provides a clearer view of the relationships established between acoustic and non-acoustic parameters (Figure 10). The network plot shows that the variable "frequency" occupies a central position in the network, connecting with duration, overall acoustic profile, and physiological or behavioral aspects. Complementarily, the UpSet plot (Figure 11) shows that the most frequent combinations involve "Frequency" alongside "Animal behavior" or "Physiology/health".

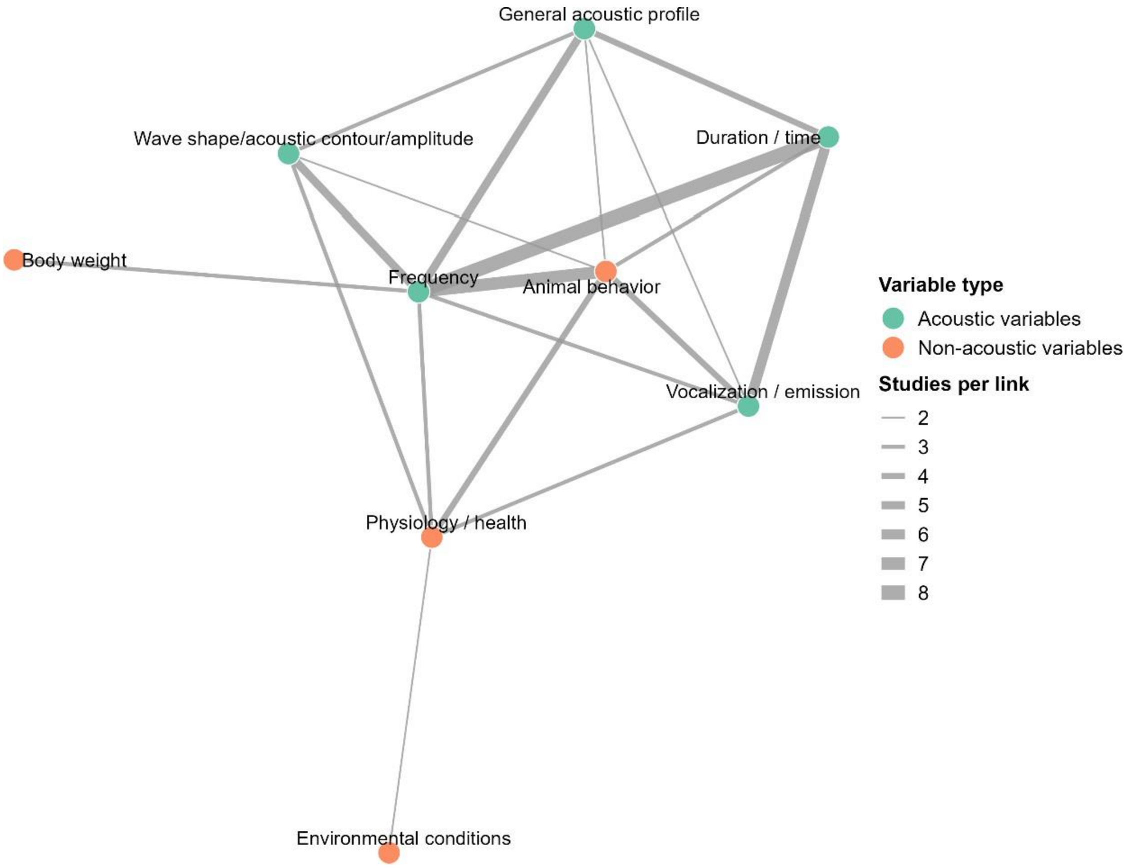


Figure 10. Co-occurrence network of acoustic and non-acoustic variables identified in the 36 selected studies. Note: The network includes only variable pairs that co-occurred in at least two of the 36 selected studies. Source: Authors.

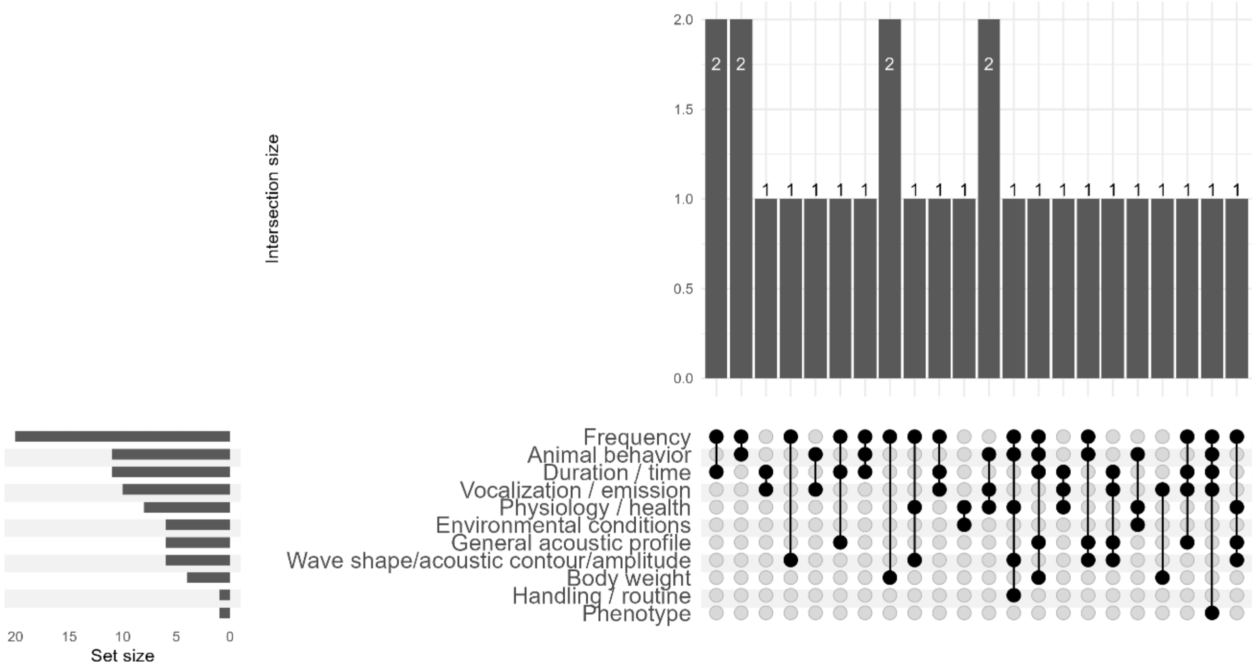


Figure 11. Co-occurrence of acoustic and non-acoustic variables in 26 out of the 36 selected studies, displayed using an UpSet plot. Note: Although the complete dataset includes 36 studies, only 26 are represented in the intersection plot, corresponding to those with co-occurrence of two or more variables. The set size bars on the left reflect all 36 studies. Source: Authors.

Finally, the risk of bias assessment showed clear inclusion criteria, adequately described exposure measurements, and appropriate statistical analyses across studies (Figure 12). Overall, 35 out of 36 studies presented a "Low" risk of bias, while 1 out of 36 was classified as "High". Questions Q5 and Q6, related to the identification and management of confounding factors, accumulated the majority of judgments other than "Yes".

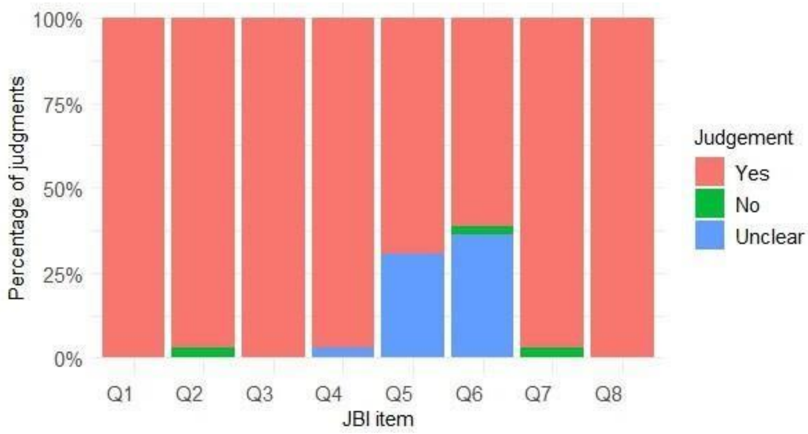


Figure 12. Risk-of-bias judgments for cross-sectional studies using the JBI checklist (Q1–Q8). Bars show the proportion of Yes/No/Unclear/NA per item. JBI items (Q1–Q8): Q1 Inclusion criteria; Q2 Subjects and setting described; Q3 Exposure measured validly; Q4 Standard criteria for the condition; Q5 Confounders identified; Q6 Strategies for confounders; Q7 Outcomes measured validly; Q8 Appropriate statistical analysis. Abbrev.: NA = not applicable. Source: Authors.

4. Discussion

4.1. General Overview of Studies

The prominence of terms in Figure 2 such as pigs, vocalization, animal welfare, noise, environment, acoustic and stress corroborates the notion that sound is primarily explored as an indicator of environmental conditions, management practices, or animal health in production systems. These preliminary findings indicate a particular concentration of research on swine, with frequent references to acoustic monitoring, sound analysis, and precision livestock farming.

The predominance of vocalization-focused studies in Figure 3 indicates a clear trend toward using animal-generated acoustic parameters to infer physical and emotional states. Conversely, the small proportion addressing responses to external noise suggests relatively limited attention to this approach within the reviewed literature.

Consistent with this trend, animal vocal emissions can reflect fear, pain, illness, or stress, and their spectral and temporal analysis has become a key tool for inferring physiological, health, or emotional conditions. Vocalizations are used from different perspectives as non-invasive indicators of animal welfare. For instance, they have been applied to monitor heat stress [59], which strengthens their role as a complementary tool in welfare assessment.

These data lay the groundwork for estimating the animals' actual noise exposure and for proposing operational limits. The discussion presented by [28] stands out, in which the difficulty of separating coughing sounds from background noise in production environments is detailed. Years later, ref. [53] provided a means of differentiating vocalizations from environmental interferences such as noise generated by fans. These studies demonstrate the challenge of analyzing vocalizations when mechanical and biological signals coexist, reinforcing the importance of acoustic source differentiation in welfare-focused research.

Exposure to unpleasant or unwanted sounds, which are defined as noise, may act as a relevant environmental stressor with physical and psychological effects [84]. Although not part of the 36 articles included in this review, ref. [85] highlighted that anthropogenic noise may lead to behavioral alterations, disrupted sleep, and even hearing damage in livestock animals. Additionally, ref. [86] reported that heifers show a clear preference for quiet environments over noisy milking parlors, as indicated by increased heart rate in the latter. These findings underscore the dual role of sound as both a potential stressor and a tool for welfare improvement in controlled environments.

Finally, the steady increase in research activity shown in Figure 4 may be attributed to enhanced accessibility to recording devices, as well as significant advances in signal processing and machine learning in industrial settings [87]. In particular, the rise in artificial intelligence has led to new applications in acoustic monitoring of animals, a trend clearly reflected in recent studies [88]. Institutional interest in promoting PLF has also strengthened this line of research. A notable example is the European Precision Livestock Farming (EU-PLF) initiative, launched in 2012, which brought together universities and companies, such as SoundTalks NV, with the aim of transferring PLF technologies to the industrial scale [89].

4.2. Animal Production Context

The histogram in Figure 5 suggests that slaughterhouses processing multiple animal species may face additional challenges related to traceability, since animals arriving at the facility can differ in characteristics such as breed and age. Additionally, Figure 6 reveals a low representation of acoustic research conducted in slaughterhouse facilities among the 36 selected articles. This knowledge gap may represent a significant opportunity for future studies, especially considering that the acoustic environment in slaughterhouses can have an impact on animal welfare. Evidence of this are the studies presented by [60,90] who observed handling resistance behaviors associated with noise from a noisy truck near the facility and documented sound intensity levels of up to 100 dB that could affect both animal and staff welfare.

In this sense, early detection of stress indicators through monitoring technology that combines sound sensors and artificial intelligence algorithms could represent an effective solution to mitigate animal welfare problems. This facilitates timely interventions and helps optimize inspection and quality control processes. A successful example is the STREMODO system, which employs sound analysis and neural networks to detect stress-related vocalizations in swine [91]. Furthermore, recent research shows that sensors integrated with artificial intelligence and acoustic analysis can identify anomalies by detecting vocal patterns associated with animal stress [92].

In the same way, the larger number of studies that examine the farrowing stage, many centered on piglets, could reflect the intensive handling routine procedures associated with pain, and the weaning stress characteristic of this period. A similar rationale may explain the attention given to finishing pigs, where management practices in the final production phase, including those that precede slaughter, raise specific welfare concerns. In comparison, the nursery stage has received less attention, leaving limited knowledge about the environmental and acoustic conditions that pigs encounter soon after weaning. Further research could fill this gap.

In cattle, acoustic research has mainly focused on the study of vocalizations as a tool for assessing physiological and emotional states. Complementing this line of research, ref. [93] demonstrated that the use of music significantly increased the voluntary approach of dairy cows to the pre-milking area, indicating a behavioral improvement associated with a favorable acoustic environment. Despite the advances observed in the dairy sector, the reviewed studies show limited attention to heifers and few investigations addressing acoustic aspects in beef cattle, particularly during critical stages such as finishing, where stress levels are considerable and could be assessed through specific sound patterns.

Although attempts have been made to use vocalizations as welfare indicators in beef cattle, the results have been limited and inconclusive. A meta-analysis on vocalizations during castration in beef cattle identified a high risk of bias, largely due to the lack of objective methods and the subjectivity involved in acoustic interpretation [94]. Similarly, ref. [95] found insufficient evidence to support the use of vocalizations as clear indicators of welfare in these animals.

Considering that acoustic research in cattle farming is still developing, it is necessary to apply multivariate analyses that enable an integrated evaluation of both animal welfare indicators and noise emissions in production facilities [96]. This methodological approach would support informed decision-making to optimize the acoustic environment, ensuring acceptable sound levels for animals in production and improving overall welfare conditions.

In poultry production, the ambiguous classification regarding age or physiological stage, labelled as "unknown", limits comparability between studies. Given the short life cycle of broilers, typically around 35 to 45 days, it is possible that studies with no phase specification may have covered the entire cycle. Nonetheless, it is important to standardize the description of production stages in order to strengthen scientific rigor and enable more comparative analyses.

It is also worth noting that differences in microphone placement and calibrations in swine, short production cycles of poultry, and the underrepresentation of beef cattle studies result in heterogeneous datasets that cannot be directly correlated with one another. This variability underscores the need for harmonized methods that allow more robust cross-species comparisons.

Chloupek et al. [52] studied how sudden noise affects a range of physiological stress markers in livestock. Expanding on that work, ref. [97] developed a non-invasive system for broilers that pairs pecking sounds with video footage to identify feeding behaviors, sparing the birds the disturbance of direct human observation.

Bioacoustic tools now also support remote welfare monitoring. For example, studies with laying hens have proposed automatic vocalization detectors to gauge thermal comfort [98]. Sun et al. [99] created a model that tracks the health of white-feathered broilers through their calls, while [100] used acoustic analysis to flag avian influenza at an early stage, achieving accuracy between 84% and 90%.

These advances show that bioacoustics in poultry production has moved steadily toward automated, non-invasive methods that spot early changes in health and welfare. The growing use of real-time sound capture and analysis in birds is now beginning to take hold in other livestock sectors as well.

4.3. Sound Capture Technologies

Early microphone and recorder setups were simple but reached 40 kHz, capturing the full spectral range of animal vocalizations. With direct digital recording, data handling became easier, and post processing grew more detailed. The transition to solid state recorders, with larger memory and higher sampling rates, let researchers archive long, high quality sessions with minimal data loss. Thanks to this upgrade, complex events, like the vocalizations produced by piglets during castration, can now be captured without losing fine acoustic detail [68].

Nevertheless, the limited reporting of calibration procedures observed in numerous studies may reduce reproducibility and comparability. On the other hand, the variability in device placement found in the 36 articles could reflect the adaptation of methods to the type of signal to be captured and the specific acoustic context of each installation.

Differences in the proportion of recording technologies across animal categories, as shown in Figure 8, may be attributed to a combination of factors, including the behavioral characteristics of each species, the feasibility of using certain devices without interfering with production activities, and the objectives of each study. For instance, research aiming to link animal behavior with welfare through vocalization analysis may rely primarily on video cameras, whereas studies focused on identifying the frequency content of animal vocalizations may prioritize devices such as microphones.

The combined use of microphones with video cameras, or microphones with sound level meters, allows for a more comprehensive characterization of the acoustic environment and the behavioral or physiological responses of the animals. Although microphones and sound level meters remain the most widely used technologies (Figure 9), the incorporation of emerging tools is noteworthy. These include mobile applications for sound measurement [60] and automatic vocal pattern recognition models [62]. Such innovations reflect a growing trend towards automation, portability, and real-time analysis in acoustic monitoring systems for animal production. Nevertheless, the limited number of studies per animal category poses a constraint in this review, preventing definitive conclusions about trends in the use of recording technologies across species.

4.4. Variables and Parameters Assessed

Heterogeneous units and parameterizations of acoustic variables impede direct comparison across studies, indicating the need for standardized protocols. Figure 10 places frequency at the center of the network, showing its ability to connect diverse acoustic dimensions and to serve as a key parameter in animal-production sound analysis. By contrast, 'Environmental conditions' and 'Body weight' display limited connectivity, mainly to 'Physiology/health' and 'Frequency', suggesting room to strengthen links between acoustic metrics and environmental and physiological variables.

Taken together, the results presented in the network plot (Figure 10) and the UpSet plot (Figure 11) underscore the importance of advancing towards more integrated experimental designs that simultaneously incorporate detailed acoustic metrics alongside biological, physiological, and environmental variables. Through this multivariable approach, sound could become a reliable and robust tool to support the objective assessment of health and welfare in animal production systems.

In this regard, the classification presented in Tables 2 and 3 can serve as a basis to guide future work by clustering non-acoustic and acoustic parameters within meaningful groups, useful when designing standardized terms and measuring procedures. While this review is not in a position to provide a detailed standardization, it highlights key aspects that should be consistently reported, such as calibration methods, sampling rates, and frequency ranges. These are key points crucial when seeking greater comparability and reproducibility between species and scenarios of production and for moving toward more unified approaches in future research.

4.5. Key Findings and Perspectives of the Articles

Evidence shows that acoustic analysis is gaining ground as a tool for assessing animal welfare, even though important methodological gaps persist. In swine, several studies link high-pitched, prolonged screams to intense pain or stress during routine procedures such as castration and ear tagging [63,68,73,76,79]. In cattle, vocal behavior varies by phenotype and can reveal how animals perceive a situation, yet these shifts rarely alter the acoustic properties of the calls [77]. Studies with Holstein-Friesian cows show that peripartum calls combine sound and posture, open mouth and tongue protrusion, to project the signal over longer distances, a feature thought to reflect the urgency of calving [57].

In poultry, the call's characteristics change with age and body weight, making them potential indicators of health and growth. Broilers, for instance, show a fall in peak frequency as they mature [54], while studies in laying hens have isolated acoustic traits that let algorithms sort calls into distinct categories [53]. Recurrent neural networks trained on chick vocalizations can even pick up early behavioral patterns [62]. Still, many investigations do not cross-validate sound data with physiology, and few compare results across breeds, ages, or management systems [64,67].

Acoustic monitoring is proving useful for health surveillance as well. Trials with swine show that classifiers built from cough recordings can tell sick animals from healthy pen mates [29,70]. In a related study, ref. [65] trained support vector machines to recognize sneezes linked to swine influenza and reported accuracy levels approaching 100 percent. Similar work in dairy calves isolates coughs by frequency and duration [28]. Though outside the scope of this review, broiler studies report more than 80 percent accuracy in spotting diseases such as infectious bronchitis and Newcastle disease [101].

However, the adoption of these tools in field conditions faces significant limitations. Background noise from equipment such as fans or engines, along with high inter-individual variability, can compromise the robustness of algorithms, which are often trained on limited datasets under controlled conditions. This challenge is also evident in animal production systems, where peak noise levels often occur during routine procedures or stressful events (such as handling or pre-slaughter operations), occasionally exceeding 120 dB, even when daily averages remain below 85 dB(A) [60,61,75,78].

Noise levels also shift with time of day, season, and wind direction [71,72], whereas barn design seems to play a lesser role [42,43]. Passive measures can dampen sound [82], and mobile apps now permit quick, low-cost audits in slaughterhouses [60]. Precision-livestock projects are starting to add acoustic streams to real-time dashboards that track stress, growth, and behavior [54,55,62,66].

Even so, high background noise and lower call rates in older animals often reduce system accuracy. These issues argue for multimodal setups that blend audio with computer vision and for automated labelling workflows that toughen models against on-farm variability. It is also worth noting that control equipment meant to improve climate can itself become a stressor, especially for pigs [74]. By contrast, the acoustic sensors themselves (e.g., microphones, sound level meters) are non-invasive tools and have not been reported to cause direct adverse health effects on animals.

Bringing noise readings together with temperature, humidity and gas measurements will allow producers to set combined thresholds that reflect the true environmental load animals experience. For sound to become a routine metric in precision farming, researchers still need to link key acoustic patterns to physiological responses, test their methods under a wider variety of farm conditions and strengthen the algorithms so they keep working despite the normal background clatter of a barn.

It should also be noted that aspects related to cost, scalability, and long-term practicality of acoustic monitoring technologies were not explicitly addressed in most of the reviewed studies. This represents a relevant gap, as the economic feasibility of these tools will be critical for their effective adoption in commercial farming systems.

In addition, the synthesis indicated a predominantly low risk of bias. Even so, deficiencies clustered in Q5 and Q6, where higher "No"/"Unclear" rates suggest that confounders were not consistently identified or addressed. Clear prespecification and transparent handling of confounders are recommended to mitigate this source of bias.

Although recent advances have incorporated machine learning (ML) into acoustic monitoring, many of these papers were excluded from this review because they reported sound data only as input variables without providing details about the recording protocols or acoustic parameters. This exclusion was necessary to preserve methodological comparability among the selected studies, yet it also highlights an important limitation: promising ML approaches could not be systematically assessed. Future systematic reviews specifically focused on ML applications may be able to address this gap by compiling and comparing quantitative performance metrics (e.g., accuracy, sensitivity, specificity) across studies.

In light of the heterogeneity observed across studies, generating quantitative recommendations such as specified sampling rates or general equipment configurations was not feasible. Even so, the synthesis identifies clear priorities for future work. These are the need to adopt common reporting conventions (e.g., calibrating methods, ranges of frequency, and device placement locations), and frequent joining of acoustic parameters and physiological markers for verification. These would then permit more robust and comparable datasets that can inform future meta-analyses to distinguish species-specific technical procedures and operating blueprints.

5. Conclusions

This systematic review provided an updated and detailed overview of research assessing sound in animal production systems, particularly in cattle, poultry, and swine farming. The findings show that scientific interest in acoustic analysis has grown steadily in recent decades, driven by advancements in capture technologies, progress in signal processing methods, and the strengthening of the precision livestock farming approach. Four main research themes were identified: (1) vocalizations as indicators of animal welfare, (2) characterization of sound sources, (3) combined analysis of sound sources and vocalizations, and (4) animal responses to acoustic stimuli.

Even so, several methodological hurdles still block routine use on commercial farms. Studies rely on a wide mix of metrics, follow no shared rules for calibrating equipment or collecting data, and seldom combine sound with physiological or environmental measures. Most models are built on narrow datasets and lose accuracy when tested in real barns. Addressing these gaps will call for stricter experimental design, larger and more varied databases and sturdier instruments that can cope with the noise and other interference found in production settings.

In this context, it is essential to move towards the development of technologies that are more accessible, replicable, and suited to field conditions, allowing for the effective integration of acoustic analysis with the evaluation of relevant environmental parameters. Moreover, enhancing the linkage between acoustic signals and physiological indicators remains a key challenge in establishing sound as a reliable biomarker of welfare. The evolution of automated systems for sound capture and analysis offers a strategic opportunity to strengthen both acoustic and environmental monitoring, contributing to more efficient, sustainable, and welfare-focused animal production systems.

Nonetheless, this study has certain limitations related to the eligibility criteria applied. Only articles published in English were included, which may have excluded relevant research disseminated in other languages, particularly from regions with strong local scientific production. Studies that used acoustic data as input for ML models were excluded if they did not report quantitative metrics directly associated with sound or with relevant environmental and physiological variables. This decision aimed to ensure a sufficient technical characterization of measurement methods, rather than limiting the analysis to the predictive performance of the models. Future reviews could consider expanding these criteria to explore more deeply the role of artificial intelligence in acoustic monitoring.

The results of this review indicate that in-practice application of acoustic monitoring is possible in livestock farming. Sound analysis provides in-real-time, non-invasive information that is supplementary to environmental and physiological variables and aids in the early detection of stress or disease and contributes to automated responses in the system of Precision Livestock Farming. Recent advances, such as the use of neural networks to recognize vocalizations or mobile devices for on-farm sound measurement, illustrate that these tools are moving from the laboratory into everyday farm routines. Extending their use in real conditions will help transform current research into practical strategies that improve animal welfare, productivity, and the sustainability of farming systems.

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CHAPTER II - LOW-COST DEVICE TO AUTOMATE THERMOACOUSTIC MONITORING IN INTENSIVE DAIRY CATTLE FARMING

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LOW-COST DEVICE TO AUTOMATE THERMOACOUSTIC MONITORING IN INTENSIVE DAIRY CATTLE FARMING

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HIGHLIGHTS:

- ESP32-based device automates thermoacoustic monitoring in dairy barns.
- Multi-sensor calibration ensured reliable field performance
- Validated performance under real dairy farm conditions.
- Harmful conditions detected; behavior and physiological validation needed.
- Flexible and low-cost design enables scalable deployment.

ABSTRACT: Thermal and acoustic environmental conditions in dairy production facilities directly affect animal welfare and productivity. Therefore, the aim was to develop and evaluate a low-cost device for the automated and continuous monitoring of thermoacoustic variables in intensive dairy production systems. The prototype integrates thermal and acoustic environmental variable sensors with an ESP32 microcontroller, offering real-time data display and storage on microSD card. Laboratory calibrations showed high accuracy, with most sensors reaching R^2 values above 0.95 and data acquisition efficiency exceeding 99%. However, limitations were identified in the accuracy of relative humidity data and acoustic sensitivity under low sound levels. Tests carried out in an intensive dairy cattle production system, in the Compost Barn, in the cooling room and the milking parlor revealed that cows were exposed to environmental conditions that exceeded the thermal comfort limits: air temperature ≥ 24 °C, relative humidity ≥ 75%, Temperature-Humidity Index THI, Black Globe-Humidity Index BGHI ≥ 74 and specific enthalpy of air h ≥ 74 kJ·kg of dry air^{-1}, observed during specific periods of the day, and sound levels above 85 dB(A), with peaks reaching 95 dB(A), also recorded during certain periods. The developed device indicated that it is a viable and scalable alternative for monitoring thermal and acoustic variables in animal production systems. Future improvements, such as the adoption of

other types of microphones and an increase in the number of samples, can further increase the reliability of the device developed to assist in data-based decision-making processes for management of production systems.

Keywords: Animal welfare; Dairy farming; Sensors; Sound measurement; Precision livestock farming**.**

1. INTRODUCTION

Brazil is the third-largest milk producer in the world, with 34,6 billion liters produced in 2022 (Embrapa, 2024). It is estimated that by 2030, both in Brazil and globally, there will be an increase in milk consumption and a reduction in the number of producers. Consequently, there will be a growing demand for higher animal productivity, which can only be achieved through further intensification of production systems (Embrapa, 2019). This scenario brings new challenges in pursuing increased yet sustainable production. Only through the adoption of technological solutions will it be possible to improve animal productivity without compromising environmental preservation and animal welfare.

Environmental control in animal production units involves studying the interactions between animals and their surroundings. Hence, there is a clear need for monitoring systems capable of continuously measuring key environmental variables in animal production systems, such as air temperature, relative humidity, air velocity, radiation, noise, and lighting (Baêta and Souza, 2012; Ferreira, 2005). Among the tools used to quantify the thermal condition of animal production environments are the Temperature-Humidity Index (THI) and the Black Globe-Humidity Index (BGHI).

THI developed by Thom (1959), is a thermal comfort index that integrates dry-bulb temperature and relative humidity (Giannone et al., 2023), serving as a tool for evaluating the thermal conditions of the environment for animals (C. P. Oliveira et al., 2025). Similarly, BGHI developed by Buffington et al. (1981) is an animal index of thermal comfort, combining the effects of dry-bulb temperature, relative humidity and radiation. It is directly related to the cows' respiratory rate and inversely correlated with milk production and reproductive performance (Buffington et al., 1981). Thus, monitoring these indices is essential for making the right decisions and ensuring both animal performance and welfare.

In addition to temperature-based indices, air specific enthalpy has been applied in environmental and agricultural engineering studies as an indicator of thermal conditions within buildings and cooling systems. According to (Rodrigues et al., 2011), enthalpy expresses the amount of thermal energy that must be removed from the air to achieve adequate indoor conditions. In this context, enthalpy offers complementary insight into the energetic characteristics of the air, especially in environments operating under mechanical ventilation and evaporative cooling systems.

Noise is another relevant factor in these environments. As shown by Olczak et al. (2023), excessive noise can negatively affect animal welfare and behavior, causing anxiety and fear, thus compromising the five freedoms defined by the Farm Animal Welfare Council (FAWC, 2009). Several types of equipment commonly used in dairy production systems can produce noise levels above the thresholds tolerated by animals, leading to stress and reduced welfare, which may affect productivity. Among the main sources of noise in dairy production systems include equipment used for milking and milk cooling, ventilation systems used for thermal regulation (particularly in cooling rooms and housing areas), tractors used for feed distribution, and, specifically in Compost Barn systems, mechanical equipment used in the process of bedding turning.

Studies have also explored the use of animal vocalizations to assess thermal comfort or stress conditions (Wegner et al., 2019) and to detect feeding behavior through machine learning techniques (Aydin and Berckmans, 2016). However, most investigations on noise evaluation in animal production (Andrade et al., 2020; Donofre et al., 2018; García Castro et al., 2019; Wegner et al., 2019; Willson et al., 2021; Yang et al., 2021) have relied on spot measurements obtained manually and/or using expensive equipment (Aydin and Berckmans, 2016; Mihina et al., 2018), without the ability to record data automatically and/or may be invasive to animal. Therefore, it becomes evident that there is a need to automate the process of data collection related to noise in animal production environments. Ideally, such collection should be continuous and carried out with minimal user intervention, in order to avoid behavioral disturbances caused by human presence. In this context, devices equipped with low-cost sensors represent a promising alternative for measurement and data storage processes, serving as precise, affordable, and reliable tools.

Thus, the aim was to design, construct and validate a low-cost device for the automated acquisition of thermoacoustic variables in dairy cattle production facilities, providing an innovative and accessible methodological tool.

2. MATERIALS AND METHODS

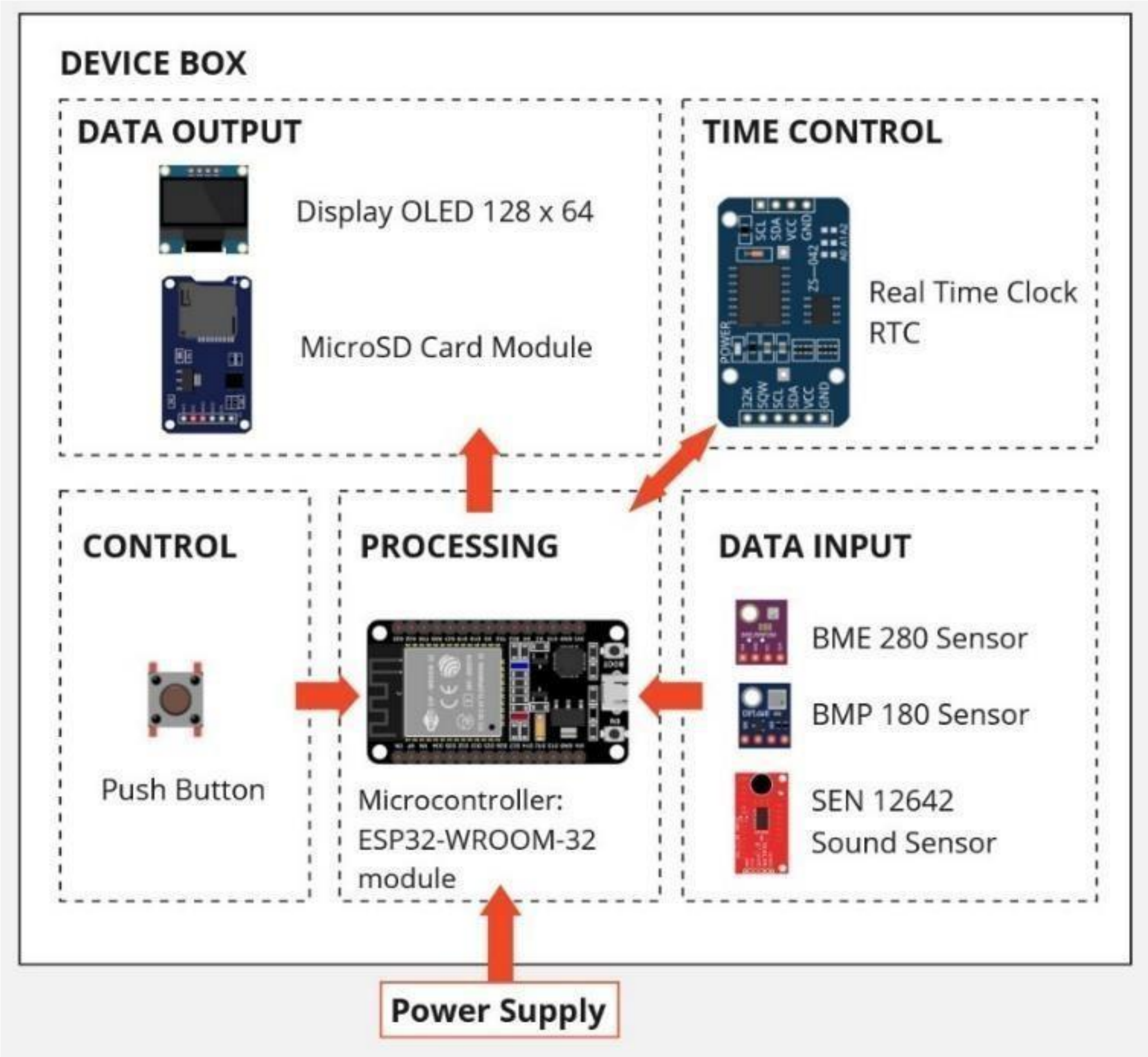
2.1. Device Development

2.1.1. Design

The development stages of the device were carried out at the Department of Agricultural Engineering (DEA) of the Federal University of Viçosa (UFV), Brazil. The hardware and software design focused on providing automated and continuous monitoring without the need for human intervention in the animal production systems. The sensor calibration procedure followed and adapted the methodologies described in the literature, specific for each sensor.

In order to determine the reproducibility of the design and assess the robustness of the data collected for field application, the developed device was produced in five replicas, applying statistical criteria to verify its reliability. It continuously and automatically measures dry-bulb temperature, black globe temperature, and relative humidity, which allows the calculation of the Temperature and Humidity Index (THI) and the Black Globe-Humidity Index (BGHI). Additionally, it records sound intensity. Data acquisition is preprogrammed prior to field deployment, allowing flexible adjustment of sampling intervals and data storage on a microSD card. To ensure replicability and maintain an economically viable solution, low-cost sensors were integrated into an ESP32 microcontroller, strategically arranged within a custom-designed and 3D-printed enclosure specifically developed for this device. Figure 1 presents the overall architecture and operational structure of the developed device.

Figure 1. Components of the device developed for monitoring the thermoacoustic environment in animal production



Source: Authors.

2.1.1.1. Hardware

The developed device is composed of various sensors and peripherals controlled by an ESP32 microcontroller. The integration of these components is designed to capture and store data, manage real-time display of information and present key variables. Dry-bulb temperature and relative humidity are measured using a BME280 sensor, while black globe temperature (used in the calculation of the BGHI) is recorded by a BMP180 sensor. Sound intensity is measured using a SEN-12642 sound sensor (featuring an electret microphone). All data are saved to an 8 GB microSD card via a dedicated module. Real-time information is displayed on a screen and can be accessed by the user through a push button, which also allows for device reset. The Real-Time Clock (RTC) module keeps track of the current time and continues operating even in the absence of power supply, thanks to the option of connecting an external battery. The technical specifications of the sensors are presented in Table 1.

Table 1. Technical characteristics of the sensors used in the developed device

Variable	**Sensor**	**Manufacture**	**Measuring range**	**Resolution**	**Operating Voltage**	**Interface / Output**
Dry bulb temperature	BME 280	Bosch Sensortec	– 40 °C a to 85 °C	±0.1 °C	1.71 V to 3.6 V	I2C and SPI
Black globe temperature	BMP 180	Bosch Sensortec	–40 °C to +85 °C	±0.1 °C	1.8 V to 3.6 V	I2C
Relative humidity	BME 280	Bosch Sensortec	0 % to 100 %	±3 % RH	1.71 V to 3.6 V	I2C and SPI
Sound intensity	SEN 12642	SparkFun Electronics	Not declared	Not declared	3.5 V to 5.5 V	Analogic (envelope and audio) and digital (gate)

Source: Authors.

The design of the device housing was carried out using the Onshape parametric design software PTC Inc (2024). Subsequently, 3D printing was carried out using the Fused Deposition Modeling (FDM) technique. Additionally, following the methodology proposed by Souza et al. (2002) for the black globe, a ping-pong ball made of polyvinyl chloride (PVC) was used, with a diameter of 0.036 m and a thickness of 0.0005 m, coated with two layers of matte black paint.

In addition to its technical functionality, assessing the economic feasibility of the proposed device is essential to ensure its replicability in similar research and development contexts. Table 2 presents a detailed breakdown of the estimated unit cost of the prototype, including electronic components, PCB manufacturing, and the material used for 3D printing the enclosure.

Table 2. Estimated Unit Cost Breakdown of the Thermoacoustic Monitoring Device

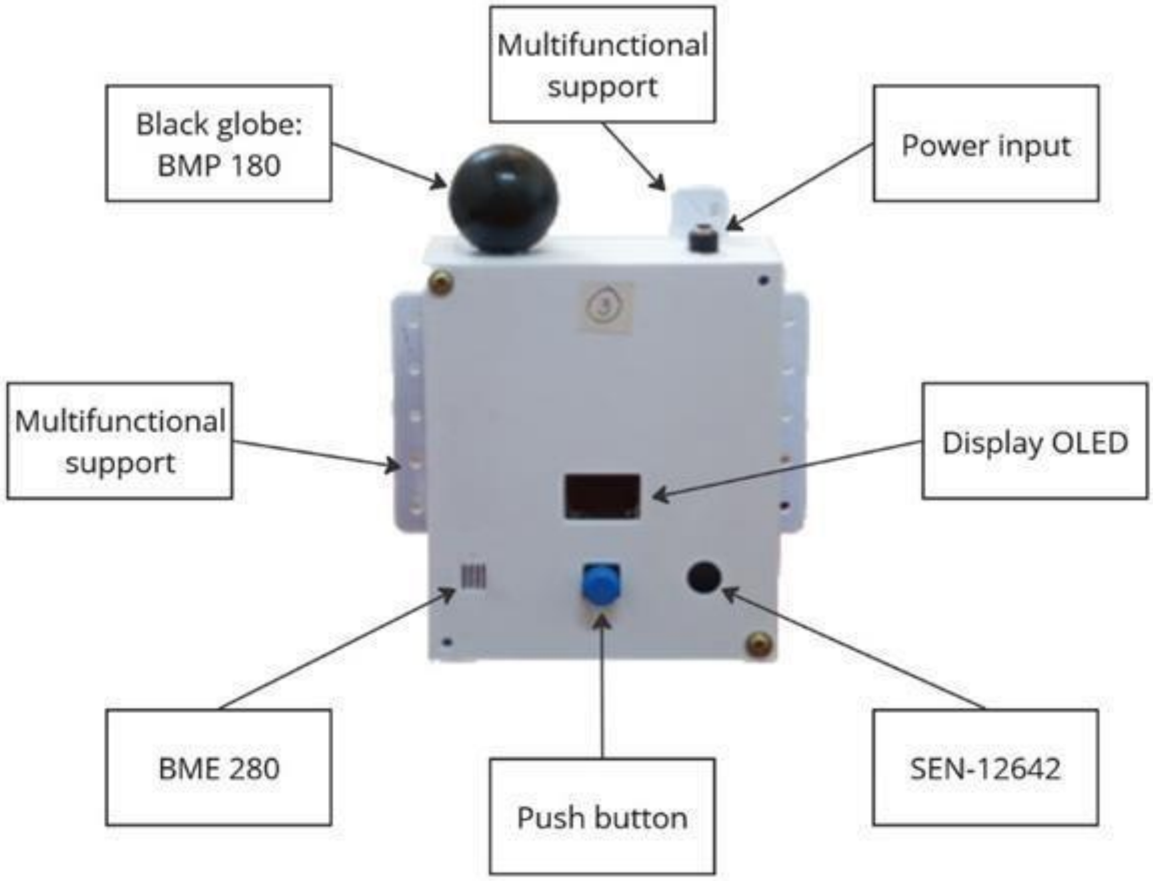
Component/Part	Estimated price per device (USD)
ESP32-WROOM-32	$ 9.0
BME280 sensor	$ 3.0
BMP180 sensor	$ 2.0
SEN12642 sensor	$ 12.5
Display OLED 128X64	$ 5.0
RTC module	$ 3.0
MicroSD card module	$ 2.0
Push Button	$ 0.2
PCB manufacturing	$ 3.0
3D printing material (PLA)*	$ 3.0
Total	**$ 42.7**

Note: Estimated prices are based on individual unit costs in early 2025 and may vary depending on geographic location, supplier, and market availability. Shipping fees and taxes are not included in the cost estimation. *The 3D printing material cost is based on an estimated use of 126.83 grams of PLA filament per enclosure.

Source: Authors.

The final prototype of the developed device is presented in Figure 2, highlighting that its design was conceived to meet the requirements for heat and moisture exchange (through the BME280 sensor's ventilation grid) and to provide versatility through mounting supports located on the sides and top. Additionally, its compact dimensions (14 cm in height, 12 cm in width, and 5 cm in depth) facilitate installation in reduced or confined structural spaces. These features allow the device to be adapted to various structural configurations within animal production systems.

Figure 2. Components of the device developed for monitoring the thermoacoustic environment in animal production



Device dimensions: 14 cm (height) × 12 cm (width) × 5 cm (depth).
Source: Authors.

2.1.1.2. Software

The device was programmed using the Arduino IDE development environment, with code written in C++. The data acquisition logic was designed to take advantage of both cores of the ESP32 microcontroller, creating two independent tasks. One core was dedicated exclusively to processing the information obtained from the sound sensor, while the other managed the acquisition of data from the remaining sensors, the operation of the push button, as well as the storage and real-time display of data on the OLED screen.

Regarding thermal comfort indices, the equations for THI and BGHI were directly embedded into the device's firmware, based on the original formulation by Thom (1959) and its refinement by Hahn (1997) for THI (Equation 1), and by Buffington et al. (1981) for BGHI (Equation 2). For this purpose, the dew point temperature (T_{dp}) was previously calculated using the equation proposed by Lawrence (2005) (Equation 3). It is worth mentioning that, because both the material and the diameter of the black globe used differ from those conventionally recommended, the black globe temperature obtained was initially incorporated into Equation 2 generating a preliminary value (BGHIpp). This value was later corrected using the equation reported by Souza et al. (2002) (Equation 4), which was specifically developed for globes made of the same material and diameter as those used in the developed device, under climatic conditions typical of Viçosa, Brazil.

$$THI = T_{db} + 0.36\,T_{dp} + 41.2 \tag{1}$$

Where: T_{db} represents the dry-bulb temperature (°C), and T_{dp} represents the dew point temperature (°C).

$$BGHI = T_{bg} + 0.36\,T_{dp} + 41.5 \tag{2}$$

Where: T_{bg} represents the black globe temperature (°C), and T_{dp} is the dew point temperature (°C).

$$T_{dp} = \frac{B_1\left[\ln\left(\frac{RH}{100}\right) + \frac{A_1 T_{db}}{B_1 + T_{db}}\right]}{A_1 - \ln\left(\frac{RH}{100}\right) - \frac{A_1 T_{db}}{B_1 + T_{db}}} \tag{3}$$

Where: T_{db} is the dry-bulb temperature (°C), RH is the air relative humidity (%), and A_1 and B_1 are constants with values of 17.625 and 234.04°C, respectively.

$$BGHI = 12.9651 + 0.80563\,BGHI_{PP} \tag{4}$$

Where: $BGHI_{PP}$ refers to the preliminary (uncorrected) Black Globe-Humidity Index.

In addition to THI and BGHI, air specific enthalpy (h) was calculated to provide a more comprehensive thermal characterization of the environment. Enthalpy was estimated using the formulation proposed by Rodrigues et al. (2011), which incorporates dry-bulb air temperature, relative humidity, and barometric pressure (Equation 5). Because the pressure sensor was not calibrated, a constant mean barometric pressure representative of the study area (760 mmHg) was assumed. Enthalpy values were calculated on an hourly basis and subsequently averaged across days to obtain mean 24-hour profiles for each monitored area and for the outdoor environment.

$$h = 1.006\, T_{db} + \frac{RH}{Pa} * 10^{\left(\frac{7.5\, T_{db}}{237.3 + T_{db}}\right)} * (71.28 - (0.052\, T_{db})) \quad (4)$$

Where: h is specific enthalpy of air (kJ·kg of dry air^{-1}), T_{db} is the dry-bulb temperature (°C), RH is the air relative humidity (%), and Pa is barometric pressure in mmHg.

2.1.2. Calibration

The sensors calibration process was carried out in climate-controlled chambers of the Research Center for Environment and Engineering of Agroindustrial Systems (AMBIAGRO), which is part of the Rural Constructions and Environment area (CRA/DEA/UFV). These climate chambers have dimensions of 3.20 m × 2.44 m × 2.38 m (length × width × height) and allow precise control of environmental variables such as air temperature and relative humidity.

The methods used to calibrate the low-cost sensors were based on the calibration of a reference device using a standard instrument supported by valid calibration certificates at the time of the experiment. The data obtained from the calibration in the climate chambers were randomly split into two datasets: 80% was used for training to generate the calibration curve, while the remaining 20% was reserved for model validation (laboratory testing), a practice adopted in low-cost sensor calibration studies, such as those by Dubey et al. (2024) and Zaidan et al. (2020).

2.1.2.1. Air Temperature and Relative Humidity

In this stage, the BME280 and BMP180 sensors were calibrated using as a reference an Onset Hobo® temperature and humidity data logger (model UX100-003), which features a temperature measurement range of −20 °C to 70 °C and a relative humidity range of 15% to 95% RH, with an accuracy of ±0.21 °C for temperature and ±3.5% for humidity. The device also allows real-time data logging at adjustable intervals. The methodology followed the calibration principles outlined by González et al. (2023), Kumar et al. (2020), and Fissore et al. (2024), with adjustments described below to suit the physical and operational constraints of the climate chamber. During the calibration process, the five devices, with their sensors mounted in their respective enclosures, were placed along with the reference device at the geometric center of the climate chamber. Both the devices and the reference were configured to record data every second. Temperature measurements were conducted in 5 °C increments, allowing stabilization at each level, ranging from −17 °C to 33 °C, under relative humidity conditions between 55% and 70%.

To calibrate the relative humidity sensor, the ambient humidity was first increased up to a maximum of 83% RH; afterward, using the air conditioning system, the environment was dehumidified, reaching a minimum of 34% RH, within a temperature range between 21 °C and 25 °C. A unified procedure was applied for the statistical analysis of sensor calibration, encompassing both air temperature (using BMP and BME sensors) and relative humidity (using BME sensor). The only difference lay in the filtering criteria, which were defined separately in each calibration subsection.

The raw data from each device were imported and consolidated into a single Excel file. The data were processed in R to eliminate transient points that introduced noise into the calibration process. Linear regression analyses were performed on the training dataset of each device, resulting in the respective calibration equations. The performance of each model was evaluated using the coefficient of determination (R^2) and the root mean square error (RMSE). Paired Student’s t-tests and analysis of variance (ANOVA) were applied to assess statistically significant differences between records, supporting decisions regarding the need for calibration adjustments.

2.1.2.2. Sound

For the calibration of the SEN-12642 sound sensor, a portable A/C digital sound level meter with datalogger was used as the reference device (model ITDEC 4050 from Instrutemp, Brazil), with a calibration certificate at 94 dB at 1 kHz. This instrument features a measurement range from 30 dB to 130 dB, an accuracy of ±1.5 dB, a resolution of 0.1 dB, and the ability to log data at configurable intervals.

The calibration methodology was based on the procedures described by Menezes (2015), Fissore et al. (2024), and Donofre et al. (2018), with the added innovation of constructing a sound isolation chamber integrated within one of the climate-controlled chambers. The sound isolation chamber, measuring 1.0 meters long, 0.5 meters wide and 0.15 meters high, achieved acoustic insulation with a background noise level of 37 dB(A). The construction method involved an outer layer of acoustic insulation foam, followed by a middle layer of expanded polystyrene, and an inner layer of acoustic insulation foam. This design not only improves acoustic isolation but, combined with the geometry of the materials used, also reduces the risk of microphone saturation caused by sound wave reflections.

During the calibration stage, the devices and the reference sound level meter were arranged in a horizontal line at 0.15 meters from the sound source. Eleven different volume levels were tested, each played for one and a half minutes, using white noise (Donofre et al., 2018; Fissore et al., 2024; Menezes, 2015) generated with Audacity software (Audacity Team, 2024). The sound source consisted of a JBL GO3 speaker (Harman International Industries, EE.UU.), which delivers an output power of 4.2 W and a dynamic frequency response of 110 Hz to 20 kHz.

The reference sound level meter was configured to A-weighting and fast mode, recording a baseline level of approximately 37 dB(A) and reaching a maximum of 94 dB(A). Both the devices and the reference were programmed to store data at one-second intervals. For the calibration of the sound sensor, a statistical approach was adopted following the same general structure used for the temperature and humidity sensors, but with adjustments suited to the acoustic nature of the data. To enhance model performance, the data were divided into 11 intervals based on the sound levels tested during calibration.

Polynomial regression analyses were then conducted on the training dataset for each of the five devices, yielding the respective calibration equations. Model performance was assessed using R^2 and RMSE, and statistical tests such as paired Student's t-tests and ANOVA were used to evaluate potential differences and the need for calibration adjustments.

The calibration equations were applied to the validation dataset to assess the performance of each model under laboratory conditions. To support this analysis, box plots were generated to visualize and compare the distribution of values recorded by the calibrated sensors and the reference instruments for relative humidity, dry-bulb temperature, and sound intensity.

2.2. Field Evaluations

Activities related to device validation and environmental characterization in an intensive dairy cattle production system were conducted at the Teaching, Research, and Extension Unit for Dairy Cattle (UEPE-GL), part of the Department of Animal Science at the Federal University of Viçosa (UFV), from January 21 to 28, 2025. The facility housed 50 dairy cows (*Bos taurus taurus*), in a mixed herd of the Holstein and Girolando breed, with an average age of 4 years, an average body weight of 638 kg, and an average milk production of 36 and 33 liters of milk per cow per day, respectively. The experiment was approved by the Ethics Committee on the Use of Production Animals of the Federal University of Viçosa (CEUAP-UFV), under protocol no. 07/2024.

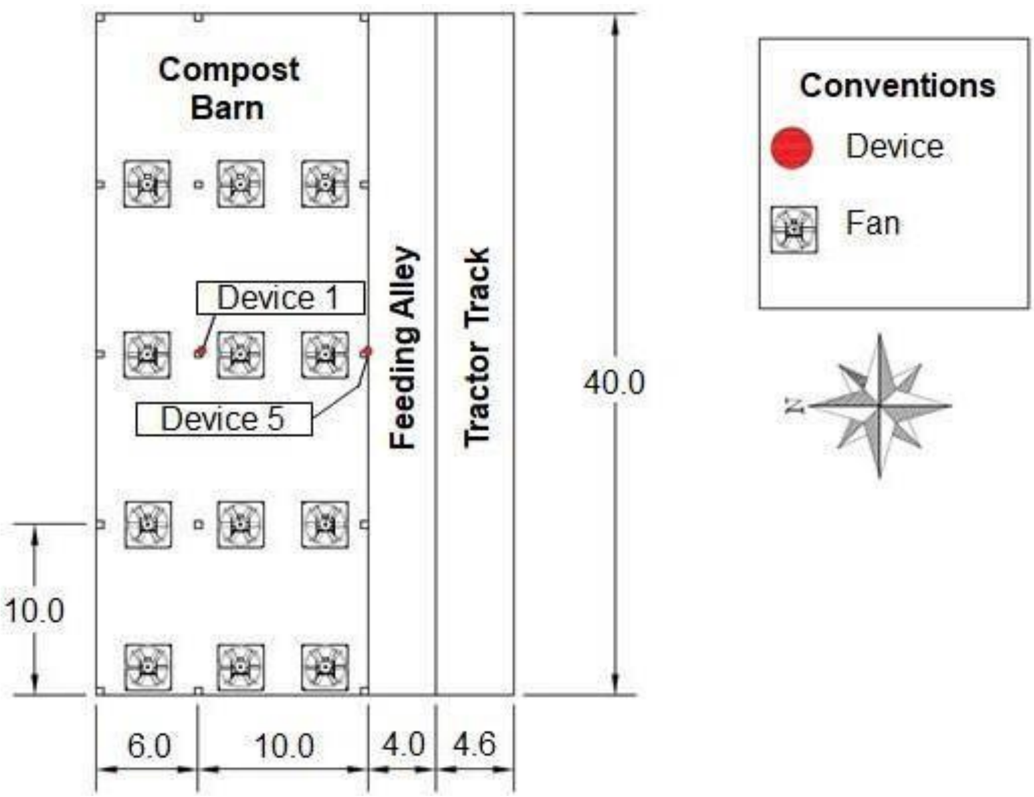
Figure 3. View of the intensive dairy cattle production system, including the evaluated locations

Source: Authors.

The field evaluation was divided into different main tests. One test involved assessing the acoustic signature of the tractor in a controlled setting, conducted in the equipment maintenance area, where general repairs and servicing are performed. This test aimed to characterize the noise generated by the tractor in isolation. A second test focused on acoustic monitoring at strategic points within the milking parlor. Finally, a more prolonged and comprehensive thermoacoustic monitoring test was conducted, involving simultaneous measurements of sound and thermal variables in the areas with the greatest acoustic variability, such as the milking parlor and the cooling room. In the bedding and feeding areas of the Compost Barn, the evaluation concentrated on thermal comfort indexes. In the Compost Barn, the tractor evaluated in the first test operates periodically to turn the bedding and distribute feed, contributing significantly to the ambient noise levels during those activities.

The Compost Barn (Figure 4) is equipped with 12 intelligent electronic axial fans from the brand Ziehl-Abbeg, model ZN091-ZIQ.DG.V4P3, featuring ECblue technology. These 910 mm “square full bell mouth” fans deliver an airflow rate of 19,660 m³/h, generate a pressure of 163 Pa, and operate at a frequency of 50/60 Hz. It is also important to note that the tractor used for bedding turning (twice a day) and feed distribution has a significant impact on the acoustic environment of the facility.

Figure 4. Illustration of the internal area of the Compost Barn, highlighting the positioning of the fans, the feeding areas and device installation sites. Units in meters

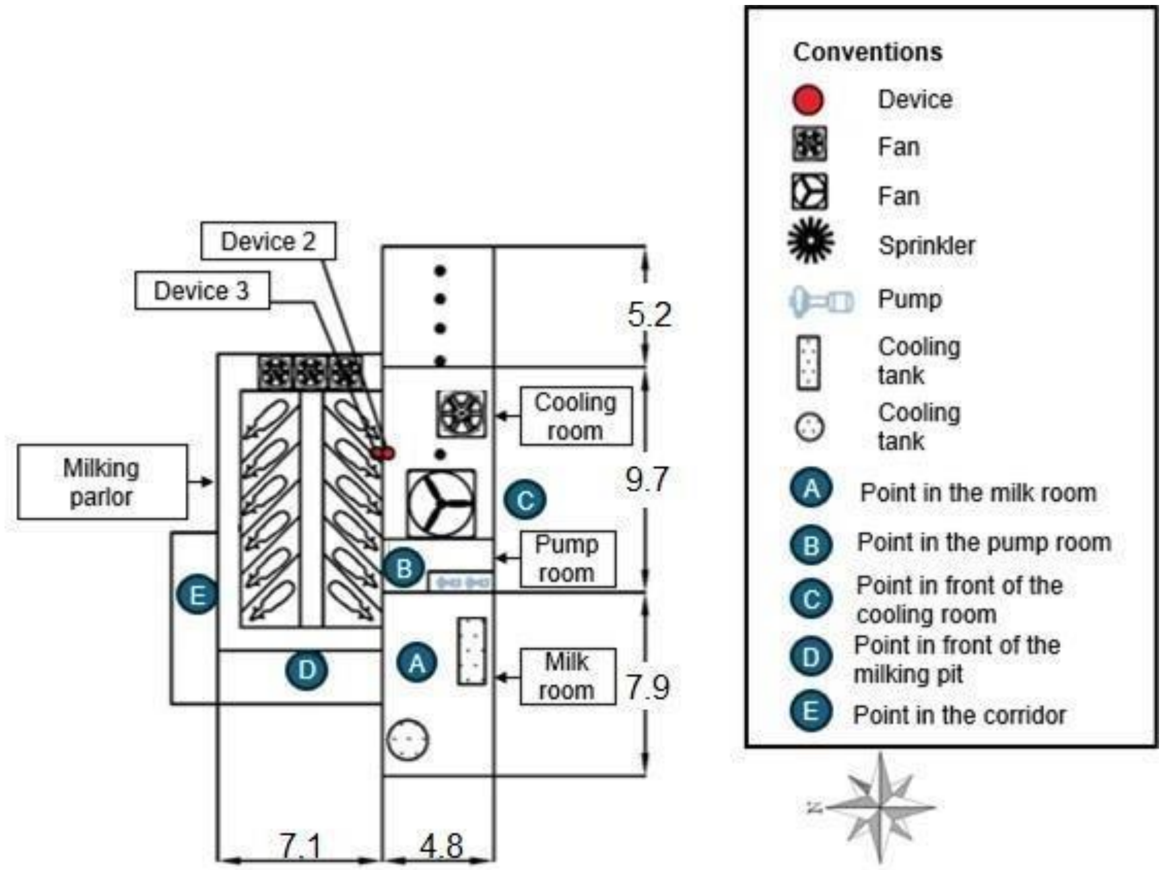


*Red points indicate the measurement devices installed (Device 1 and Device 5).

Source: Authors.

The closed-loop milking system, arranged in a herringbone configuration, accommodates 12 cows in the milking area. As shown in Figure 5, the facility is divided into four zones: cooling room, pump room, milking parlor, and milk room.

Figure 5. Illustration of the facility with the cooling room, milking room, pump room and milk room. Units: meters



*Red points indicate the measurement devices installed (Device 2 and Device 3). Lettered points (A–E) represent reference locations assigned for thermal and acoustic characterization of critical zones.

Source: Authors.

In the milking parlor, there are three Ziehl-Abbeg fans (a smaller version than those used in the Compost Barn) for environmental control. Two types of fans are used in the cooling room: one is the Magnum 60 model, with a power of 1 hp, equipped with 1.52 m blades and a belt-driven transmission, and the other is identical to the model used in the Compost Barn. Additionally, this area features eight sprinklers positioned approximately 2 m above the floor, which operate as part of an evaporative cooling system.

Several additional noise sources were identified in the facility, including two pumps located in the pump room, two tanks used for milk cooling and storage in the milk room, and a milk collection truck that parks parallel to this area and collects milk daily around midday. These elements contributed to the acoustic complexity of the monitored environment.

In this context, a total of five previously calibrated devices were deployed. These devices were configured to measure relative humidity, dry-bulb temperature, black globe temperature, and sound intensity. Based on these measurements, the thermal comfort indices THI and BGHI were subsequently calculated using the equations embedded in the device’s firmware. Data were collected at five-minute intervals, except for sound intensity, which was recorded continuously every second.

Other sources of noise identified in the facility include two pumps located in the pump room, two tanks used for milk cooling and storage in the so-called milk room, and a milk collection truck that parks parallel to the milk room and collects milk daily around midday.

Throughout the entire experimental period, continuous visual monitoring was conducted to identify and record additional noise sources, as well as other environmental variables that could potentially interfere with the measurements. This field supervision enabled the documentation of relevant events such as tractor activity and the operation of additional equipment, which were taken into account in the subsequent data analysis.

2.2.1. Field Test: Comparison with Reference Device (Tractor Noise)

In this test, a low-power Massey Ferguson 265 tractor was used, which performs bed turning and feed distribution activities in the Compost Barn. The tractor is equipped with a diesel engine of approximately 50 hp at the drawbar and 60 hp at the power take-off (PTO), with a mechanical transmission. The test involved recording sound intensity using one randomly selected device (Device 4) alongside the reference sound level meter, at distances of 1.0 m, 1.5 m, 2.0 m, and 2.5 m, each for a duration of 1 minute. Two tests were conducted with the tractor in a stationary position, operating at approximately 800 rpm and 1600 rpm, corresponding to the working power during feed distribution.

The analysis of the results obtained during the tractor test included the calculation of the average sound intensity and the standard error of the mean (SEM). A line chart was presented to compare the responses of the reference device and the low-cost acoustic sensor over time, along with an evaluation of the fit between the two devices.

2.2.2. Field Test: Noise in the Milking Parlor

This test aimed to verify the performance of the sound sensor, and the data obtained from the reference device allowed the characterization of the acoustic environment inside the milking parlor. The device was tested in parallel with a standard decibelimeter at five designated points of interest, labeled A to E, as shown in Table 3 and represented in Figure 5 which corresponded to specific functional zones within the facility: Point A corresponds to the milk room, B to the pump room, C to the front of the cooling room, D to the front of the milking pit (external area immediately in front of the milking stalls), and E to the corridor adjacent to the exit lane, located parallel to the milking pit.

At each point, three signal acquisition repetitions were performed, each lasting approximately two minutes. For analysis, each repetition was treated as an independent time block, and the three were subsequently presented in sequence to support the subsequent statistical and graphical analysis of the device's performance in relation to the reference signal.

Table 3. Identifying the location of noise data collection points in the milking parlor facility. Points A to E correspond to specific areas where sound pressure levels were measured using both the reference sound level meter and the tested low-cost device: A – Milk room; B – Pump room; C – Front of the cooling room; D – Front of the milking pit (external zone facing the stalls); and E – Corridor adjacent to the exit lane, located parallel to the milking pit.

Point/device	Reference Axis	Coordinate (x,y) [m]	Height [m]	Positioning height reference
A	Xm, Ym	(9.5), (-1.45)	1.2	Floor
B	Xm, Ym	(1.0), (1.1)	1.2	Floor
C	Xm, Ym	(13.0), (10.7)	1.2	Floor
D	Xm, Ym	(3.5), (-0.2)	1.2	Floor
E	Xm, Ym	(-0.2), (2.5)	1.2	Floor

Source: Authors.

Descriptive statistics (mean, standard deviation, median, range, and count) were calculated to summarize the sound intensity levels recorded by both devices at different points within the milking environment (A, B, C, D, and E). For visual analysis, line plots with dual y-axes, box plots, residual plots, histograms of residuals, and scatter plots with identity lines were generated. Together, these tools enabled a comprehensive evaluation of sound behavior in the environment and the performance of the low-cost device relative to the reference.

2.2.3. Field Test: Thermoacoustic Monitoring in Intensive Dairy Cattle Production System

In this test, four devices were deployed to record environmental variables at the coordinates indicated in Table 4, which uses two coordinate systems: Xc and Yc for the Compost Barn facility (Figure 4) and Xm and Ym for the milking system facility (Figure 5). The devices were installed at strategic points within the facility: device 1 was placed in the bedding area of the Compost Barn, device 2 in the cooling room, device 3 in the milking parlor, and device 5 in the feeding alley. In addition, another calibrated device was positioned in a meteorological shelter approximately 60 meters from the facility to monitor outdoor conditions. Data collection during this test was carried out automatically and continuously over a total period of seven days during the conduct of the experiment.

Table 4. Identifying the location of noise data collection points in the bedding and feeding areas of the Compost Barn and in the milking parlor. Devices 1, 2, 3, and 5 correspond to the bedding area, cooling room, milking parlor, and feeding alley, respectively

Point/device	Reference Axis	Coordinate (x,y) [m]	Height [m]	Positioning height reference
1	Xc, Yc	(6.0), (20.0)	2.4	Composted bedding
2	Xm, Ym	(7.2), (8.1)	2.7	Floor
3	Xm, Ym	(7.0), (8.1)	2.5	Floor
5	Xc, Yc	(16.0), (20.0)	2.4	Composted bedding

Note: Device 4 was reserved for paired measurements with the reference sound level meter and was not included in the continuous 7-day data acquisition.
Source: Authors.

Continuous data collection in the areas of interest, bedding area and feeding alley of the Compost Barn facility and in the cooling room and milking parlor of the intensive dairy cattle production system, involved various analyses aimed at evaluating device performance under field conditions, characterizing the recorded environmental variables, and assessing correlations between them. For this purpose, only the data acquired during the period from January 21 to January 28, 2025, were considered.

To assess the device's efficiency, the expected number of records for each sensor was defined based on the configured acquisition interval and the total duration of the test. This expected value was then compared to the actual number of data acquired points. Only valid numerical records were considered in this comparison, enabling the calculation of the percentage of effective data acquisition for each sensor.

Data (dry-bulb temperature, relative humidity, sound intensity, THI, and BGHI) were summarized in a descriptive statistics table. The date and time of each record were extracted, and the hourly average for each variable was calculated for every available day. These hourly averages were then averaged across the entire study period, resulting in a representative value for each of the 24 hours of the day.

2.3. Software and Data processing

For statistical procedures, software such as Excel (Microsoft Corporation, 2025) and R (R Core Team, 2025), executed via RStudio (Posit team, 2023), was used for data handling and processing. The R packages employed included: ggplot2 (Wickham, 2016), ggpubr (Kassambara, 2023), lmtest (Zeileis and Hothorn, 2002), readxl (Wickham and Bryan, 2023), writexl (Ooms, 2024), dplyr (Wickham et al., 2023a), tidyr (Wickham et al., 2023d), lubridate (Grolemund and Wickham, 2011), readr (Wickham et al., 2023b), GGally (Schloerke et al., 2021), scales (Wickham et al., 2023c), and stringr (Wickham, 2022).

3. RESULTS AND DISCUSSION

3.1. Device Development: calibration and validation of devices

The calibration equations presented in Table 5 for the BME280 sensors of the devices explain approximately 99% of the data variability ($R^2 \approx 0.9$), indicating a strong correlation and, consequently, an adequate calibration. Within this context, Device 1 demonstrated the best performance, with an R^2 of 0.997 and the lowest RMSE (0.27), while Device 3 presented the worst performance, with an RMSE of 0.63. These RMSE values are consistent with those previously reported by (C. E. A. Oliveira et al., 2025).

Table 5. Calibration equations and statistical parameters for dry bulb temperature measurement (BME280 sensors)

Device	Calibration equation*	R^2*	RMSE*	Paired t-test p-value*	Paired t-test p-value**
1	$-2.465 + (1.045\,x)$	0.997	0.27	< 2.2e-16	0.003422
2	$-2.352 + (1.048\,x)$	0.995	0.36	< 2.2e-16	0.1899
3	$-4.265 + (1.066\,x)$	0.986	0.63	< 2.2e-16	0.4105
4	$-2.923 + (1.041\,x)$	0.992	0.48	< 2.2e-16	0.1222
5	$-1.606 + (0.987\,x)$	0.995	0.38	< 2.2e-16	0.8798

*Values obtained from the calibration dataset (80% of the total data used to generate the calibration equation).
**Values obtained from the validation dataset (20% of the total data used to test the calibration equation)
Source: Authors.

In the BME280 temperature calibration (Table 5), slopes ranged from 0.987 to 1.066, and intercepts varied from –1.606 to –4.265, confirming a good fit with the proposed linear model. According to González et al. (2023), factory-calibrated sensors for temperature, relative humidity, or carbon dioxide typically follow a linear model, with intercepts and slopes approximating 0 and 1, respectively. Paired Student's t-tests for each device yielded p-values < 0.05 (Table 5), justifying the application of individual calibration equations. Similarly, the overall comparison of devices using ANOVA also produced p-values < 0.05 (Table 6), indicating that a common calibration equation cannot be applied across all devices.

Regarding the validation performed using the 20% of data not employed in the calibration curve generation, it was observed that the corrected measurements from the BME280 sensor mostly yielded p-values greater than 0.05 (Table 5). The only device that showed statistically significant differences was Device 1; however, the discrepancy observed (approximately 0.023 °C) is negligible in terms of data reliability in animal production, especially considering the sensor resolution of ±0.1 °C

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Table 6. ANOVA summary for differences among devices prior to calibration using the calibration dataset* for dry bulb temperature measurement (BME280 sensors)

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Device	5	31701	6340.2	223.96	< 2.2e-16
Residuals	28067	794561	28.3		

*Calibration dataset corresponds to 80% of the total data, used to generate the calibration equations
Source: Authors.

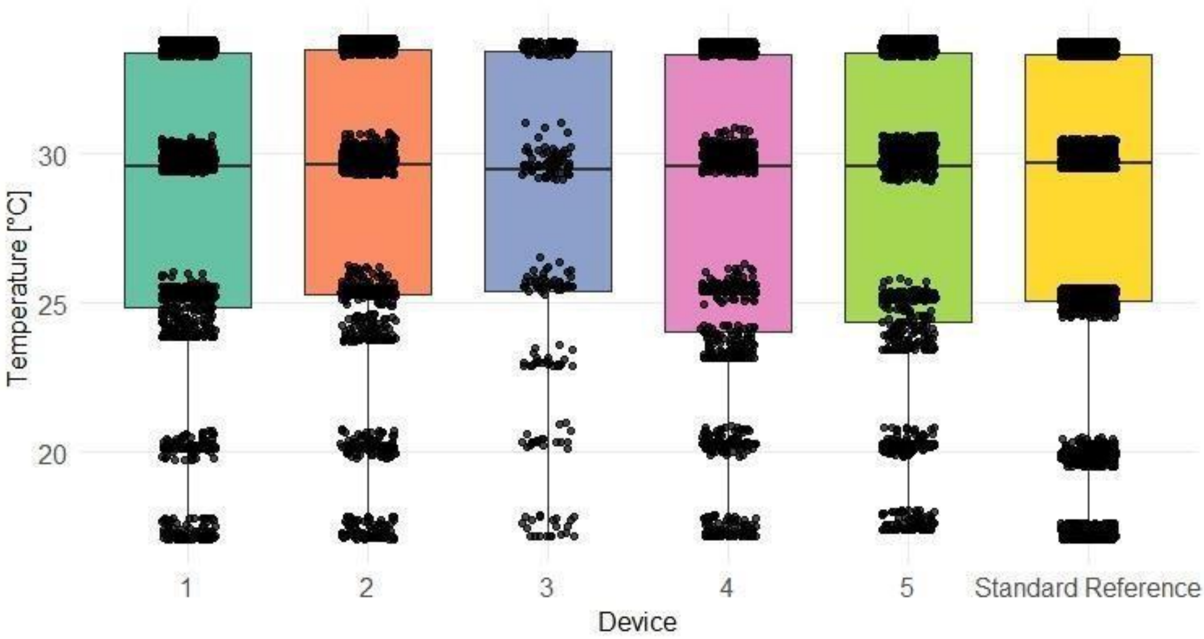
Moreover, the ANOVA performed on the corrected data (Table 7) indicated no significant effect between devices ($p > 0.05$), and the boxplot (Figure 6) confirmed the absence of noticeable differences between medians. Therefore, the device measurements are comparable and unbiased, making them suitable for simultaneous use in multi-point monitoring scenarios.

Table 7. ANOVA summary for differences among devices after calibration using the validation dataset* for dry bulb temperature measurement (BME280 sensors)

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Device	5	282	56.496	2.1092	0.06129
Residuals	7013	187845	26.785		

*Validation dataset corresponds to 20% of the total data, not used to generate the calibration equations. Calibration equations were applied prior to analysis.
Source: Authors

Figure 6. Boxplot of corrected BME temperature values and standard reference (HOBO) measurements



Source: Authors.

As with the analysis conducted for temperature, the intercepts and slopes of the relative humidity calibration equations for each device were reviewed, with the results presented in Table 8. According to González et al. (2023), when calibrating relative humidity sensors, it is desirable for the intercept and slope to approximate 0 and 1, respectively, in order to minimize deviations from the reference instrument and avoid potential calibration issues or sensor defects.

Table 8. Calibration equations and statistical parameters for relative humidity measurement (BME 280 sensors)

Device	Calibration equation*	R^2*	RMSE*	Paired t-test p-value*	Paired t-test p-value**
1	$-24.778 + (1.460 * x)$	0.933	3.09	< 2.2e-16	0.1526
2	$-11.083 + (1.267 * x)$	0.959	2.44	< 2.2e-16	0.06213
3	$-24.332 + (1.470 * x)$	0.552	8.06	< 2.2e-16	0.6218
4	$-2.827 + (1.087 * x)$	0.918	3.34	< 2.2e-16	0.4441
5	$-15.456 + (1.262 * x)$	0.975	1.90	< 2.2e-16	0.7846

*Values obtained from the calibration dataset (80% of the total data used to generate the calibration equation)
**Values obtained from the validation dataset (20% of the total data used to test the calibration equation)
Source: Authors.

For the relative humidity variable, the intercepts ranged from –2.827 to –24.778 (Table 8), and the slopes varied between 1.087 and 1.470, indicating a notable deviation from the ideal values in most devices. Device 3 stood out for having the lowest fit ($R^2 = 0.552$) and a RMSE of 8.06, suggesting a potential calibration issue or sensor malfunction. In contrast, Device 5 exhibited the best performance ($R^2 = 0.975$, RMSE = 1.90), although its intercept (–15.456) and slope (1.262) also deviated from the recommended parameters. These findings are consistent with the observations of Sari et al. (2022), who emphasize the importance of applying correction equations when the intercept and slope significantly differ from 0 and 1, respectively. In addition, paired Student's t-tests (Table 8) and ANOVA (Table 9) revealed statistically significant differences ($p < 0.05$) between the relative humidity values recorded by the BME sensors and the HOBO reference, ruling out the possibility of applying a single calibration model for all devices. This approach ensures that the sensor measurements reliably align with the reference values, thereby increasing the accuracy and reliability of the recorded data.

Table 9. ANOVA summary for differences among devices prior to calibration using the calibration dataset* for relative humidity measurement (BME 280 sensors)

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Device	5	243177	48635	614.61	< 2.2e-16
Residuals	76792	6076721	79		

*Calibration dataset corresponds to 80% of the total data, used to generate the calibration equations

Source: Authors.

When using 20% of the data reserved for the validation of relative humidity, the paired Student's t-tests (Table 8) revealed no statistically significant differences between the corrected BME280 sensor values and the HOBO reference measurements ($p > 0.05$). Similarly, the ANOVA (Table 10) indicated no considerable discrepancies among the devices, supporting the effectiveness of the calibration in aligning the sensor readings with those of the reference instrument.

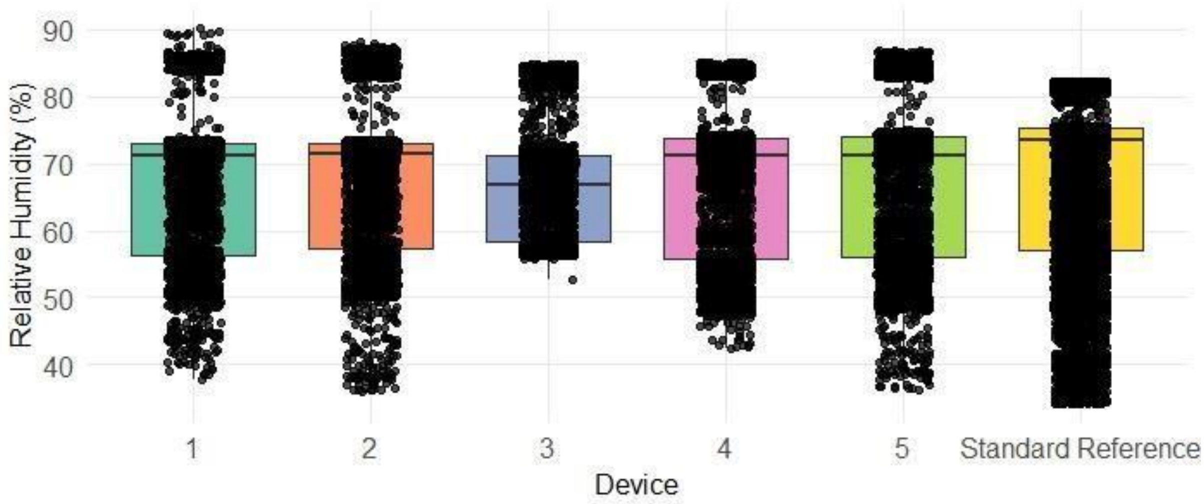
Table 10. ANOVA summary for differences among devices after calibration using the validation dataset* for relative humidity measurement (BME280 sensors)

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Device	5	700	139.91	1.1084	0.3534
Residuals	19194	2422826	126.23		

*Validation dataset corresponds to 20% of the total data, not used to generate the calibration equations. Calibration equations were applied prior to analysis.
Source: Authors.

Although Device 3 exhibited a relatively low R^2 (0.552) in Table 8, the average difference with the reference device was not statistically significant, suggesting that while its measurements showed greater dispersion, the mean bias was adequately reduced after correction. This is also reflected in the boxplot (Figure 7), where the median of Device 3 appears slightly shifted compared to the others, but its interquartile range is similar to that of the other devices. This indicates that, despite the variability, there is no pronounced systematic deviation that would compromise the reliability of the measurements.

Figure 7. Boxplot of corrected BME280 relative humidity values and standard reference (HOBO) measurements



Source: Authors.

As shown in Table 11, the calibration equations for black globe temperature obtained from all devices exhibited R^2 values between 97% and 99%. The best performance was observed in Device 4, with an RMSE of 0.47, while the lowest performance was found in Device 5, which recorded an RMSE of 0.75. Paired

Student’s t-tests yielded p-values < 0.05 (Table 11), indicating statistically significant differences between the BMP180 measurements and those of the reference device prior to the application of correction equations. Notably, Device 2 in Table 11 presented a p-value of 0.2543, suggesting that the difference between the BMP180 and the reference device was not statistically significant for this particular unit. Nevertheless, individual calibration equations were generated for all devices to improve measurement accuracy and enhance data reliability.

Table 11. Calibration equations and statistical parameters for black globe temperature measurement (BMP180 sensors)

Device	**Calibration equation*,***	R^2*	**RMSE***	**Paired t-test p-value***	**Paired t-test p-value****
1	$1.251 + (0.968 * x)$	0.983	0.67	< 2.2e-16	0.2171
2	$1.689 + (0.939 * x)$	0.983	0.67	0.2543	0.05996
3	$2.471 + (0.920 * x)$	0.988	0.58	< 2.2e-16	0.5125
4	$0.239 + (0.947 * x)$	0.992	0.47	< 2.2e-16	0.1481
5	$1.705 + (0.911 * x)$	0.979	0.75	< 2.2e-16	0.2154

*Values obtained from the calibration dataset (80% of the total data used to generate the calibration equation).
**Values obtained from the validation dataset (20% of the total data used to test the calibration equation)
*** The dry bulb temperature obtained from this equation is the variable named T_{bg}(black globe temperature) used in Equation 2.
Source: Authors.

The analysis of variance (ANOVA) revealed significant differences among the devices (Table 12), confirming the need for device-specific calibration equations and ruling out the feasibility of applying a single model to all units.

Table 12. ANOVA summary for differences among devices prior to calibration using the calibration dataset* for black globe temperature measurement (BMP180 sensors)

Source	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**
Device	5	28139	5627.9	179.13	< 2.2e-16
Residuals	28067	881791	31.4		

*Calibration dataset corresponds to 80% of the total data, used to generate the calibration equations
Source: Authors.

After applying the corrections to the BMP180 sensor values in the 20% of the data reserved for validation, paired t-tests (Table 11) confirmed that no significant differences existed between each device and the HOBO reference ($p > 0.05$). The discrepancies observed were in the order of hundredths of a degree, which is negligible considering the BMP180 sensor resolution of ±0.1 °C.

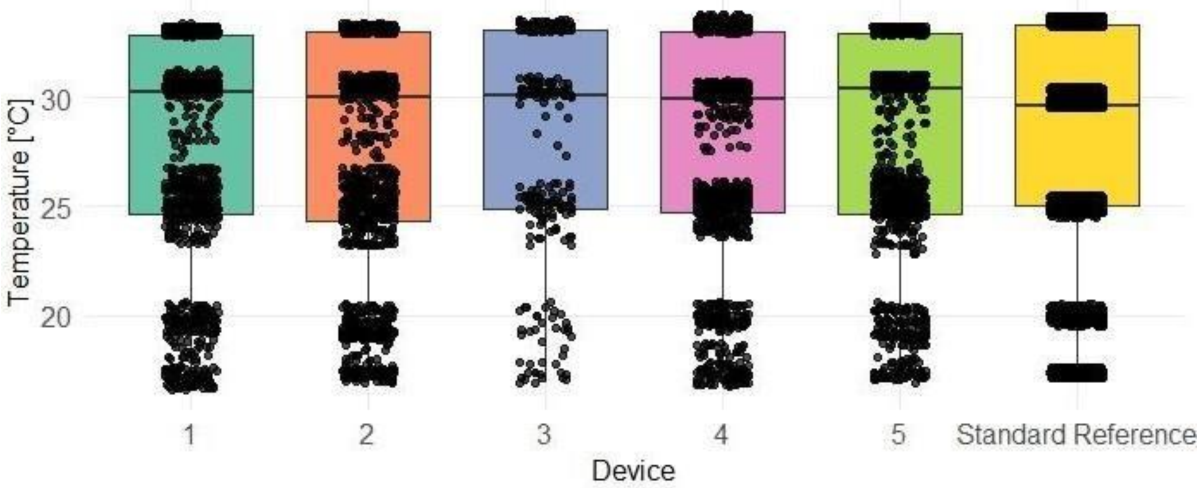
The ANOVA test yielded a p-value of 0.4507 (Table 13), indicating no significant differences among the devices. This can be seen in Figure 8, which illustrates the proximity of the medians between the devices and the HOBO reference logger.

Table 13. ANOVA summary for differences among devices after calibration using the validation dataset* for black globe temperature measurement (BMP180 sensors)

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Device	5	130	25.995	0.9446	0.4507
Residuals	7013	193001	27.520		

*Validation dataset corresponds to 20% of the total data, not used to generate the calibration equations. Calibration equations were applied prior to analysis
Source: Authors.

Figure 8. Boxplot of corrected BMP180 temperature values and standard reference (HOBO) measurements



Source: Authors.

The calibration equations for sound intensity, along with the corresponding model fit parameters for the five devices, are summarized in Table 14. Each device was fitted using a second-degree polynomial model, resulting in device-specific equations that describe the relationship between the average sound intensity level measured by the reference sound level meter and the low-cost SEN-12642 sensor.

Table 14. Calibration equations and statistical parameters of devices with SEN-12642 sensors for sound intensity measurement

Device	Calibration equation*	R^2*	RMSE*	Paired t-test p-value*	Paired t-test p-value**
1	$-5737.066 + (23.557\,x) - (0.02\,x^2)$	0.918	4.01	< 2.2e-16	0.0003772
2	$-2679.389 + (10.667x) - (0.01\,x^2)$	0.858	5.18	1.278e-11	0.459
3	$-1005.582 + (4.047\,x) - (0.04\,x^2)$	0.758	6.76	1.313e-09	0.1412
4	$-4621.879 + (16.264\,x) - (0.01\,x^2)$	0.763	6.69	3.458e-15	2.2e-16
5	$-5395.281 + (15.703\,x) - (0.01\,x^2)$	0.934	3.55	< 2.2e-16	0.7181

*Values obtained from the calibration dataset (80% of the total data used to generate the calibration equation).
**Values obtained from the validation dataset (20% of the total data used to test the calibration equation).
Source: Authors.

According to the calibration values, R^2, and RMSE presented in Table 14, most SEN-12642 sensors demonstrated an acceptable fit. Device 5 stood out with the highest R^2 (0.934) and the lowest RMSE (3.55), while Device 3 and 4 exhibited the lowest performance, with an R^2 of 0.758 and 0.763 respectively. Paired Student's t-tests, applied to each device and shown in Table 14, revealed extremely low p-values ($p < 2.2 \times 10^{-16}$ in several cases), indicating statistically significant differences between the sensor measurements and those of the reference device prior to correction. This strongly supports the need to develop individual calibration equations to reduce measurement bias.

As with the temperature and relative humidity calibration, the corrected data were used for validation, applying paired Student's t-tests and ANOVA (Tables 14 and 15 respectively) to evaluate statistical significance and model adequacy.

Table 15. ANOVA summary for differences among devices with SEN-12642 prior to calibration using the calibration dataset* for sound intensity

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Device	4	22.1	5.531	0.0259	0.9986
Residuals	41	8755.7	213.55		

*Calibration dataset corresponds to 80% of the total data, used to generate the calibration equations

Source: Authors.

Although Table 15 showed no significant differences in uncorrected mean measurements between devices ($p = 0.9986$), an ANOVA including the interaction between device and sound sensor values revealed a significant interaction effect ($p < 0.001$), indicating that the calibration relationship differs across devices. This finding confirms that each device responds differently to variations in sound level, thereby justifying the application of device-specific calibration equations.

To validate these corrections, paired Student's t-tests were conducted using the 20% validation dataset, as shown in Table 14. Devices 1 and 4 exhibited statistically significant differences when compared to the decibelimeter, whereas Devices 2, 3, and 5 did not. However, the global analysis of variance (ANOVA) in Table 16, still revealed a highly significant difference among devices ($p < 2.2e-16$), indicating that the correction did not fully standardize their behavior.

Table 16. ANOVA summary for differences among devices with SEN-12642 after calibration using the validation dataset* for sound intensity

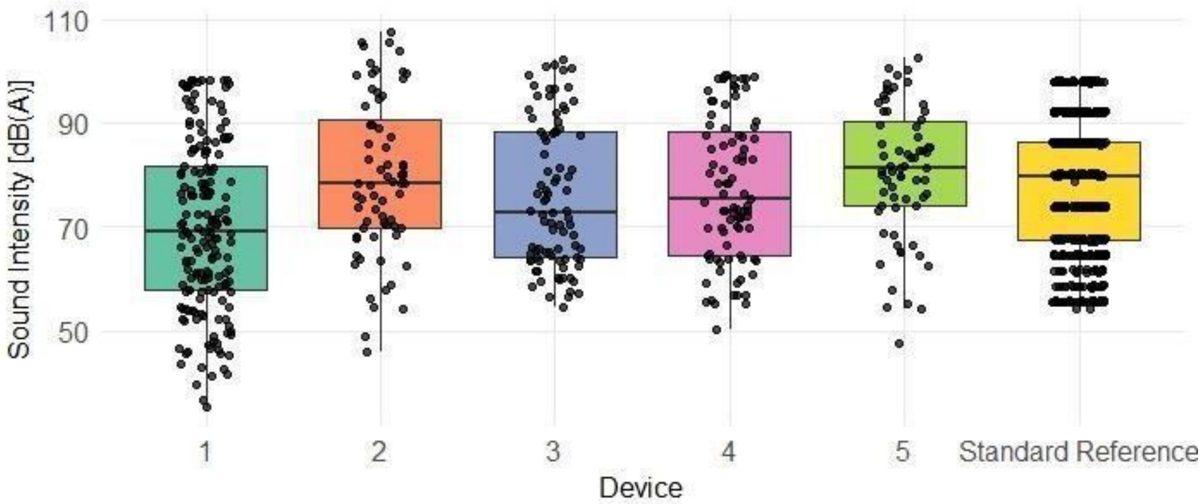
Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Device	4	1360335	340084	1237.8	< 2.2e-16
Residuals	482	132433	275		

*Validation dataset corresponds to 20% of the total data, not used to generate the calibration equations. Calibration equations were applied prior to analysis

Source: Authors.

In the validation of the SEN12642 sensor, Figure 9 reveals data dispersion, differences in medians, and outliers that exceed the maximum value recorded by the reference meter. Together, these findings indicate that the sensor is highly sensitive to intensity variations, particularly at low levels, with the risk of producing measurements that exceed the actual sound intensity.

Figure 9. Boxplot of corrected SEN12642 sound intensity values and standard reference (decibelimeter) measurements



Source: Authors.

Based on the overall analysis of the sound sensor performance, one key factor that may contribute to the observed overestimation bias in low-intensity conditions is the sampling rate used for data acquisition, as it directly affects the quality and representativeness of the collected information. It is important to note that high sampling frequencies (between 44.1 kHz and 48 kHz) pose greater challenges for microcontroller units, due to the high real-time processing demands (Picaut et al., 2020). Numerous studies (Ferrari et al., 2010, 2008; Green et al., 2020; Lenner et al., 2024; Silva et al., 2009; Yang et al., 2021) applying audio signals in machine learning predictive models for animal production use sampling rates of 44.1 kHz. However, the tests conducted showed that the current system only reaches approximately 21 kHz, partly due to the analog communication of the sensor, which may affect both the responsiveness and reliability of the measurements.

To improve the accuracy and reliability of sound data, especially in applications requiring higher sampling rates, it is advisable to consider sensors with faster communication interfaces (e.g., I2C). According to (Picaut et al., 2020), replacing electret condenser microphones (ECM) with microelectromechanical system (MEMS) microphones has been justified, as MEMS sensors have demonstrated more consistent results in acoustic measurements. It is also recommended to verify whether the ESP32 microcontroller can handle the required data throughput or whether it would be necessary to switch to a more powerful platform, such as a Raspberry Pi, which offers greater processing capabilities and enables the implementation of advanced methods, such as the Fast Fourier Transform (FFT).

Among the technical considerations described above, economic viability is a key consideration in the acceptance of environmental monitoring technologies within livestock facilities. Commercial devices currently available for temperature and humidity measurements using data loggers usually range between US$75 and over US$200, while sound level meters with integrated dB(A) weighting and data logging range from US$300 up to US$1,000, with professional equipment reaching more than US$2,000. In this context, the proposed device intends to be much more economical because it brings together thermoacoustic monitoring on one platform, with far lower investment, thus reinforcing its prospects for scalability both in research and practical applications in dairy production facilities.

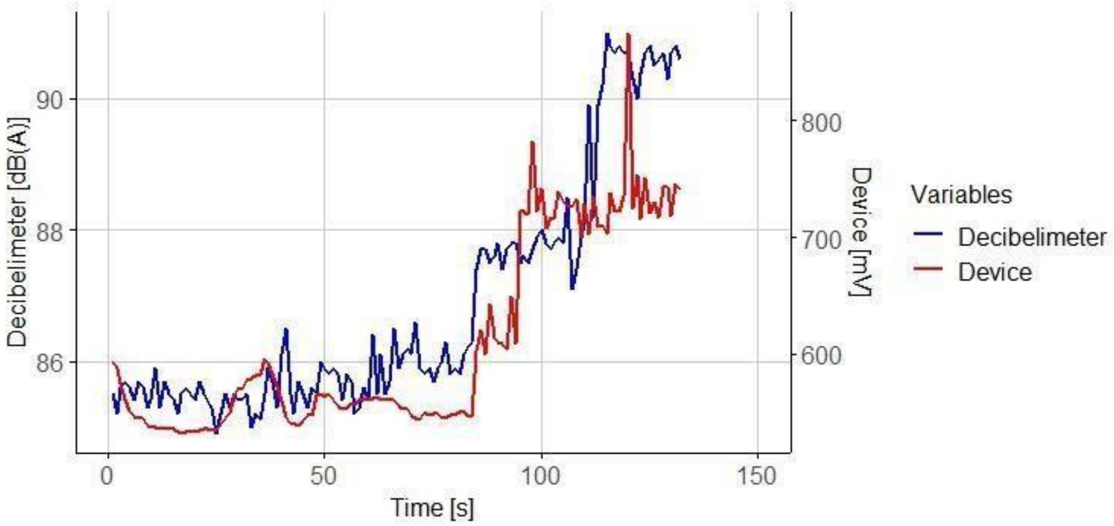
3.2. Field Evaluations

3.2.1. Field Test: Comparison with Reference Device (Tractor Noise)

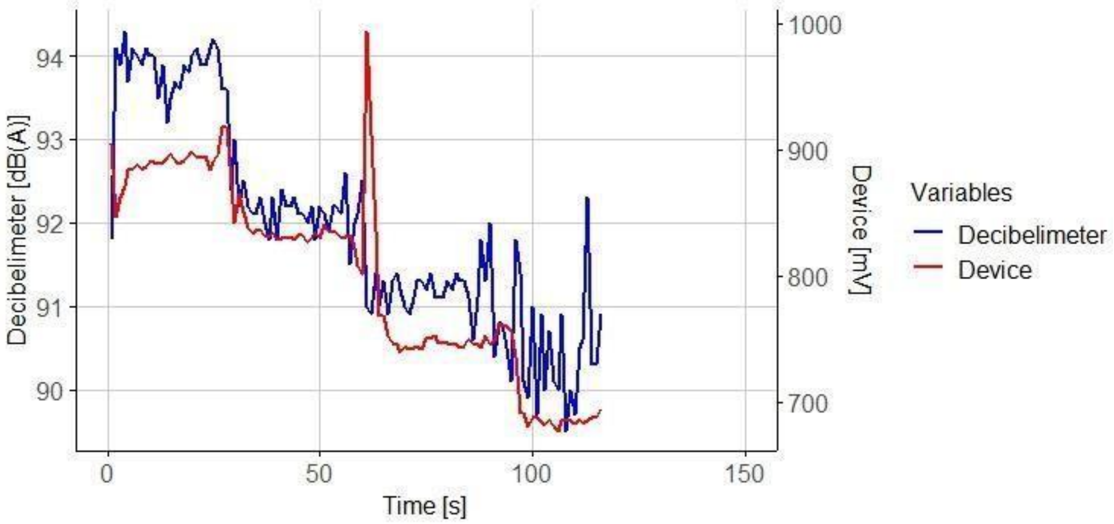
The tests conducted to characterize the sound intensity produced by the tractor at different RPM levels yielded average values of 86.86 ± 0.16 dB(A) at 800 RPM and 91.94 ± 0.12 dB(A) at 1600 RPM. These values were calculated based on the data presented in Figure 10, which illustrates the sound intensity recorded over time at varying distances using both the standard decibelimeter and the developed device. Such results are consistent with those reported by Dewangan et al. (2023), who indicated tractor noise values ranging between 92 dB(A) and 97.5 dB(A).

Figure 10. Sound intensity tests at variable distances using Device 4 and a decibelimeter at 800 RPM (A) and 1600 RPM (B).

A)



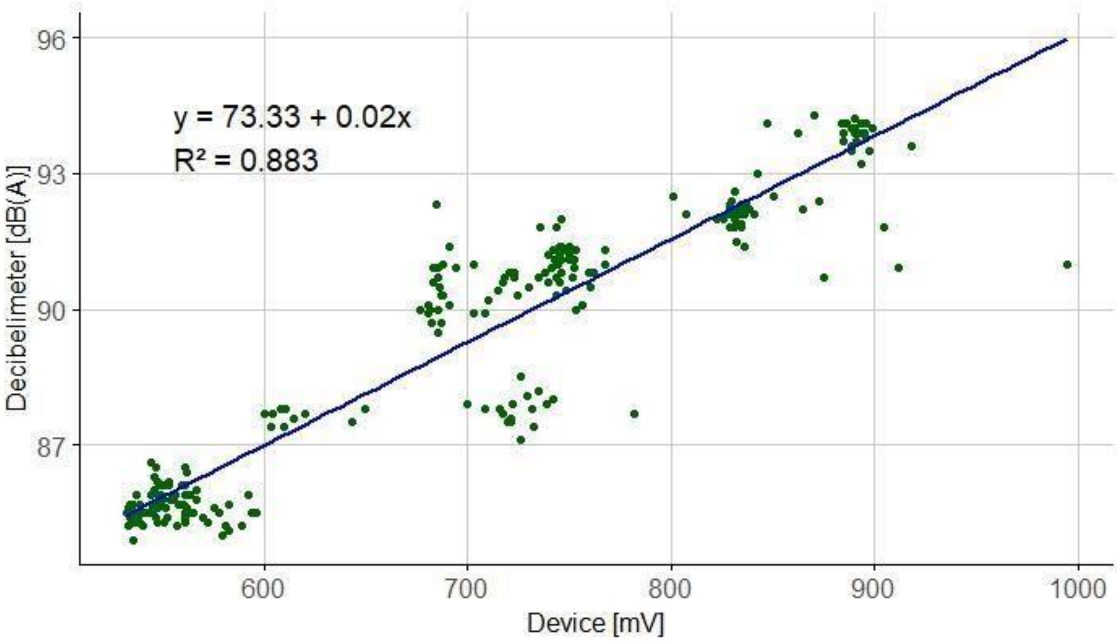
B)



Source: Authors.

The trends shown in Figure 11 clearly illustrate the comparative behavior between the low-cost acoustic sensor (device) and the reference sound level meter (decibelimeter). In both tests, the device exhibited a trend similar to that of the decibelimeter. It is important to note that, although the calibration equation obtained in the laboratory was applied, the conditions of this test suggest it may not have been fully appropriate. This issue is further addressed in Section 3.2.2 (Field Test: Noise in the Milking Parlor), where the persistence of residual error after calibration is evaluated. Nonetheless, the device maintained a linear relationship with the decibelimeter, achieving a fit of approximately 88% within the range of 85 dB(A) to 95 dB(A). This result may be attributed to previous laboratory observations, in which the low-cost sensor demonstrated better performance at higher sound intensity levels, likely due to microphone saturation effects.

Figure 11. Relationship between sound data obtained with the standard decibelimeter and with the device



Source: Authors.

3.2.2. Field Test: Noise in the Milking Parlor

Table 17 presents descriptive statistical data from both the reference (decibelimeter) and device. It was observed that both the decibelimeter and device identified Point B (pump room) as the loudest location, recording 85.12 dB(A) and 571.74 mV, respectively. This result indicates that the device is capable of consistently detecting high sound levels in agreement with the reference instrument (decibelimeter). It is likely that this area, along with the cooling room, is mutually influenced by the proximity of noise-generating machinery.

Table 17. Descriptive statistics of sound data obtained with the decibelimeter, and the device grouped by point. A – Milk room; B – Pump room; C – Front of the cooling room; D – Front of the milking pit (external zone facing the stalls); and E – Corridor adjacent to the exit lane, located parallel to the milking pit

Decibelimeter	Point	Mean [dB(A)]	Median [dB(A)]	SD [dB(A)]	Min. Value [dB(A)]	Max. Value [dB(A)]
	A	79.63	79.40	1.24	77.30	88.2
	B	85.12	85.00	1.37	82.00	95.3
	C	79.77	79.90	3.17	63.90	92.9
	D	76.26	76.00	2.49	71.90	93.1
	E	74.40	74.20	2.07	69.10	86.5
Device	**Point**	**Mean [mV]**	**Median [mV]**	**SD [mV]**	**Min. Value [mV]**	**Max. Value [mV]**
	A	470.43	472.17	36.08	413.06	591.76
	B	571.74	561.52	55.49	429.44	707.37
	C	489.29	476.03	51.32	399.18	644.27
	D	478.61	472.84	32.20	422.17	585.00
	E	489.63	478.02	40.66	399.18	632.14

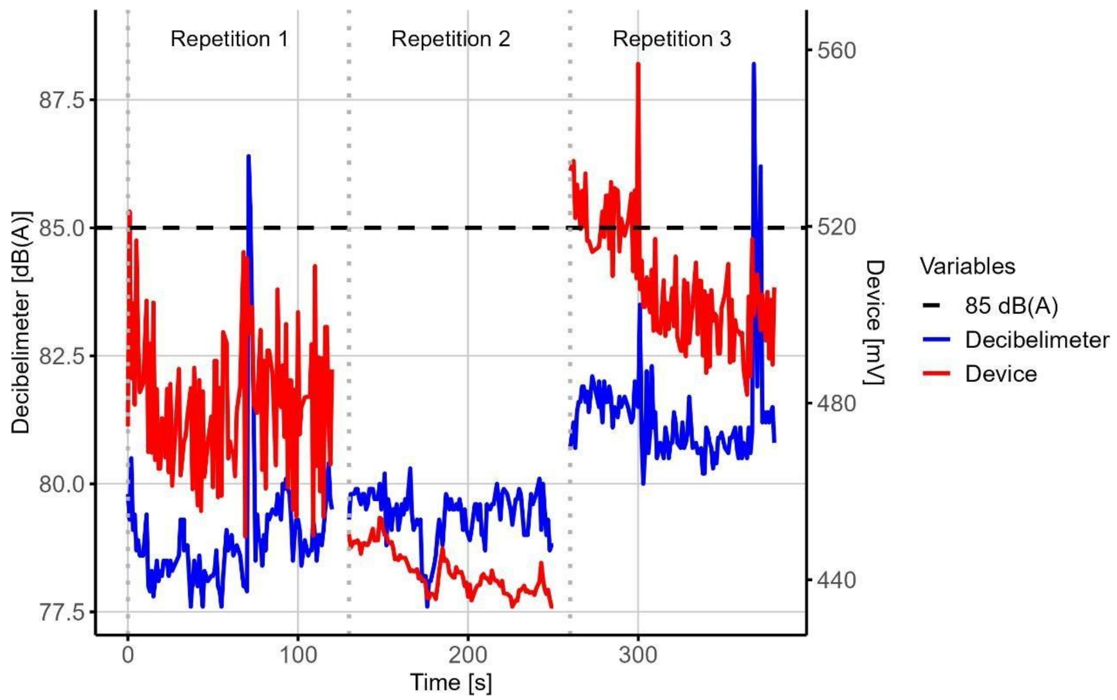
Source: Authors.

Beyond point B, discrepancies arise in the ranking of the remaining points. While the sound level meter identified Point E as the quietest environment (74.40 dB(A)), device recorded a higher voltage for E (489.63 mV) than for A (470.43 mV) and D (478.61 mV), which disrupts the expected correlation. This divergence is consistent with observations made during the tractor noise test, suggesting the need to recalibrate or adjust the conversion equation to more accurately capture sound levels across different ranges.

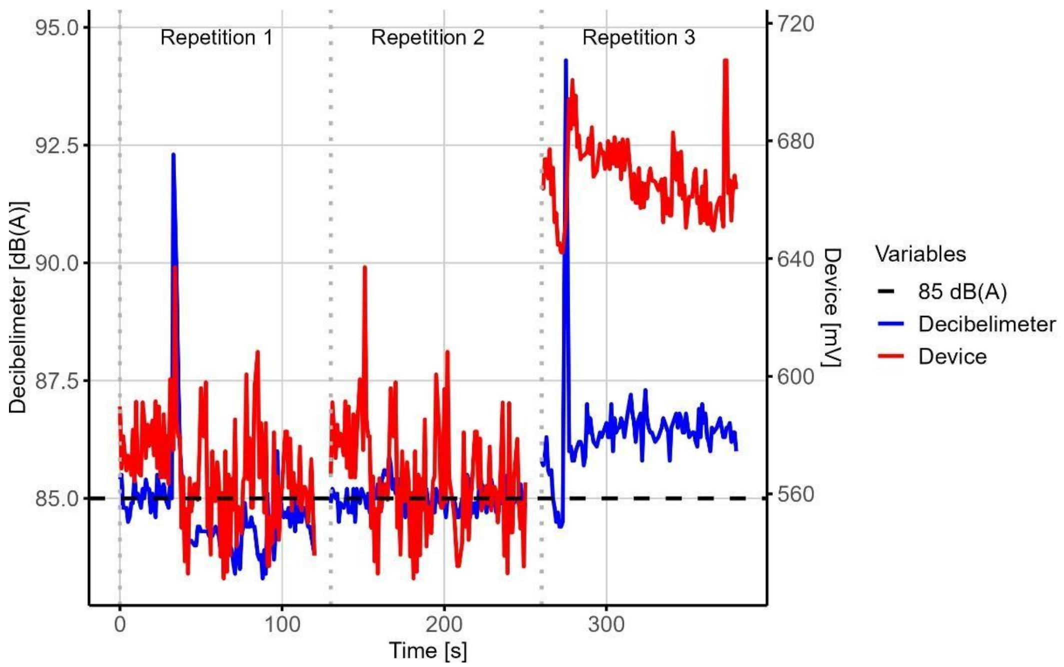
The dual-axis line graphs (Figure 12) simultaneously display the sound intensity recorded by the decibelimeter in dB(A) and the voltage measured by device (in mV) as a function of time.

Figure 12. Line graphs of sound intensity measurements taken by the standard decibelimeter [dB(A)] and Device 4 [mV] as a function of time at points A) Milk room; B) Pump room; C) Front of the cooling room; D) Front of the milking pit (external zone facing the stalls); and E) Corridor adjacent to the exit lane, located parallel to the milking pit. Each graph displays three sequential measurement repetitions, separated by vertical dotted lines

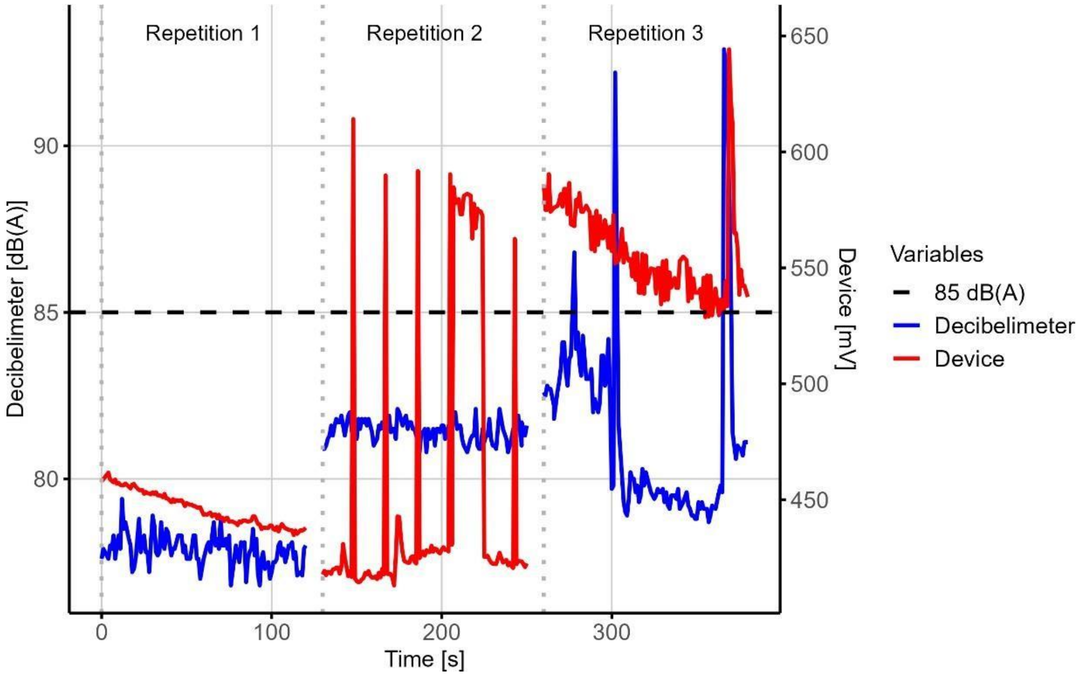
A)



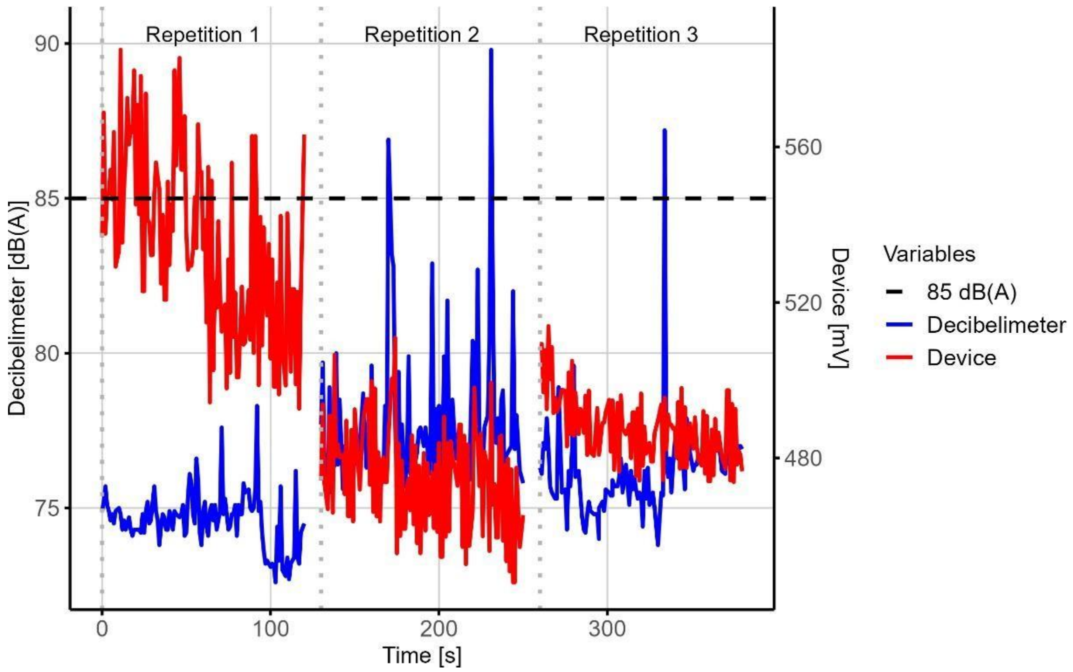
B)



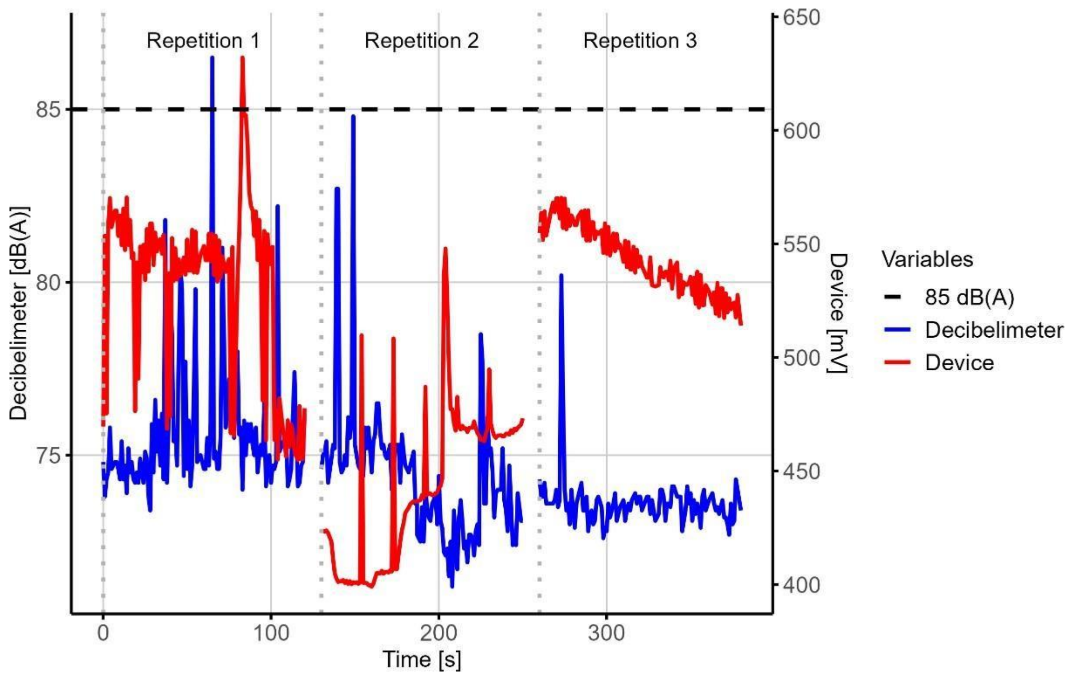
C)


Repetition 1
Repetition 2
Repetition 3
90
85
80
650
600
550
500
450
Decibelimeter [dB(A)]
Device [mV]
0
100
200
300
Time [s]
Variables
85 dB(A)
Decibelimeter
Device

D)


Repetition 1
Repetition 2
Repetition 3
90
85
80
75
560
520
480
Decibelimeter [dB(A)]
Device [mV]
0
100
200
300
Time [s]
Variables
85 dB(A)
Decibelimeter
Device

E)



Note: The blue line represents the reference sound level (decibelimeter), while the red line corresponds to the voltage signal [mV] of the low-cost acoustic sensor, normalized for visual comparison. The y-axis on the left refers to sound pressure levels in dB(A), and the secondary y-axis on the right corresponds to the raw sensor output in millivolts. A horizontal dashed line indicates the threshold of 85 dB(A), often considered a limit for occupational noise exposure. Each graph contains three repetitions of approximately two minutes each, presented sequentially along the x-axis and delimited by vertical dotted lines to prevent misinterpretation of continuity between segments.

Source: Authors.

The dispersion values (standard deviation and range) indicate that certain locations, such as C and D for the decibelimeter, and B and C for the device, showed greater variability or noise peaks (Table 17 and Figure 12). These fluctuations are attributed to the cooling process of the cows in the cooling room, before the three daily milkings, with the activation of the Magnum 60 fan (belt-driven) being responsible for the highest sound peaks in the milking area. This trend of peaks caused by the Magnum 60 fan can be seen in the sound intensity curves recorded by the sound level meter at all points (Figure 12).

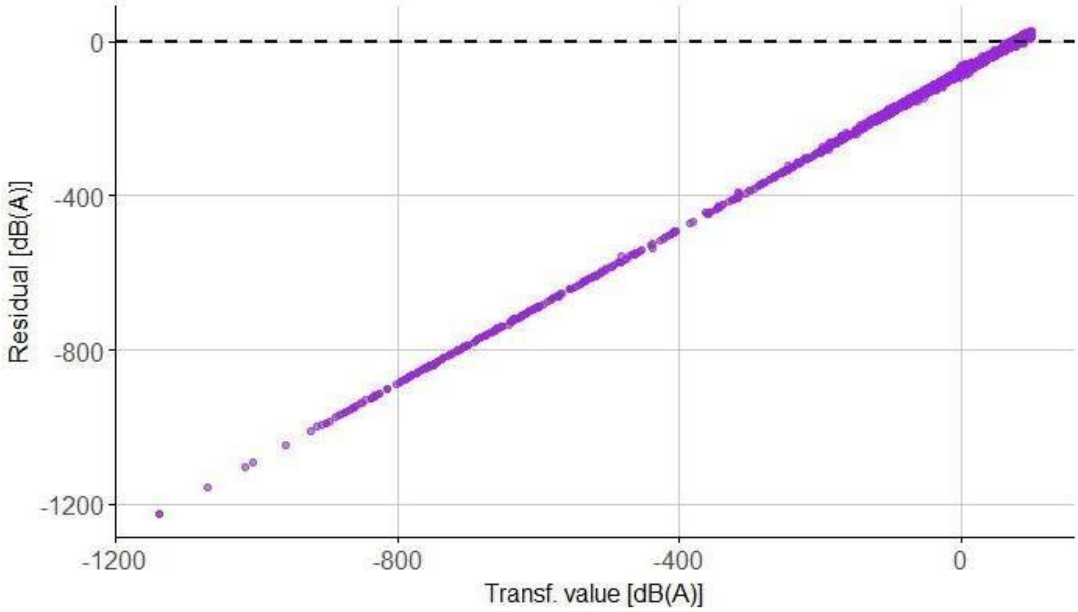
Other noise sources, both constant and intermittent, include the ventilation system of the milking area, continuously operating pumps, cooling tanks, opening and closing of doors (through which workers enter), staff behavior (whistling, shouting, clapping, finger whistling), biological sounds (birds), and spontaneous impacts, such as the dropping of metal carts used for transporting milk for calves. In line with the values reported by (Mihina et al., 2018), the average sound intensity measurements remained below 85 dB(A), except at point B (Table 17), which slightly exceeded this threshold. However, the maximum recorded values (spontaneous peaks) surpassed this limit in all evaluated areas, reaching 95.3 dB(A) in the pump room and 92.9 dB(A) in the cooling room (Figure 12). This represents a potential risk to the welfare of the cows during the milking process, as it exceeds the 90 dB(A) moderate noise threshold that Esmail (2017) identifies as the upper limit of tolerance for cattle.

Differences were observed among the three repetitions at each measurement point (Figure 12). Except for Point B, all locations exhibited at least one repetition where the sound intensity exceeded the 85 dB(A) threshold, and another where it did not. These variations highlight the dynamic nature of the acoustic environment during milking. Future studies may explore the relationship between sound levels and the milking schedule to better understand time-dependent acoustic fluctuations.

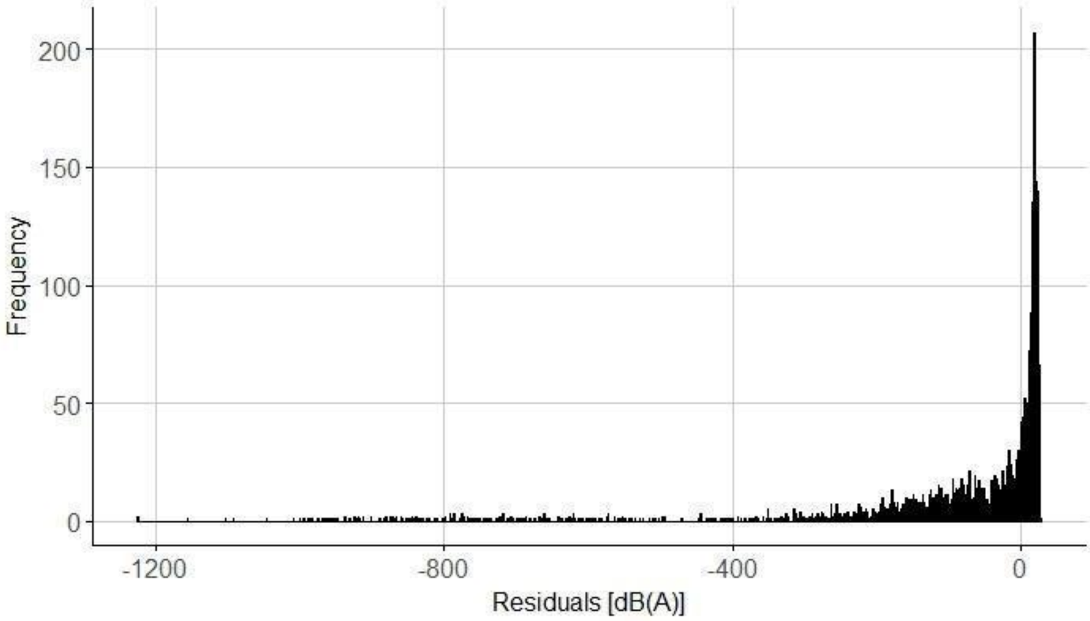
To verify whether a systematic error persisted in the sound intensity calibration, similar to what was observed during the tractor tests, a residual versus transformed values plot was generated using the adjusted readings from the device (Figure 13A). The distribution of points along a negatively sloped line, ranging from –1200 to 0 dB(A), indicates a consistent underestimation by the calibration equation, deviating from the ideal pattern of random dispersion around zero. This trend is further supported by the residual histogram (Figure 13B), which exhibits a strong skew toward negative values, with a concentration near 0 dB(A), and by the comparison plot between the decibelimeter and the device's transformed readings (Figure 13C). The scatterplot in Figure 13C shows a clear deviation from the identity line (y = x), indicating low correlation and reinforcing the presence of systematic bias. Statistical analysis corroborates this finding, with a highly significant result in the paired Student's t-test ($p < 2.2 \times 10^{-16}$) and a root mean square error (RMSE) of 193.10.

Figure 13. Diagnostic plots for the sound intensity calibration of the device. (A) Residuals versus transformed values after applying the laboratory calibration equation. (B) Histogram of residuals showing a skew toward negative values. (C) Comparison between decibelimeter and device readings (transformed values)

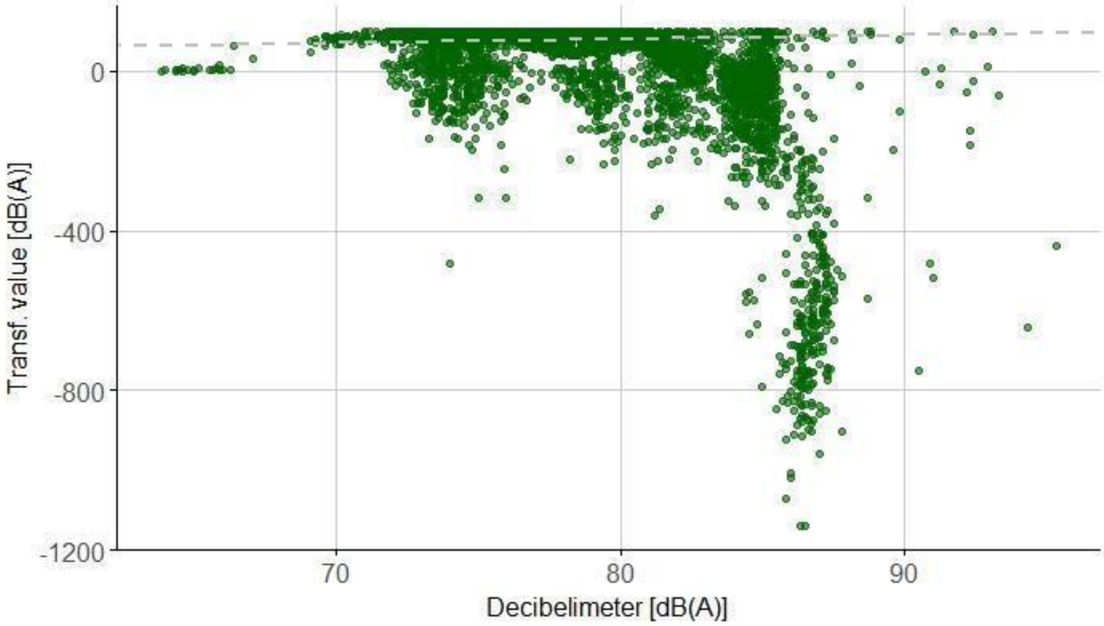
A)



B)



C)



Source: Authors.

3.2.3. Field Test: Thermoacoustic Monitoring in Intensive Dairy Cattle Production System

3.2.3.1. Device Efficiency

The field test in an intensive dairy cattle production system made it possible to evaluate the performance of the devices in terms of data acquisition. All devices demonstrated high performance in data collection, and overall, the data storage system using a microSD card proved to be satisfactory, considering that efficiencies above 99% were achieved (Table 18).

Table 18. Number of data acquired per sensor and point of interest

Sensor	Composted Bedding Area	Cooling Room	Milking Parlor	Feeding Alley	Percentage per Sensor (%)
BME 280	4583.00	4604.00	4604.00	4584.00	99.69
BMP 180	2292.00	2302.00	2302.00	2292.00	99.70
SEN-12642	-	686912.00	686919.00	-	99.38
Percentage by area (%)	99.46	99.38	99.39	99.47	-

Source: Authors.

3.2.3.2. Values of Dry-Bulb Temperature, Relative Humidity, THI, BGHI, and Sound Intensity

Table 19 presents the descriptive statistics of the data and the average curves of the variables recorded by each device in the bedding area and feeding alley of the Compost Barn facility and in the cooling room and milking parlor of the intensive dairy cattle production system. Table 19 includes the data recorded outside the facility, revealing that the average dry-bulb temperatures in the internal zones were approximately 4 °C lower than the average recorded outdoors. In contrast, the average relative humidity values recorded in the internal zones were approximately 10% higher than those recorded externally.

Table 19. Descriptive statistics of variables for the different zones analyzed in the field test. Variables notation: Dry bulb temperature (DBT); Relative Humidity (RH); Temperature and Humidity Index (THI); Black Globe Temperature and Humidity Index (BGHI); Sound Intensity (Sound)

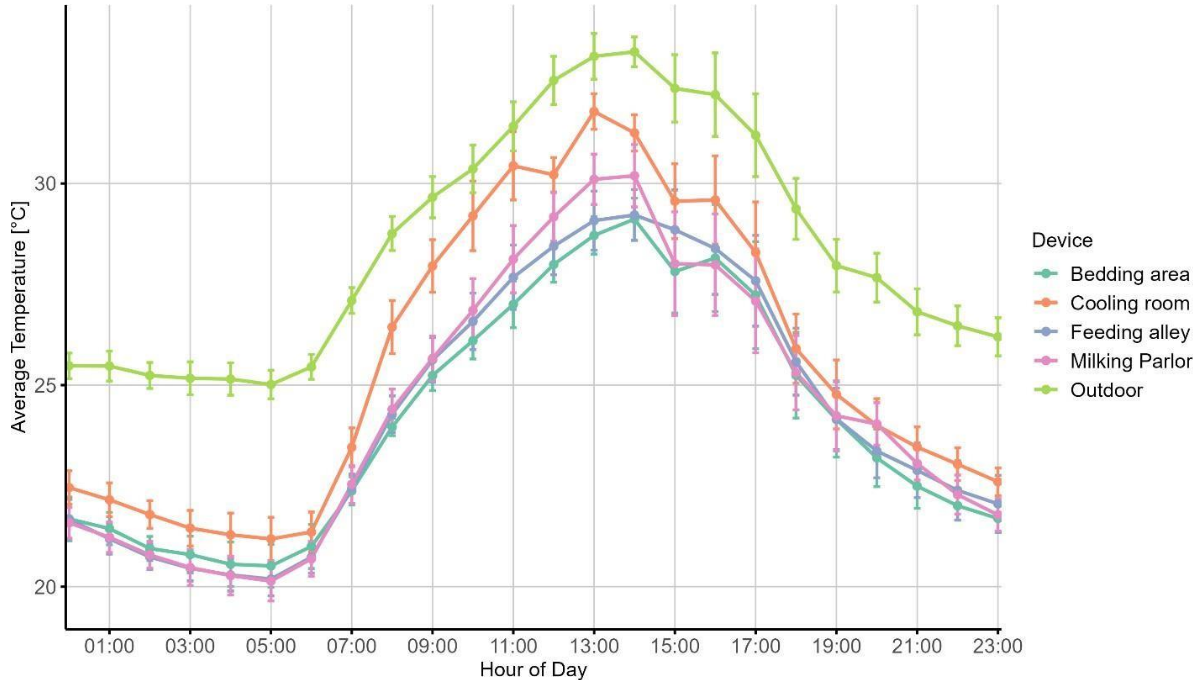
Variable	Units	Area	Cooling Room	Milking Parlor	Feeding Alley	Outside
DBT min.	°C	19.25	20.04	19.12	18.61	23.46
DBT max.	°C	32.08	34.02	32.73	32.29	37.31
DBT mean	°C	24.12	25.46	24.28	24.17	28.57
DBT SD	°C	3.09	3.73	3.44	3.49	3.16
RH min.	**%**	37.83	38.93	35.43	39.10	32.84
RH max.	**%**	99.78	99.88	99.37	99.99	94.54
RH mean.	**%**	79.75	76.56	75.95	78.65	67.74
RH SD	**%**	16.60	15.51	16.06	17.33	14.72
THI min.	dimensionless	67.77	68.54	67.23	66.97	-
THI max.	dimensionless	80.06	82.76	80.57	80.75	-
THI mean	dimensionless	73.00	74.58	72.92	72.97	-
THI SD	dimensionless	2.93	3.81	3.39	3.39	-
BGHI min.	dimensionless	69.98	70.69	70.23	69.08	-
BGHI max.	dimensionless	79.12	82.57	79.89	79.35	-
BGHI mean	dimensionless	73.95	75.20	74.48	73.47	-
BGHI SD	dimensionless	2.20	2.88	2.44	2.47	-
Sound min.	mV	-	0.00	0.00	-	-
Sound max.	mV	-	768.86	847.68	-	-
Sound mean	mV	-	303.19	349.37	-	-
Sound SD	mV	-	27.02	31.25	-	-

Source: Authors.

As shown in Table 19, standard deviation of the relative humidity data exceeded 14% in all evaluated areas, indicating a considerable dispersion in the recorded values. This variability may be partially explained by limitations in the performance of the BME280 sensor. In this regard, (C. E. A. Oliveira et al., 2025) also reported substantial errors in relative humidity measurements from multiple BME280 sensors when compared to a reference device. These authors reported average root mean square errors (RMSE) of up to 16.20%, mainly attributed to various operational factors inherent to the functioning of these low-cost capacitive sensors. For this reason, future studies are advised to use the reference device alongside the sensors during field operation, to more accurately verify their performance and reliability under real-world conditions. Another relevant aspect was the occurrence of 0.00 mV values recorded by some acoustic sensors installed in different monitored areas. These values are attributed to signal acquisition issues within the sensor's processing chain.

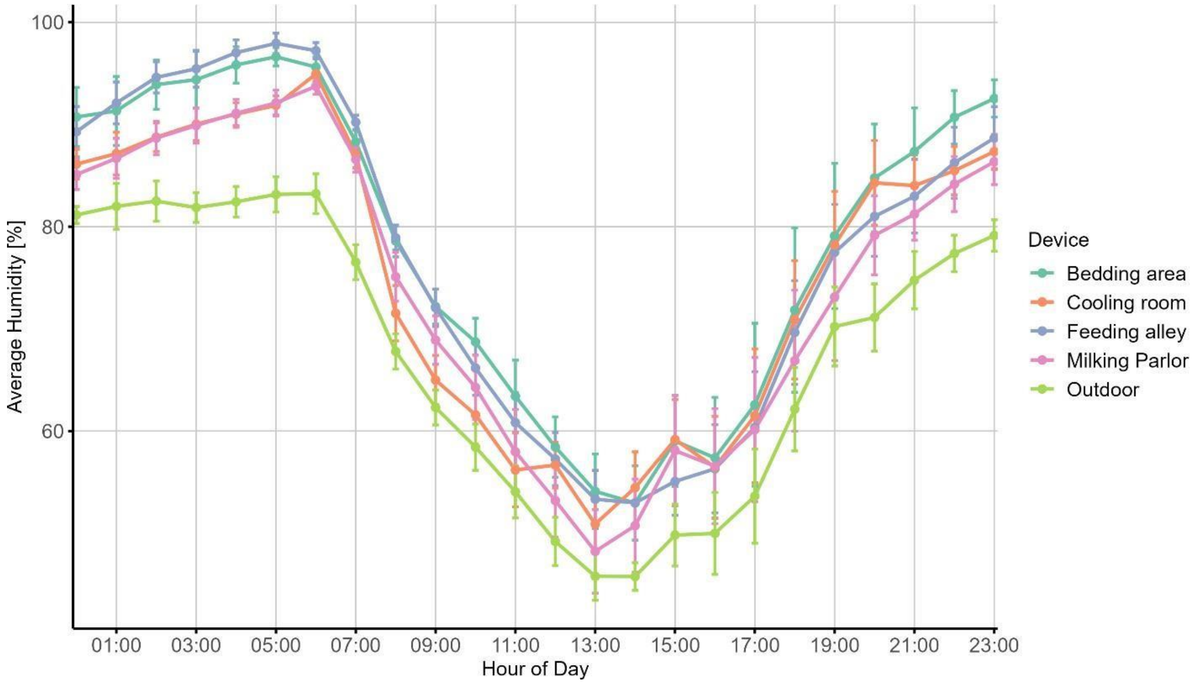
Figures 14 and 15 show the diurnal profiles of dry-bulb temperature (Tdb) and relative humidity (RH) across the monitored points. A temperature peak was consistently observed around 1:00 p.m., coinciding with the lowest RH levels, a pattern that reflects the typical climatic conditions of the region, as reported by Souza et al. (2025) and C. E. A. Oliveira et al. (2025). According to the comfort ranges consolidated by Oliveira et al. (2022) for Holstein dairy cows, based on prior expert literature (e.g., Baêta and Souza (2012); Perissinotto and De Moura (2007)), the optimal thermal comfort ranges are defined as 12.0°C ≤ Tdb < 18.0°C and 50.0% ≤ RH < 60.0%, while critical thresholds are considered at Tdb ≥ 24.0°C and RH ≥ 75.0%. In the present study, dry-bulb temperatures remained above the critical threshold for more than 10 hours per day and never entered the optimal range. Relative humidity, in contrast, only remained within optimal values for approximately five hours daily and frequently exceeded the upper critical limit during midday periods.

Figure 14. Average hourly dry-bulb temperature profiles by device in the zones: bedding area and feeding alley of the Compost Barn facility and in the cooling room and milking parlor of the intensive dairy cattle production system



Source: Authors.

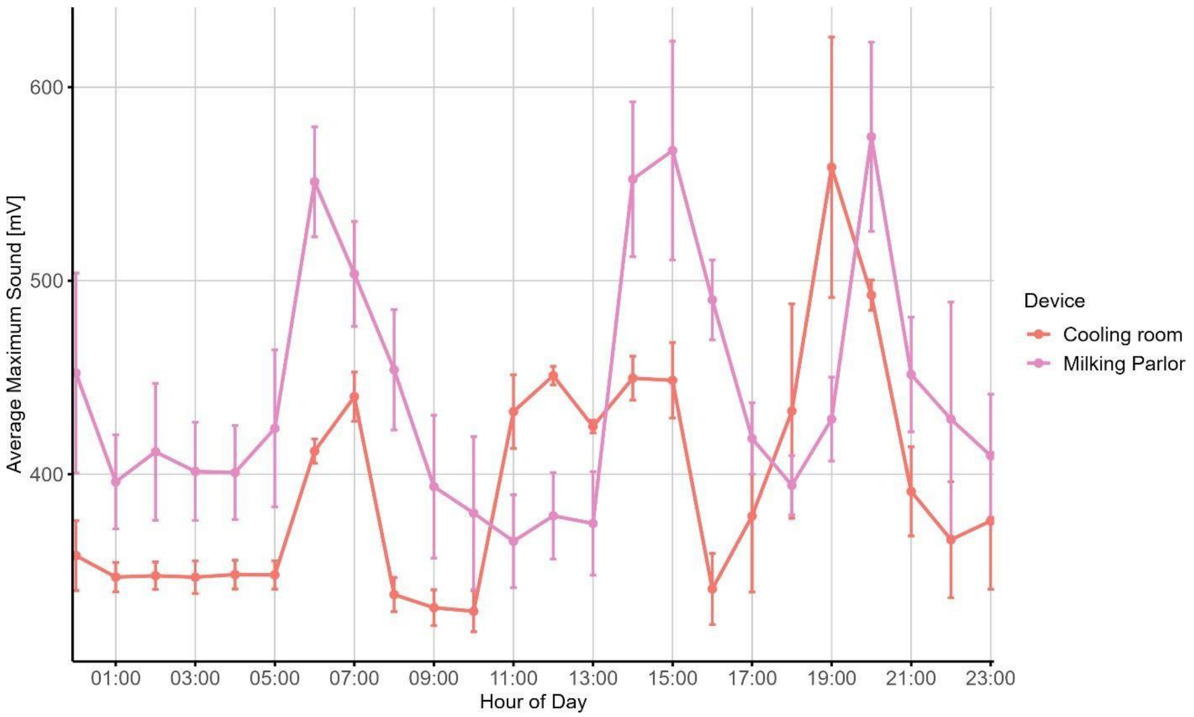
Figure 15. Average hourly relative humidity profiles by device in the zones: bedding area and feeding alley of the Compost Barn facility and in the cooling room and milking parlor of the intensive dairy cattle production system



Source: Authors.

The trend observed in the average maximum sound intensity (in mV) recorded by the devices (Figure 16) reveals marked differences among the measurements obtained in the different evaluated zones. Notably, there is greater variability in the milking parlor compared to the cooling room, with three clearly defined peaks identified in both zones, corresponding approximately to the milking times (7:00 a.m., 2:00 p.m., and 7:00 p.m.), as well as an additional increase around midday, likely associated with the arrival of the milk collection truck. In this regard, Dimov et al. (2023) point out that noise levels in milking systems depend not only on machinery operation, but also on specific operational conditions. Therefore, it is likely that the observed variability in the milking parlor is related not only to the pump room and milking equipment, but also to frequent anthropogenic activities, such as whistling, shouting, and the repeated use of metal doors.

Figure 16. Average hourly profiles of maximum sound by device in the zones: bedding area and feeding alley of the Compost Barn facility and in the cooling room and milking parlor of the intensive dairy cattle production system



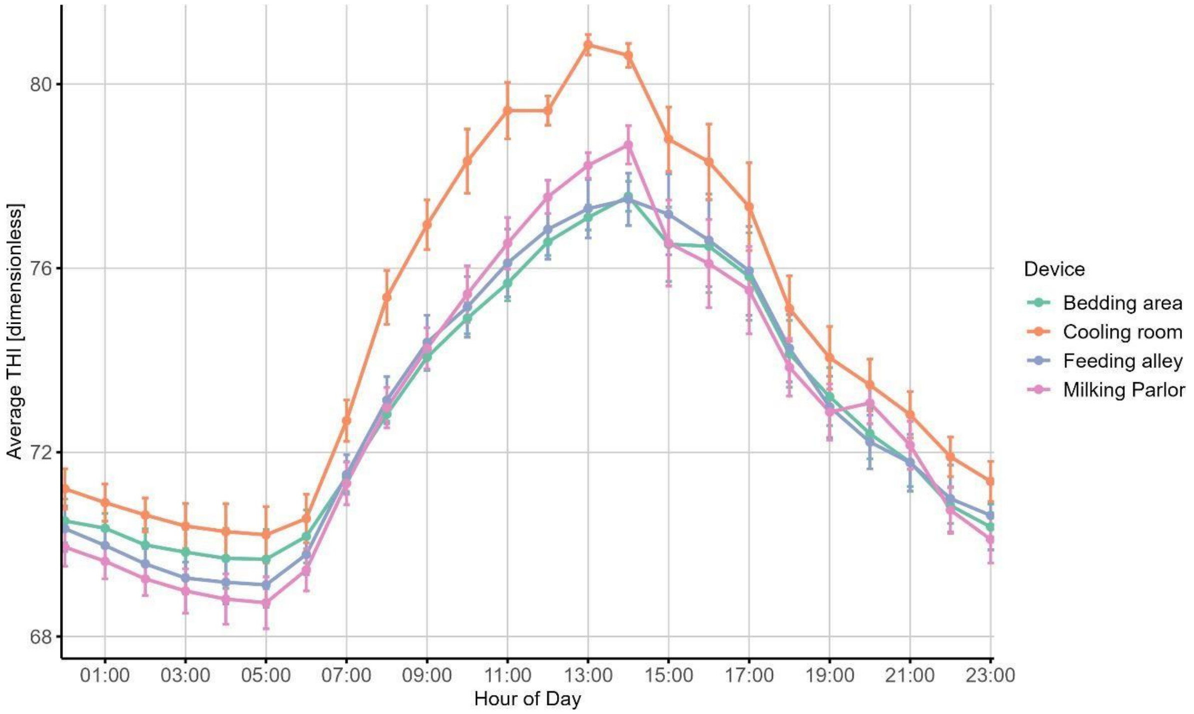
Source: Authors.

Regarding the differences in trend observed between the two devices throughout the day (Figure 16), where generally lower voltage levels (below 400 mV) were recorded in the cooling room compared to the milking parlor, these differences may be attributed to two main factors: residual electronic noise under low sound intensity conditions and electromagnetic interference captured by the sensors. Concerning these first two factors, Picaut et al. (2020) emphasize the critical importance of the signal acquisition chain in acoustic sensors, highlighting the susceptibility of such devices to electrical and radiofrequency interference. As a result, the performance of acoustic sensors may be compromised at low sound intensity levels. Therefore, the elevated voltage values observed and the differences between the devices shown in Figure 16 may not truly correspond to higher sound intensities, but rather to increased residual noise caused by the specific environmental characteristics of each evaluated area. During periods of the day when actual noisy activities occur, such as milking or intense animal movement, the quality of the acoustic signal captured by the sensor may substantially improve, increasing the signal-to-noise ratio and reducing or stabilizing the voltage to values that are more representative of actual sound levels.

Various researchers have proposed thresholds for identifying heat stress in dairy cattle. According to Armstrong (1994) and Ravagnolo et al. (2000), milk, protein, and fat productivity remains relatively constant up to a THI value of 72. This value is derived from the formula described by Kendall and Webster (2009), which is based on the original proposal of the National Research Council (1971). Pinto et al. (2019), working specifically with high-producing Holstein cows, observed increases in respiratory rate at THI values above 68. Schüller et al. (2014) reported that heat stress begins to impair conception rates at THI = 73.

In this regard, Ravagnolo et al. (2000) suggested that the growing heat sensitivity observed in modern Holstein cows may be a consequence of intensive genetic selection, which could explain the variation in thresholds reported across studies. Therefore, THI values above 68, as well as those equal to or exceeding 74 (used as the reference in this study), should be considered indicative of potentially stressful conditions for the animals. In this study, THI values > 74 (Figure 17) were recorded for approximately 10 hours per day, between 9 am and 5 pm, in the four areas of interest. This highlights the need to further investigate the relationship between environmental conditions in the different milking system areas and the physiological responses of the cows, to define THI thresholds more aligned with current production realities.

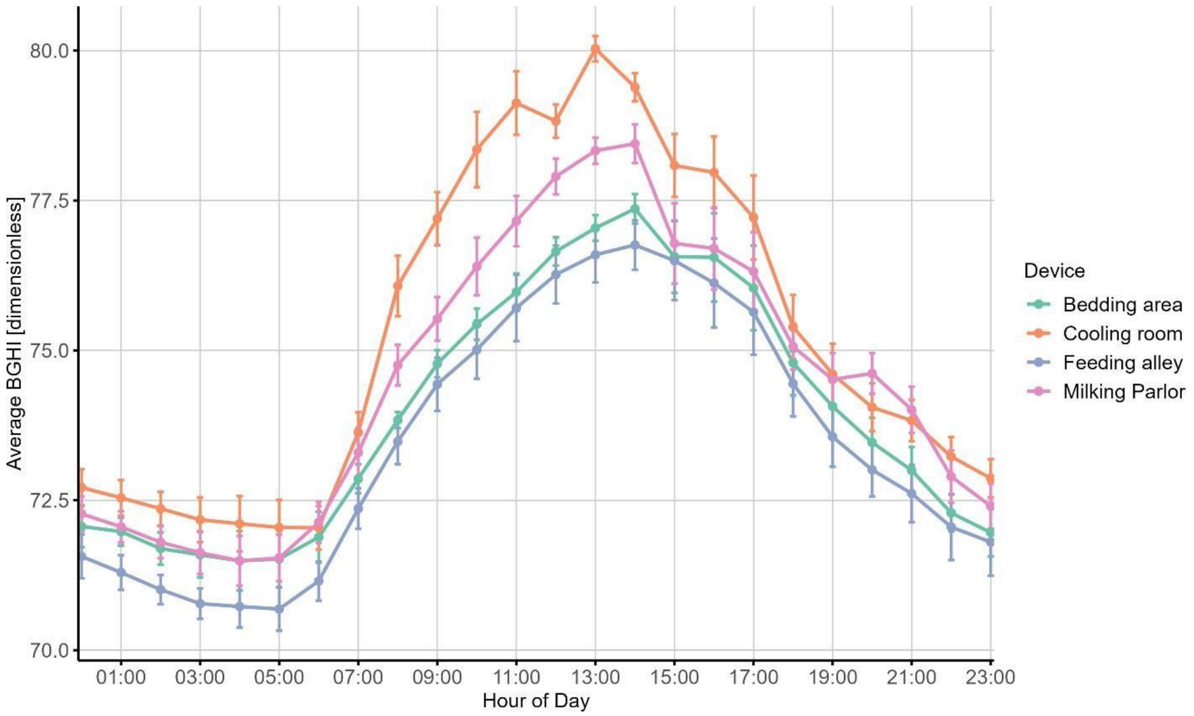
Figure 17. Average hourly Temperature and Humidity Index (THI) profiles by device in the zones: bedding area and feeding alley of the Compost Barn facility and in the cooling room and milking parlor of the intensive dairy cattle production system



Source: Authors.

In this study, BGHI values above 74 (Figure 18) were recorded around 1:00 p.m. These maximum values can be attributed to the climatic behavior of the region, characterized by peaks in temperature and humidity near midday. For example, Martello et al. (2004) reported similar results in a study conducted in dairy cow facilities during the summer, observing peak average values of both BGHI and THI around 1:00 p.m.

Figure 18. Average hourly Black Globe Temperature and Humidity Index (BGHI) profiles by device in the zones: bedding area and feeding alley of the Compost Barn facility and in the cooling room and milking parlor of the intensive dairy cattle production system

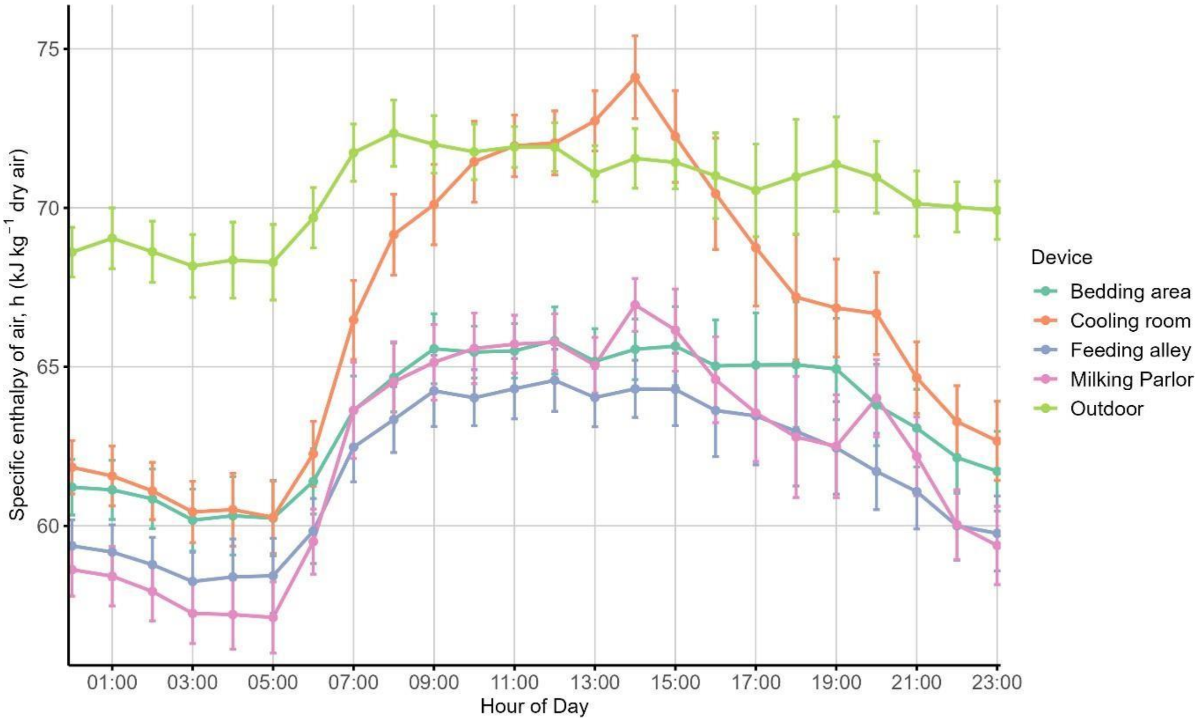


Source: Authors.

It is also important to emphasize that the most critical THI and BGHI values were observed in the cooling room and the milking parlor. However, these indices showed a declining trend starting with the afternoon milking session (around 2:00 p.m.), likely due to the simultaneous activation of fans and sprinklers. This effect is also reflected in the sound intensity data (Figure 16), which show a peak during the most critical periods of the day, precisely when a drop and stabilization in temperature are observed (Figure 14), likely due to the activation of cooling mechanisms. In contrast, the bedding area in the Compost Barn and the feeding alley likely exhibited less critical thermal conditions, benefiting from structural characteristics and continuous ventilation throughout the day.

To complement the interpretation of THI and BGHI, the specific air enthalpy (h) was calculated using the model proposed by Rodrigues et al. (2011), which combines dry-bulb air temperature, relative humidity, and local barometric pressure, thus incorporating both sensible and latent heat components. Figure 19 presents the mean diurnal enthalpy profiles for the different areas of the milking system as well as for the outdoor environment. The highest enthalpy values were observed in the cooling room during the central hours of the day, reaching approximately 74 kJ·kg^{-1} of dry air, even though air temperature was partially reduced by ventilation.

Figure 19. Hourly averaged profiles of air specific enthalpy for different areas of the milking system and outdoor environment



This pattern is mainly associated with the increase in latent heat linked to elevated relative humidity under evaporative cooling conditions. In the outdoor environment, enthalpy values remained consistently high throughout the day, which reflects the persistent external thermal load characteristic of the region and the limited potential for passive heat dissipation.

Cooling strategies were effective in lowering temperature-based indices such as THI and BGHI during the most critical periods of the day. However, the enthalpy profiles show that the total energetic content of the air may remain high under conditions of elevated ambient humidity. Values within a similar range have been reported for Holstein cows in dairy facilities by Oliveira et al. (2022), but variations in climatic context, seasonality, and facility design hinder direct comparisons regarding thermal comfort thresholds. Consequently, enthalpy is included here as a complementary variable to describe the thermal environment, and its interpretation is deliberately limited in the absence of direct physiological data.

It should be noted that both THI and BGHI describe only the potential for heat stress in the different zones of the milking system. Therefore, as mentioned in the previous paragraph, it is not possible to confirm the actual presence of heat stress in cows without direct physiological measures. This distinction is particularly relevant in zones such as the cooling room, where the highest values for both indices were recorded, yet cows are subjected to a management routine that includes forced ventilation and intermittent sprinkling during all three milking periods.

In this context, D'Emilio et al. (2017) reported that the use of sprinklers, in combination with forced ventilation, did not significantly alter the microclimatic conditions in a free-stall barn. However, they observed positive effects on the animals' physiological responses, particularly in terms of reduced respiration rates and lower rectal temperatures. Regarding the latter, Flamenbaum et al. (1986) also documented a beneficial impact of sprinkling on rectal temperature reduction. Air movement plays a critical role in facilitating water evaporation from the animal's coat and, consequently, in regulating ambient humidity (Flamenbaum et al., 1986). Therefore, when forced ventilation and intermittent sprinkling are properly implemented, a significant increase in relative humidity is not expected. As noted by Perissinotto et al. (2006), the primary objective of sprinkling is to wet the cows, thereby enhancing heat dissipation and improving animal comfort.

4. CONCLUSIONS

The prototype of the low-cost device (total estimated cost of $42.7 USD), composed of temperature, humidity, and sound sensors integrated into an ESP32 microcontroller, achieved data acquisition efficiencies above 99%, with coefficients of determination (R^2) greater than 0.95 in most calibration procedures. However, relevant limitations were observed regarding the accuracy of relative humidity readings and the acoustic sensitivity at low sound intensity levels.

In the field application, the device successfully characterized the thermal and acoustic environment of an intensive dairy cattle production system. Environmental conditions frequently exceeded comfort thresholds, with air temperature ≥ 24 °C, relative humidity ≥ 75%, THI/BGHI ≥ 74 and specific enthalpy of air h ≥ 74 kJ·kg of dry air^{-1}. Sound levels above 85 dB(A) were recorded, particularly associated with tractor operations (≥ 91 dB(A)), peaks in the cooling room (up to 95 dB(A)), and sustained exposure in pump rooms (near 85 dB(A)).

These results confirm the device's potential as a cost-effective and scalable alternative for integrated and continuous thermoacoustic monitoring in intensive livestock systems. Future improvements are recommended, including the replacement of the electret microphone with more sensitive sensors, increasing the sampling rate, and optimizing microcontroller performance. Such enhancements could significantly improve the device's reliability and expand its application to other animal production contexts, supporting data-driven environmental management in increasingly technified agricultural settings.

CRediT AUTHORSHIP STATEMENT

Conceptualization, J.N.R.N., F.C.S., A.L.F.C., and R.O.H.; Methodology, J.N.R.N., F.C.S., A.L.F.C., and R.O.H.; Writing – original draft, J.N.R.N.; Writing – review & editing, J.N.R.N., F.C.S., A.L.F.C., and R.O.H.; Supervision, F.C.S., A.L.F.C., and R.O.H.; Project administration, F.C.S.; Funding acquisition, F.C.S.

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ETHICAL APPROVAL

All procedures involving animals were approved by the Ethics Committee on the Use of Production Animals of the Federal University of Viçosa (CEUAP-UFV), under protocol no. 07/2024.

DATA AVAILABILITY

The datasets generated and analyzed during the study are available from the corresponding author upon reasonable request.

DECLARATION OF COMPETING INTEREST

The authors declare no competing interests.

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GENERAL CONCLUSION

The review chapter shows that research on acoustic analysis in poultry, swine, and cattle production systems has steadily advanced due to technological progress in sensing devices and signal processing techniques. Four main lines of research were identified: vocalizations as indicators of welfare, characterization of sound sources, combined analysis of sources and vocalizations, and animal responses to acoustic stimuli.

Although sound has been recognized as a variable with potential for animal welfare assessment, the diversity of metrics used, the lack of standardized calibration protocols, and the limited availability of large datasets continue to hinder the adoption of acoustic tools on commercial farms. Future research, in addition to further exploring the role of artificial intelligence in acoustic monitoring, should focus on strengthening experimental designs and integrating physiological and environmental variables into multidimensional datasets.

The thermoacoustic prototype based on an ESP32 microcontroller had an approximate cost of \$42.7 USD. It showed good performance in field conditions, achieving acquisition efficiencies above 99% and coefficients of determination greater than 0.95. The device successfully contributed to identifying thermal stress conditions (THI/BGHI ≥ 74 and h ≥ 74 kJ·kg of dry air^{-1}), and through comparisons with reference devices, it also detected noise peaks (≥ 85 dB(A)) in an intensive dairy cattle production system. These results confirm its potential as a low-cost and continuous monitoring tool in livestock environments.

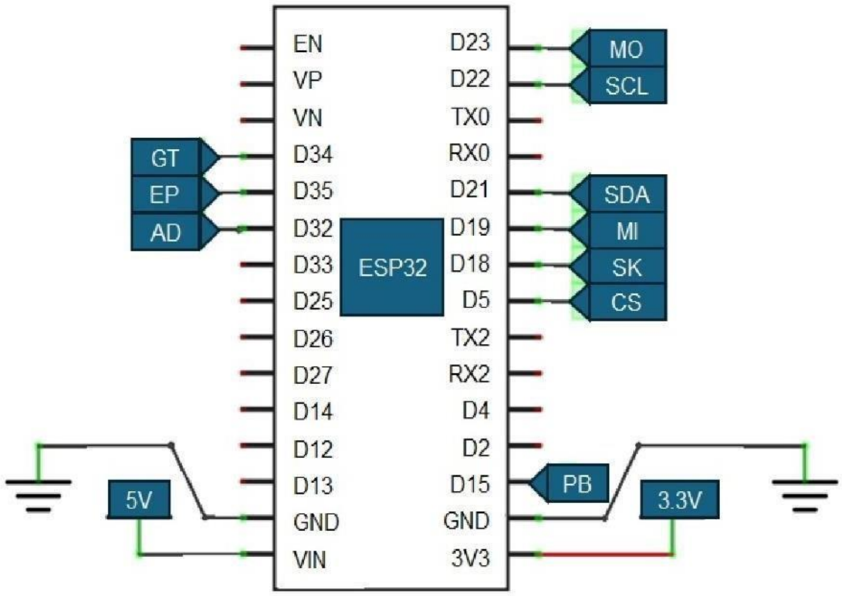
Its main weaknesses involve the microphone's limited sensitivity and small errors in relative-humidity measurements. Future versions should install a more responsive microphone, raise the sampling rate, refine signal filtering, and test long-term durability across multiple species and housing systems.

Taken together, the systematic review and the field trial confirm both the need and the practical possibility of pairing sound with other environmental variables to assess welfare. They suggest that thermoacoustic monitoring could become a routine feature of precision livestock farming for both researchers and producers, once the outstanding issues of technology, standardization, accuracy, and scalability are resolved.

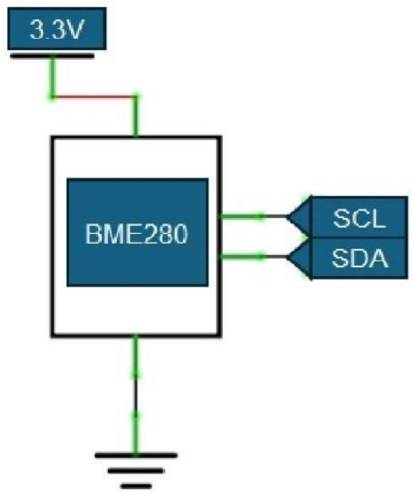
APPENDIX

A) SCHEMATIC DIAGRAM OF THE CONNECTIONS USED IN THE DEVICE, A) ESP32 MODULE, B) BME280, C) BMP180, D) SEN12642, E) DISPLAY OLED 128X64, F) RTC MODULE, G) MICROSD CARD MODULE, H) PUSH BUTTON

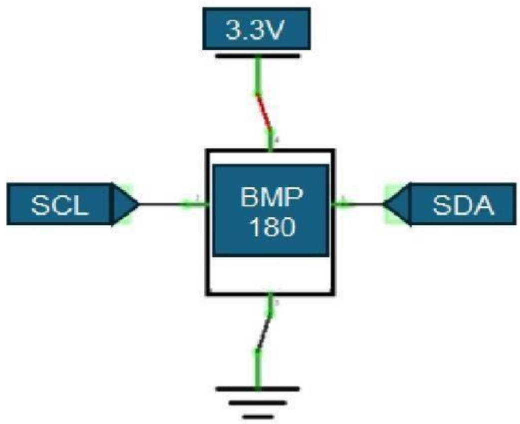
A)



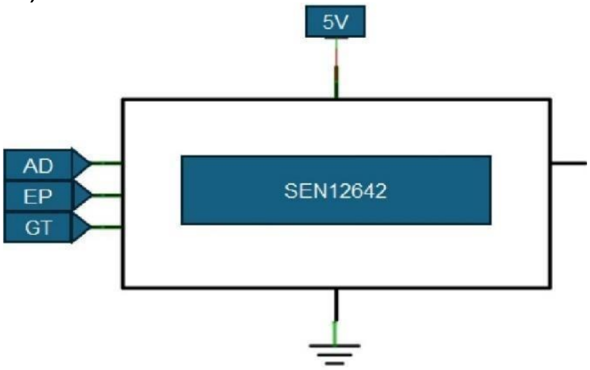
B)



C)



D)



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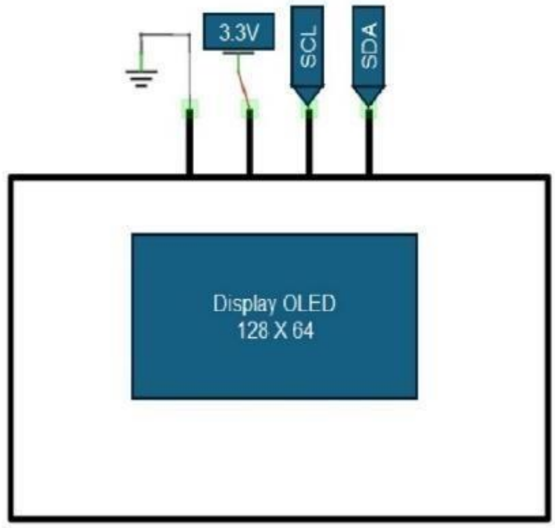

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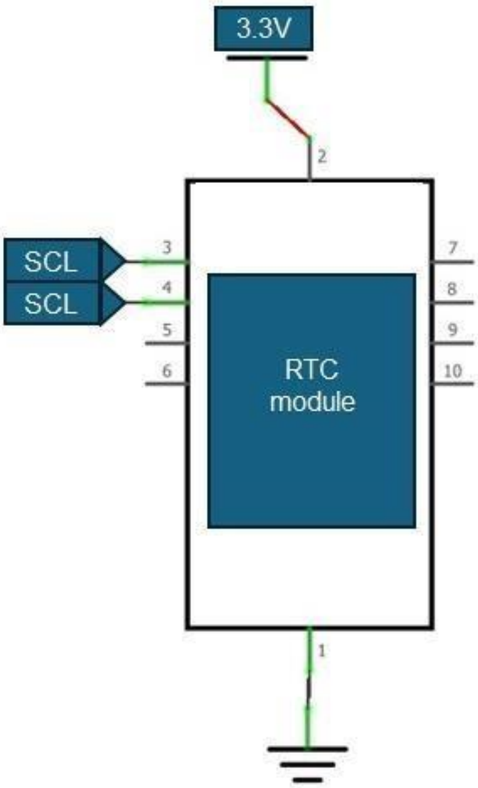
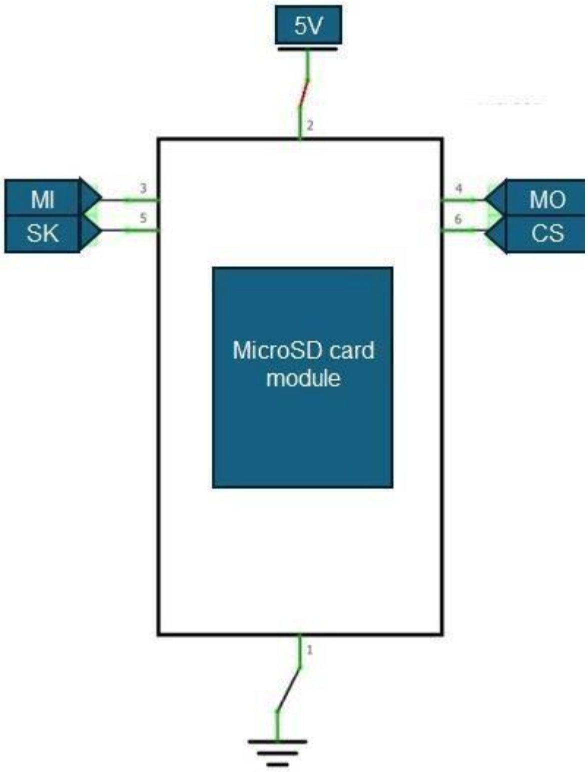
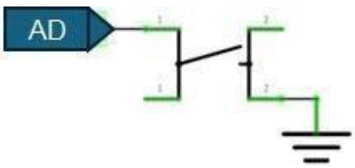


G)



H)



Source: Authors.

B) PSEUDOCODE AND SOURCE CODE

Table. Pseudocode implemented in the device for monitoring the thermoacoustic environment in animal production.

Input	Device number and corresponding sensor calibration equations. • Wi-Fi credentials. • Sensor configuration (BME280, BMP180, sound sensor). • SD card chip select and file paths. • Network Time Protocol (NTP): chosen according to the region of use.
Output	• Data displayed in real time on the OLED display: RTC and other measured variables • Logged sensor data (dry bulb temperature, pressure, altitude, black globe temperature, relative humidity and acoustic) stored in CSV files on microSD. • Time synchronization via RTC (updated from NTP when available). • Black Globe Temperature and Humidity Index (BGHI).

System Setup	• Initialize libraries and communication interfaces (Serial, I2C, SPI).
	• Configure GPIOs (e.g., button pin, OLED reset).
	• Initialize peripherals:
	  o OLED display (welcome screen message).
	  o RTC (DS3231).
	  o Sensors (BME280 and BMP180).
	  o MicroSD card (open CSV files and write headers).
	• Time management:
	  o If Wi-Fi connection is true, then:
	    ▪ NTP time update.
	  o Else:
	    ▪ Retrieving the time stored in the RTC
	• Create a separate concurrent task for sound sensor processing (Task *loop2* on a dedicated core).

Main Loop	• While (true) do:
	  o Update system time and refresh RTC display on the OLED.
	  o BME280 Sensor Handling:
	    ▪ If the BME280 update interval has elapsed, then:
	      • Read temperature, pressure, altitude, and humidity
	      • Apply calibration adjustments.
	      • Display data on OLED if the BME280 screen is active.
	  o BMP180 Sensor Handling:
	    ▪ If the BMP180 update interval has elapsed, then:
	      • Read temperature, pressure, and altitude.
	      • Apply calibration adjustments and compute THI and BGHI.
	      • Display data on OLED if the BMP180 screen is active.
	  o Sound Sensor Display:
	    ▪ At the designated sound sensor update interval, update the OLED display if the sound screen is active.
	  o Data Logging and SD Card Check:
	    ▪ Periodically verify the SD card status and attempt reinitialization if errors occur.

	▪ At scheduled intervals, log sensor data (temperature, relative humidity, etc.) and per-second aggregated sound data to CSV files on the SD card. o User Button Handling: ▪ Monitor the button for short presses (to change OLED screens) or long presses (to display a progress bar and restart the device).
Concurrent Sound Processing Task (Task *loop2* in the second core)	• While (true) do: o Acquire sound sensor samples continuously (targeting ~21 kHz, divided into chunks). o For each sample chunk: ▪ Replace zero readings with the chunk's mean to reduce noise. ▪ Calculate the average and maximum sound level. ▪ Apply an adaptive filter to smooth the readings. ▪ Accumulate the processed chunks to compute per-second sound metrics. o Introduce a minimal delay to maintain proper sampling.

Source: Authors.

C) SOURCE CODE

```
// ##############LOW-COST DEVICE TO AUTOMATING THE MEASUREMENT OF THERMOACOUS-
TIC VARIABLES######################################

// Space to set the device number. Important for selecting the correct cali-
bration equation

int device = 3;  // Set the device number

//LIBRARIES
#include <Wire.h>
#include <SPI.h>
// Display
#include <Adafruit_GFX.h>
#include <Adafruit_SSD1306.h>
//BME280
#include <Adafruit_Sensor.h>
#include <Adafruit_BME280.h>
//BMP180
#include <Adafruit_BMP085.h>
//microSD
#include <SD.h>
//wifi
#include <WiFi.h>
//RTC
#include <NTPClient.h>
#include <WiFiUdp.h>
#include <RTClib.h>
//descriptive statistics
#include <Average.h>  //library for descriptive statistics


// PINS AND VARIABLES
// Variable to control execution time
unsigned long currentMillis;  //principal loop
// button
const int buttonPin = 15;              // Define the button pin
#define BUTTON_PRESS_TIME 5000         // Press time in milliseconds (5 sec-
onds)
unsigned long buttonPressStart = 0;    // Start time of pulsation
bool buttonPressed = false;            // Button status
unsigned long welcomeScreenStart = 0;  // To measure the time in the welcome
screen
//Display Oled
int currentScreen = 1;         // Display status: Initial screen (BME)
Adafruit_SSD1306 display(-1);  // OLED configuration
//BME280
#define SEALEVELPRESSURE_HPA (1013.25)
```

```
Adafruit_BME280 bme;
double sensorBME[4];
const unsigned long BME_INTERVAL = 1900; // Timing variables; Interval in
milliseconds
unsigned long lastBMEUpdate = 0;          // Last updated
//bmp180
Adafruit_BMP085 bmp;
double sensorBMP[3];
unsigned long lastBMPUpdate = 0;          // Last updated BMP280
const unsigned long BMP_INTERVAL = 1900; // Interval in milliseconds for the
BMP280

// - Dew point calculation constants - - -
const double dew_a = 17.27;
const double dew_b = 237.7;

// — Variables para índices —
double dewPoint;   // Tpo °C
double BGHIindex; // BGHI index
double THIindex;   // THI index

// SEN12642 SOUND SENSOR
int soundsensorPin = 32;
unsigned long lastSoundUpdate = 0;         // Last update time for sound sen-
sor
const unsigned long SOUND_INTERVAL = 250;  // Interval in milliseconds
float soundLecture;                        // To store sensor reading in the
array every 25 ms
float maxSound;                            // Maximum value of the array gen-
erated every 25 ms
float averageSound;                        // Average value of the array gen-
erated every 25 ms
float rawMaxSound;                         // Maximum raw value of the array
generated every 25 ms
float rawAverageSound;                     // Average raw value of the array
generated every 25 ms

#define SAMPLES_PER_SECOND 21000                              // Target 21 kHz
sampling rate (21000 samples per second; theoretical time, actual ~0.8 s)
#define NUM_CHUNKS 4                                          // Changed defi-
nition of SOUND_SENSOR_SIZE_PER_SECOND
#define SAMPLES_PER_CHUNK (SAMPLES_PER_SECOND / NUM_CHUNKS)  // Number of sam-
ples per chunk
int currentChunk = 0;                                         // Current chunk
index (0..3)
float localArray[SAMPLES_PER_CHUNK];
double averageSoundMatrix[4];
double maxSoundMatrix[4];
double rawAverageSoundMatrix[4];  // Raw data matrix every second
```

```
double rawMaxSoundMatrix[4];        // Raw data matrix every second
double averageSoundperSecond;       // To store microSD data: average of a ma-
trix generated every second (4 average sound values)
double maxSoundperSecond;           // To store microSD data: max value of a ma-
trix generated every second (4 maxSound values)
double rawAverageSoundperSecond;  // To store raw microSD data: average of a
matrix generated every second (4 average sound values)
double rawMaxSoundperSecond;        // To store raw microSD data: max value of a
matrix generated every second (4 maxSound values)

Average<float> intensityBuffer(SAMPLES_PER_CHUNK); // Generates a data vector
for the library to calculate directly

// microSD
const int chipSelect = 5;                            // GPIO5 for CS
const unsigned long SAVE_INTERVAL_BMEBMP = 300000;  // Interval of 5 minutes
unsigned long lastSaveBMEBMP = 0;                    // Last time BME and BMP
data were saved
unsigned long lastSaveSound = 0;                     // Last time sound data
was saved
const unsigned long SAVE_INTERVAL_SOUND = 1000;      // Interval of 1 second
bool errorSD = false;                                // microSD error flag
const unsigned long SD_CHECK_INTERVAL = 5000;        // Check every 5 seconds
unsigned long lastSDCheck = 0;                       // Last microSD check time

//wifi
// WiFi credentials
const char* ssid = "USER";
const char* password = "PASSWORD";
//RTC
// NTP settings
const long utcOffsetInSeconds = -3 * 3600;  // -3 is because BRT is UTC-3
WiFiUDP ntpUDP;
NTPClient timeClient(ntpUDP, "pool.ntp.org", utcOffsetInSeconds);

// DS3231 RTC
RTC_DS3231 rtc;
bool inicioRTC = true;  //conditional to present different info when starting
the program
char timeBuffer[9];      // Variable para almacenar la hora en formato texto
HH:MM:SS
char dateBuffer[9];

// — Variable for enthalpy —
double enthalpy_kJkg;  // kJ/kg of dry air (Rodrigues et al., 2010)

// Local barometric pressure (mmHg) for Viçosa-MG
const double P_VICOSA_MMHG = 760.0;
```

```
void setup() {
  Serial.begin(115200);
  Wire.begin(); // Allows communication with devices via I2C bus (Inter-Inte-
grated Circuit or 2-wire).
  pinMode(buttonPin, INPUT_PULLUP);

  // OLED
  if (!display.begin(SSD1306_SWITCHCAPVCC, 0x3C)) {
    Serial.println("Failed to initialize OLED.");
    while (true)
      ;  // Halt execution
  }
  display.clearDisplay();
  showMessage("Welcome to your");
  display.print("BarnCare Tracker");
  display.display();

  welcomeScreenStart = millis(); // Register the start time of the welcome
screen

  // WiFi
  WiFi.begin(ssid, password); // Initialize WiFi
  connectToWiFi();

  // RTC
  // Initialize DS3231 RTC
  if (!rtc.begin()) {
    Serial.println("Couldn't find RTC.");
    while (1)
      ;  // Halt execution
  }
  // Conditional update of RTC time: update from NTP if WiFi connected, other-
wise use stored RTC time
  if (WiFi.status() == WL_CONNECTED) {
    updateRTCWithNTP();
  } else {
    DateTime now = rtc.now(); // Retrieve stored time from RTC
    Serial.print("Time recovered from RTC: ");
    Serial.println(now.timestamp());
  }
  inicioRTC = false;  // Indicate that initial time has been printed

  // microSD
  Serial.println("Initializing SD card...");
  // Initialize SD card
  initSD();

  // Create and write initial header line in BME and BMP data file
  File myFileBMEBMP = SD.open("/bme_bmp_data.csv", FILE_APPEND);
```

```
  if (myFileBMEBMP) {
    myFileB-
MEBMP.println("Date;Hour;Temp_BME(C);Pres_BME(hPa);Alt_BME(m);Hum_BME(%);Tg(C)
;Pres_BMP(hPa);Alt_BMP(m);DewPoint(C);BGHI;THI;Enthalpy(kJkg)");
    myFileBMEBMP.close();  // Close the file
    Serial.println("Initial header written to BME/BMP data file.");
  } else {
    Serial.println("Error opening BME/BMP data file for initial write");
  }

  // Create and write initial header line in sound data file
  File myFileSound = SD.open("/sound_data.csv", FILE_APPEND);
  if (myFileSound) {
    myFileSound.println("Date;Hour;Sound level average (dBA);Max Value Sound
Level (dBA);Raw Sound level average (dBA);Raw Max Value Sound Level (dBA)");
    myFileSound.close();  // Close the file
    Serial.println("Initial header written to sound data file");
  } else {
    Serial.println("Error opening sound data file for initial write");
  }


  //bme280
  if (!bme.begin(0x76)) {
    Serial.println("Could not find a valid BME280 sensor, check wiring!");
    while (1)
      ;
  }
  //bmp180
  if (!bmp.begin()) {
    Serial.println("BMP180 Not Found. CHECK CIRCUIT!");
    while (1) {}
  }

  xTaskCreatePinnedToCore(loop2, "loop2", 8192, NULL, 1, NULL, 0);  //gener-
ates the separation of cores so that one core can be used exclusively for
sound
}

//void to work with the sound sensor
void loop2(void* z) {

  while (1) {
    soundDataAcquisition();  // Acquire sensor data every 250 ms (2 ms delay
between a matrix of 125 samples)
    AdaptiveFilter();         // Adaptive filter to reduce noise in data col-
lection
    soundDatapersecond();     // Calls function to generate the data to be
saved every second
```

```
    delay(1);                  // Necessary to prevent device reset
  }
}

//void principal
void loop() {

  currentMillis = millis();
  // Automatically switch from the welcome screen after 3 seconds
  if (welcomeScreenStart > 0 && currentMillis - welcomeScreenStart > 3000) {
    welcomeScreenStart = 0;         // Stop this condition
    displayScreen(currentScreen); // Go to the initial screen
  }
  //RTC
  if (currentMillis % 1000 == 0) {  // Every second
    printRTCTime(inicioRTC);
    printOledRTC();
  }
  //bme280
  // Update BME280 data and display on console and OLED every 1900 ms
  if (currentMillis - lastBMEUpdate >= BME_INTERVAL) {
    lastBMEUpdate = currentMillis;  // Update last reading time
    lecturaBME();                   // Take sensor readings
    printBME();                     // Print data to console
    if (currentScreen == 1) {       // If on BME display screen
      displayScreen(currentScreen);
    }
  }

  // BMP180
  // Update BMP180 data and display on console and OLED every 1900 ms
  if (currentMillis - lastBMPUpdate >= BMP_INTERVAL) {
    lastBMPUpdate = currentMillis;
    lecturaBMP();
    printBMP();
    if (currentScreen == 2) {  // If on BMP display screen
      displayScreen(currentScreen);
    }
  }

  // SEN12642 sound sensor
  if (currentMillis - lastSoundUpdate >= SOUND_INTERVAL) {
    lastSoundUpdate = currentMillis;
    printSound();
    if (currentScreen == 3) {
      displayScreen(currentScreen);
    }
  }
```

```
  if (currentScreen == 4) {
    displayScreen(currentScreen);
  }

  // microSD
  // Periodically check microSD status
  if (currentMillis - lastSDCheck >= SD_CHECK_INTERVAL) {
    lastSDCheck = currentMillis;
    checkAndInitSD();
  }

  if (!errorSD) {  // Only save data if microSD has no errors
    // Save BME and BMP sensor data to microSD every 5 minutes
    if (currentMillis - lastSaveBMEBMP >= SAVE_INTERVAL_BMEBMP) {
      lastSaveBMEBMP = currentMillis;
      // 1) Calculate indices
      calculateIndices();
      // 2) Save data with dewPoint, BGHIindex, THIindex, enthalpy
      registrasdBME_BMP(
        dateBuffer, timeBuffer,
        sensorBME[0], sensorBME[1], sensorBME[2], sensorBME[3],
        sensorBMP[0], sensorBMP[1], sensorBMP[2],
        dewPoint, BGHIindex, THIindex,enthalpy_kJkg);
    }
    // Save sound sensor data to microSD every second
    if (currentMillis - lastSaveSound >= SAVE_INTERVAL_SOUND) {
      lastSaveSound = currentMillis;
      registrasdSound(dateBuffer, timeBuffer, averageSoundperSecond, maxSound-
perSecond, rawAverageSoundperSecond, rawMaxSoundperSecond);
    }
  }

  // Button handling
  if (digitalRead(buttonPin) == LOW) {
    if (!buttonPressed) {
      buttonPressStart = currentMillis; // Record button press start time
      buttonPressed = true;
    }
    unsigned long pressDuration = currentMillis - buttonPressStart;
    if (pressDuration >= BUTTON_PRESS_TIME) {
      showProgressBar("Restarting...", 2000);  // Show progress bar for 2 sec-
onds
      ESP.restart();
    } else if (pressDuration >= 1500 && pressDuration < BUTTON_PRESS_TIME) {
      showMessage("Button pressed\n5 seconds to\nrestart");
    }
  } else {
    // Button released
    if (buttonPressed) {
```

```
      buttonPressed = false;  // Reset button state
      unsigned long pressDuration = millis() - buttonPressStart;
      if (pressDuration < 1500) {
        currentScreen = (currentScreen % 4) + 1;  // Change screen
        displayScreen(currentScreen);
      } else if (pressDuration > 2000 && pressDuration < BUTTON_PRESS_TIME) {
        // Return to main screens after message
        displayScreen(currentScreen);
      }
      Serial.println("Button released.");
    }
  }
}
  // FUNCTIONS
// OLED
// Function to display the corresponding screen
void displayScreen(int screen) {
  if (screen != 4) {
    display.fillRect(0, 8, 128, 56, BLACK);  // Clear area below the time
    display.setCursor(0, 9);                  // Set cursor below the time
  } else {
    display.clearDisplay();
  }

  switch (screen) {
    case 1:
      printOledBME();
      break;
    case 2:
      printOledBMP();
      break;
    case 3:
      printOledSound();
      break;
    case 4:
      printOledRTC();
      break;
    case 5:
      currentScreen = 1;  // Return to screen 1
      displayScreen(currentScreen);
      return;
  }
  // Display SD status
  // displaySDStatus();
  display.display();
}

// Function to show messages on OLED
void showMessage(const char* message) {
```

```
  display.clearDisplay();
  display.setCursor(0, 0);
  display.setTextSize(1);
  display.setTextColor(SSD1306_WHITE);
  display.println(message);
  display.display();
}

// Print necessary BME data on OLED display
void printOledBME() {
  display.println("BME280");
  display.print("Temp = ");
  display.print(sensorBME[0]);
  display.print("(");
  display.cp437(true);
  display.write(248);
  display.print("C");
  display.println(")");

  display.print("Humidity = ");
  display.print(sensorBME[3]);
  display.println("%");
}

// Print necessary BMP data on OLED display
void printOledBMP() {
  display.println("BMP180");
  display.print("Tglobe = ");
  display.print(sensorBMP[0]);
  display.print("(");
  display.cp437(true);
  display.write(248);
  display.print("C");
  display.println(")");
  display.print("BGHI = ");
  display.println(BGHIindex);
}

// Print sound sensor data on OLED display
void printOledSound() {
  display.println("Sound sensor");
  display.print("Average: ");
  display.print(averageSound);
  display.println(" dB(A)");
  display.print("Max: ");
  display.print(maxSound);
  display.print(" dB(A)");
}
```

```
// OLED restart progress bar
void showProgressBar(const char* message, int durationMs) {
  display.clearDisplay(); // Clear the screen
  display.setCursor(0, 0);
  display.setTextSize(1);
  display.setTextColor(SSD1306_WHITE);
  display.println(message); // Show initial message

  int barWidth = 100;                                 // Total width of the
bar
  int barHeight = 10;                                 // Height of the bar
  int barX = (display.width() - barWidth) / 2;        // Center horizontally
  int barY = (display.height() - barHeight) / 2 + 10; // Center vertically +
text adjustment

  display.drawRect(barX, barY, barWidth, barHeight, SSD1306_WHITE); // Draw
the bar frame

  int steps = 20;                        // Number of bar steps
  int stepDelay = durationMs / steps;   // Delay between steps

  for (int i = 0; i <= steps; i++) {
    int fillWidth = (i * barWidth) /
steps;                                 // Calculate progress width
    display.fillRect(barX + 1, barY + 1, fillWidth, barHeight - 2,
SSD1306_WHITE); // Fill the bar progressively
    display.dis-
play();                                                         // Update
the display
    de-
lay(stepDelay);
// Wait between steps
  }
}


  // Print date and time on OLED display
void printOledRTC() {
  DateTime now = rtc.now();

  sprintf(dateBuffer, "%02d/%02d/%02d", now.day(), now.month(), now.year() %
100);
  sprintf(timeBuffer, "%02d:%02d:%02d", now.hour(), now.minute(), now.sec-
ond());

  // Check microSD status
  const char* sdStatus = errorSD ? "SD: ERR" : "SD: OK";

  // Draw time at the top
```

```
  display.setTextSize(1);                // Small text size
  display.setTextColor(WHITE);           // Text color
  display.setCursor(0, 0);               // Coordinates (x, y)
  display.fillRect(0, 0, 128, 8, BLACK); // Clear top strip

  if (currentScreen == 4) {
    display.print(dateBuffer);  // Display date
    display.print(" ");         // Space between date and time
  }
  display.print(timeBuffer);    // Display time

  if (currentScreen == 4) {
    display.println();
    display.println(sdStatus);
    if (WiFi.status() == WL_CONNECTED) {
      display.println("WiFi: connected");
    } else {
      display.println("WiFi: disconnected");
    }
  } else {
    display.setCursor(128 - (strlen(sdStatus) * 6), 0); // Align status text
to right
    display.print(sdStatus);
  }

  display.display();  // Update OLED
}


  // BME280
// Function to read sensor variables and store in array, aiming to reduce
lines in loop
void lecturaBME() {
  sensorBME[0] = bme.readTemperature();
  sensorBME[0] = adjustTempBME(device, sensorBME[0]);
  sensorBME[1] = bme.readPressure() / 100.0F;
  sensorBME[2] = bme.readAltitude(SEALEVELPRESSURE_HPA);
  sensorBME[3] = bme.readHumidity();
  sensorBME[3] = adjustHumBME(device, sensorBME[3]);
}

// Print BME280 sensor values to Serial Monitor
void printBME() {
  Serial.print("BME: ");
  Serial.print("Temperature = ");
  Serial.print(sensorBME[0]);
  Serial.print("°C; ");

  Serial.print("Pressure = ");
```

```
  Serial.print(sensorBME[1]);
  Serial.print("hPa; ");

  Serial.print("Altitude = ");
  Serial.print(sensorBME[2]);
  Serial.print("m; ");

  Serial.print("Humidity = ");
  Serial.print(sensorBME[3]);
  Serial.println("%");
}

// BMP180
// Function to read sensor variables and store in array, aiming to reduce
lines in loop
void lecturaBMP() {
  sensorBMP[0] = bmp.readTemperature();
  Serial.println(sensorBMP[0]);
  sensorBMP[0] = adjustTempBMP(device, sensorBMP[0]);
  Serial.println(sensorBMP[0]);
  sensorBMP[1] = bmp.readPressure() / 100;                      // Raw reading
in Pa; divided by 100 to get hPa
  sensorBMP[2] = bmp.readAltitude(SEALEVELPRESSURE_HPA * 100); // Considers
pressure in Pa; multiplied by 100 to convert hPa to Pa
}

// Print BMP180 sensor values to Serial Monitor
void printBMP() {
  Serial.print("BMP: ");
  Serial.print("Temperature = ");
  Serial.print(sensorBMP[0]);
  Serial.print("°C; ");

  Serial.print("Pressure = ");
  Serial.print(sensorBMP[1]);
  Serial.print("hPa; ");

  Serial.print("Altitude = ");
  Serial.print(sensorBMP[2]);
  Serial.println("m");

  Serial.print("BGHI = ");
  Serial.println(BGHIindex);
}

// SEN12642
// Function to read data from sound sensor
void soundDataAcquisition() {
  for (int i = 0; i < SAMPLES_PER_CHUNK; i++) {
```

```
    localArray[i] = analogRead(soundsensorPin);
  }
  replaceZerosWithMean_local(localArray, SAMPLES_PER_CHUNK);

  intensityBuffer.clear();
  for (int i = 0; i < SAMPLES_PER_CHUNK; i++) {
    intensityBuffer.push(localArray[i]); // push adds an element at position
i in the vector. Function from average.h package
    // no delay to maximize sampling capacity
  }

  averageSound = intensityBuffer.mean();
  maxSound = intensityBuffer.maximum();
  rawAverageSound = intensityBuffer.mean();  // RAW values
  rawMaxSound = intensityBuffer.maximum();  // RAW values
  intensityBuffer.clear();                    // clear buffer to avoid errors
}

// Adaptive filter function to avoid noise problems in readings
void AdaptiveFilter() {
  float alpha;                          // Adaptive factor
  float threshold = 100.0;              // Change depending on expected magni-
tude of peaks
  static float smoothedAverage = 0;  // Defined static to initialize once and
avoid filter issues
  static float smoothedMax = 0;

  // Calculate alpha based on detected change
  if (abs(averageSound - smoothedAverage) > threshold) {
    alpha = 0.5;  // Fast response for large changes
  } else {
    alpha = 0.2;   // Slow response for small changes
  }

  // Smooth the values
  smoothedAverage = (smoothedAverage * (1 - alpha)) + (averageSound * alpha);
  smoothedMax = (smoothedMax * (1 - alpha)) + (maxSound * alpha);

  // Update smoothed values
  averageSound = smoothedAverage;
  maxSound = smoothedMax;
}

 // Function to acquire data every second. Average of 4 samples per second
void soundDataperSecond() {
  if (currentChunk < NUM_CHUNKS) {
    averageSoundMatrix[currentChunk] = averageSound;
    maxSoundMatrix[currentChunk] = maxSound;
    rawAverageSoundMatrix[currentChunk] = rawAverageSound;
```

```
    rawMaxSoundMatrix[currentChunk] = rawMaxSound;

    currentChunk++;
  } else if (currentChunk == NUM_CHUNKS) {
    averageSoundperSecond = 0.0;
    maxSoundperSecond = maxSoundMatrix[0];
    rawAverageSoundperSecond = 0.0;
    rawMaxSoundperSecond = rawMaxSoundMatrix[0];
    for (int i = 0; i < NUM_CHUNKS; i++) {
      averageSoundperSecond += averageSoundMatrix[i];
      rawAverageSoundperSecond += rawAverageSoundMatrix[i];
      if (maxSoundMatrix[i] > maxSoundperSecond) {
        maxSoundperSecond = maxSoundMatrix[i];
        rawMaxSoundperSecond = rawMaxSoundMatrix[i];
      }
    }
    averageSoundperSecond /= NUM_CHUNKS;
    rawAverageSoundperSecond /= NUM_CHUNKS;
    currentChunk = 0;
  }
}

// Function to replace zeros in array with the mean of non-zero values
void replaceZerosWithMean_local(float arr[], int numSamples) {
  float sum = 0.0;
  int count = 0;

  // 1) Sum all non-zero values
  for (int i = 0; i < numSamples; i++) {
    if (arr[i] != 0) {
      sum += arr[i];
      count++;
    }
  }

  // 2) Calculate mean of non-zero values
  if (count > 0) {
    double meanNonZero = sum / (float)count;

    // 3) Replace zeros with the calculated mean
    for (int i = 0; i < numSamples; i++) {
      if (arr[i] == 0) {
        arr[i] = meanNonZero;
      }
    }
  } else {
    // If all values are zero, set entire buffer to zero
    for (int i = 0; i < numSamples; i++) {
      arr[i] = 0;
```

```
    }
  }
}

// Function to print sound sensor data to Serial Monitor
void printSound() {
  Serial.print("Sound Sensor: ");
  Serial.print("Average level = ");
  Serial.print(averageSound);
  Serial.print("; Max level = ");
  Serial.println(maxSound);
}

// Function to print connecting to WiFi message on OLED
void printConnectWifi(int dotCount) {
  display.clearDisplay();
  display.setTextSize(1);
  display.setCursor(0, 0);
  display.println("Connecting to WiFi");

  // Show dynamic dots
  display.setCursor(0, 10);
  for (int i = 0; i < dotCount; i++) {
    display.print(".");
  }

  display.display();
}

// microSD
// Function to initialize microSD card
void initSD() {
  if (!SD.begin(chipSelect)) {
    Serial.println("Error initializing SD card.");
    errorSD = true;  // Indicate SD card problem
  } else {
    Serial.println("SD card initialized successfully.");
    errorSD = false;  // Everything OK
  }
}

// Function to save sensor data to microSD
void registrasdBME_BMP(String date, String time,
                       double temperatureBME, double pressureBME, double alti-
tudeBME, double humidityBME,
                       double temperatureBMP, double pressureBMP, double alti-
tudeBMP,
                        double dewPoint_C, double BGHI, double THI, double En-
thalpy_kJkg) {
```

```
  File myFileBMEBMP = SD.open("/bme_bmp_data.csv", FILE_APPEND);
  if (myFileBMEBMP) {
    myFileBMEBMP.print(date);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(time);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(temperatureBME);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(pressureBME);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(altitudeBME);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(humidityBME);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(temperatureBMP);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(pressureBMP);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(altitudeBMP);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(dewPoint_C);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(BGHI);
    myFileBMEBMP.print(";");
    myFileBMEBMP.print(THI);
    myFileBMEBMP.print(";");
    myFileBMEBMP.println(Enthalpy_kJkg);

    myFileBMEBMP.close();  // Close file

    Serial.println("Successfully saved");
    Serial.println("Data written to bme_bmp_data.csv");
  } else {
    errorSD = true;
    Serial.println("Error saving BME/BMP data to microSD");
    Serial.println("Saving error");
  }
}
// Function to save sound sensor data to microSD
void registrasdSound(String date, String time, double averageIntensity, double
maxIntensity, double rawAverageIntensity, double rawMaxAverageIntensity) {
  File myFileSound = SD.open("/sound_data.csv", FILE_APPEND);

  if (myFileSound) {
    myFileSound.print(date);
    myFileSound.print(";");
    myFileSound.print(time);
    myFileSound.print(";");
    myFileSound.print(averageIntensity);
```

```
    myFileSound.print(";");
    myFileSound.print(maxIntensity);
    myFileSound.print(";");
    myFileSound.print(rawAverageIntensity);
    myFileSound.print(";");
    myFileSound.println(rawMaxAverageIntensity);
    myFileSound.close();
    Serial.println("Successfully saved");
    Serial.println("Data written to sound_data.csv");
  } else {
    errorSD = true;
    Serial.println("Error saving sound sensor data to microSD.");
  }
}

// Periodic check for microSD presence
void checkAndInitSD() {
  if (!SD.begin(chipSelect)) {  // Try to initialize SD
    if (!errorSD) {              // If previously working but now not
      errorSD = true;            // Change error state
      showMessage("Error\nSD not\ninitialized");
      Serial.println("microSD not detected.");
    } else if (errorSD) {
      showMessage("Error\nSD not\ninitialized");
      Serial.println("microSD not detected.");
    }
  } else {
    if (errorSD) {       // If there was an error but now SD is detected
      errorSD = false;  // Change error state
      showMessage("microSD recovered\nTrying to save\ndata...");
      Serial.println("Module detected, attempting to save files to microSD");
    }
  }
}

// WiFi
// Function to connect to WiFi
void connectToWiFi() {
  unsigned long startAttemptTime = millis();
  int dotCount = 0;

  while (WiFi.status() != WL_CONNECTED && millis() - startAttemptTime < 15000)
{
    if (millis() % 1000 < 50) { // Update OLED approximately every second
      printConnectWifi(dotCount);
      dotCount++;
      if (dotCount > 3) dotCount = 0;
    }
    delay(10);  // Small delay to prevent ESP overload
```

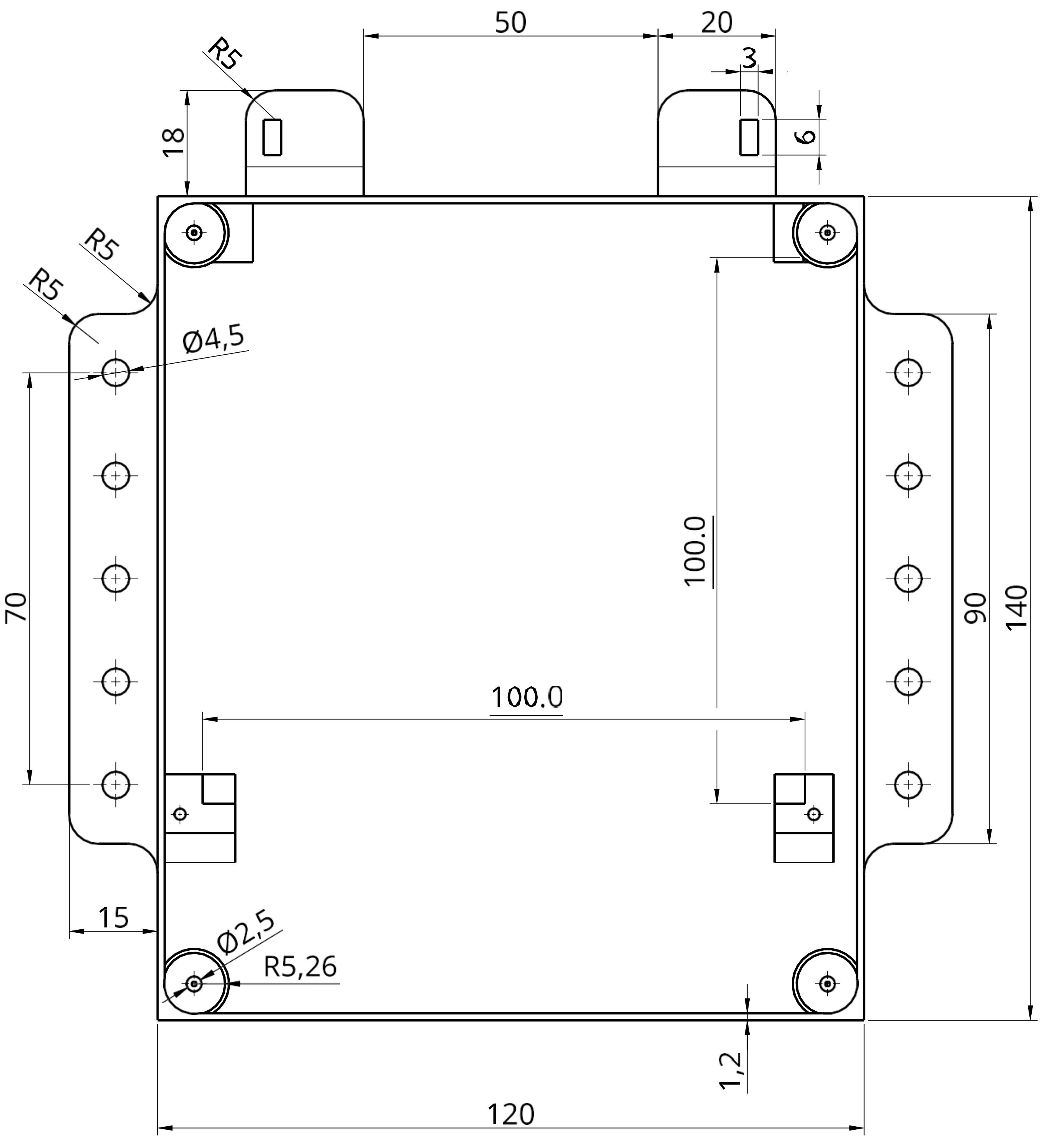
```
  }

  if (WiFi.status() == WL_CONNECTED) {
    Serial.println("WiFi connected.");
    display.clearDisplay();
    display.setTextSize(1);
    display.setCursor(0, 0);
    display.println("WiFi connected!");
    display.display();
    delay(2000); // Show message briefly
    display.clearDisplay();
  } else {
    Serial.println("WiFi connection failed.");
    display.clearDisplay();
    display.setTextSize(1);
    display.setCursor(0, 0);
    display.println("WiFi failed.");
    display.display();
    delay(2000); // Show error message
    display.clearDisplay();
  }
}

// RTC

// Function to print RTC variables; no input parameters
void printRTCTime(bool isInitialRun) {
  DateTime now = rtc.now();
  snprintf(dateBuffer, sizeof(dateBuffer), "%02d/%02d/%02d", now.day(),
now.month(), now.year() % 100);
  snprintf(timeBuffer, sizeof(timeBuffer), "%02d:%02d:%02d", now.hour(),
now.minute(), now.second());

  if (isInitialRun) {
    Serial.print("RTC Time: ");
    Serial.print(dateBuffer);
    Serial.print(" ");
    Serial.println(timeBuffer);
  } else {
    Serial.print(dateBuffer);
    Serial.print(" ");
    Serial.println(timeBuffer);
  }
}

// Function to update RTC time using NTP (Network Time Protocol); no input pa-
rameters
void updateRTCWithNTP() {
```

```
  timeClient.update();                               // Get current time
from NTP server
  unsigned long epochTime = timeClient.getEpochTime(); // Extract raw time
components
  DateTime ntpTime = DateTime(epochTime);             // Convert epoch time
to DateTime object
  rtc.adjust(ntpTime);                               // Set DS3231 RTC time
  printRTCTime(inicioRTC);                           // Print the updated
RTC time
}


// Calibration equations
// Adjust raw BMP temperature data according to calibration curve for each de-
vice
double adjustTempBMP(int device_number, double rawBMPreading) {
  if (device_number == 1) {
    return 1.25084 + (0.967581 * rawBMPreading);
  } else if (device_number == 2) {
    return 1.688959 + (0.9387687 * rawBMPreading);
  } else if (device_number == 3) {
    return 2.470639 + (0.920295 * rawBMPreading);
  } else if (device_number == 4) {
    return 0.2392086 + (0.9474761 * rawBMPreading);
  } else if (device_number == 5) {
    return 1.704624 + (0.911058 * rawBMPreading);
  } else if (device_number == 6) {
    return 4.913756 + (0.8741466 * rawBMPreading);
  } else {
    Serial.print("Error in calibration equation");
  }
}

// Adjust raw BME temperature data according to calibration curve for each de-
vice
double adjustTempBME(int device_number, double rawBMEreading) {
  if (device_number == 1) {
    return -2.46577 + (1.045127 * rawBMEreading);
  } else if (device_number == 2) {
    return -2.351923 + (1.048695 * rawBMEreading);
  } else if (device_number == 3) {
    return -4.264967 + (1.066353 * rawBMEreading);
  } else if (device_number == 4) {
    return -2.923367 + (1.040889 * rawBMEreading);
  } else if (device_number == 5) {
    return -1.606135 + (0.9871868 * rawBMEreading);
  } else if (device_number == 6) {
    return 5.556561 + (0.8300874 * rawBMEreading);
  }
```

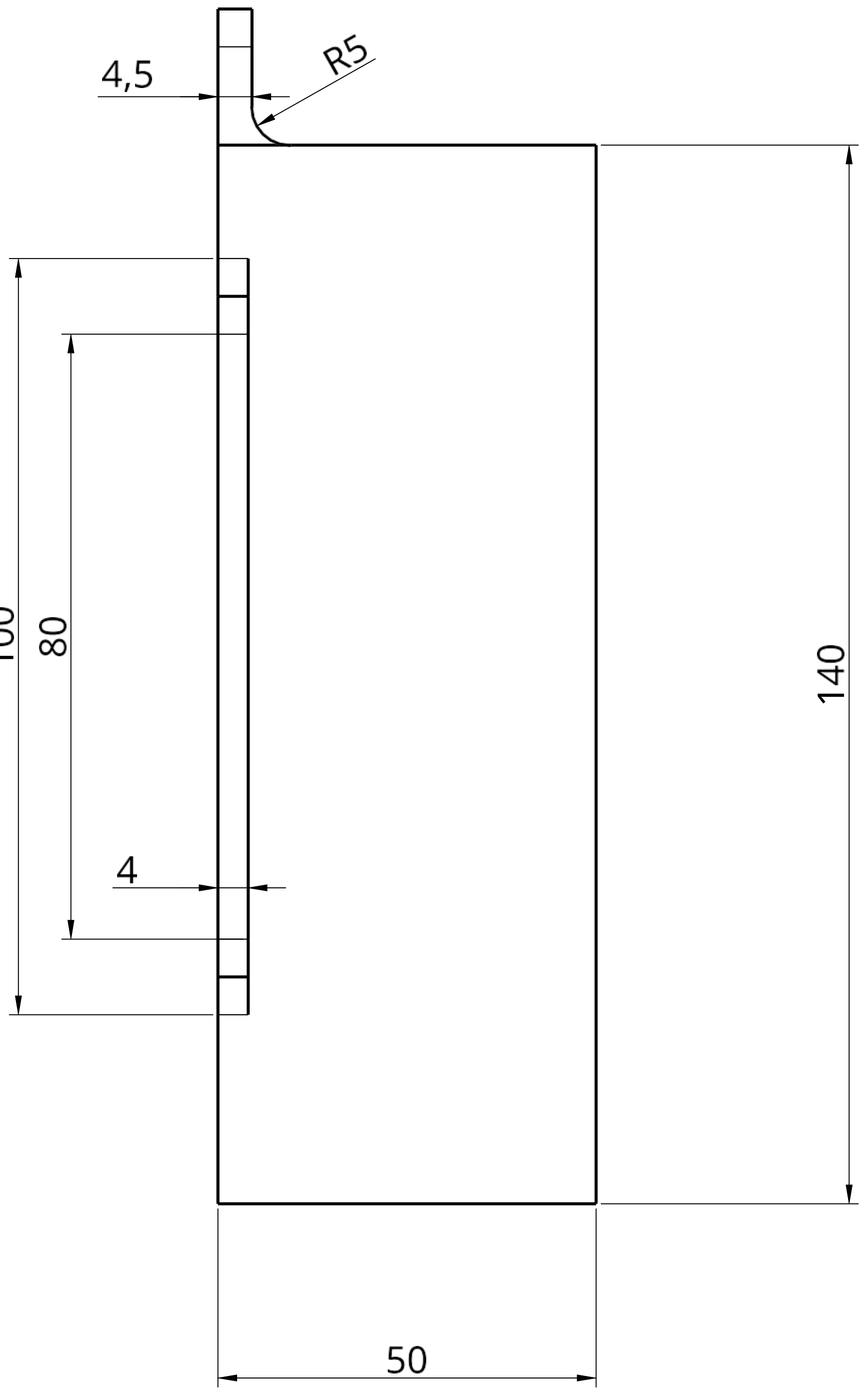
```
}

// Adjust raw BME humidity data according to calibration curve for each device
double adjustHumBME(int device_number, double rawBMEreading) {
  if (device_number == 1) {
    return -24.77756 + (1.460364 * rawBMEreading);
  } else if (device_number == 2) {
    return -11.08351 + (1.267391 * rawBMEreading);
  } else if (device_number == 3) {
    return -24.33182 + (1.470221 * rawBMEreading);
  } else if (device_number == 4) {
    return -2.827435 + (1.087248 * rawBMEreading);
  } else if (device_number == 5) {
    return -15.45667 + (1.262083 * rawBMEreading);
  } else if (device_number == 6) {
    return -12.35426 + (1.19455 * rawBMEreading);
  }
}

// Calculate air specific enthalpy using Rodrigues et al. (2010)
// Inputs: tdb (°C), RH (%), Pa (mmHg)
// Output: h (kJ/kg of dry air)
double calculateEnthalpyRodrigues(double tdb, double RH, double Pa_mmHg) {

  // Basic guards (avoid nonsense / division by zero)
  if (isnan(tdb) || isnan(RH) || isnan(Pa_mmHg)) return NAN;
  if (Pa_mmHg <= 0) return NAN;

  // Constrain RH to physical range
  if (RH < 0) RH = 0;
  if (RH > 100) RH = 100;

  // term = 10^((7.5*tdb)/(237.3+tdb))
  double expo = (7.5 * tdb) / (237.3 + tdb);
  double pow10_term = pow(10.0, expo);

  // Rodrigues et al. equation (as provided)
  double h = 1.006 * tdb
           + (RH / Pa_mmHg) * pow10_term * (71.28 + (-0.052 * tdb));

  return h; // kJ/kg dry air
}

// Calculate dew point (°C), BGHI, and THI
void calculateIndices() {
  // 1) Dew point (°C)
  double T = sensorBME[0]; // Temp_BME in °C
  double H = sensorBME[3]; // Hum_BME in %
  double alpha = (dew_a * T) / (dew_b + T) + log(H / 100.0);
```

```
  dewPoint = (dew_b * alpha) / (dew_a - alpha);

  // 2) BGHI (using Tg from sensorBMP[0])
  double Tg_K = sensorBMP[0] + 273.15;
  double Tpo_K = dewPoint + 273.15;
  BGHIindex = 12.9651 + 0.80563 * (Tg_K + 0.36 * Tpo_K - 330.08);

  // 3) THI
  THIindex = T + 0.36 * dewPoint + 41.7;

  // 4) Enthalpy (Rodrigues et al., 2010)
  enthalpy_kJkg = calculateEnthalpyRodrigues(T, H, P_VICOSA_MMHG);

}
```

D) BOX DESIGN



UNLESS OTHERWISE SPECIFIED, DIMENSIONS ARE IN MILLIMETERS		NAME	DATE	TITLE
ANGULAR = ± °	DRAWN	Jeferson dos Santos Vieira	2025-02-07	BarnCare Tracker Box for 3D Printing
SURFACE FINISH	APPROVED	Jhoan Nicolás Ramos Niño	2025-02-07	Box Front View
DO NOT SCALE DRAWING				
BREAK ALL SHARP EDGES AND REMOVE BURRS				
FIRST ANGLE PROJECTION	MATERIAL: PLA (*Polímero ácido poliláctico*)			SIZE: A4 · SCALE: 1:1 · WEIGHT: 86,23 g · SHEET: 1 of 4



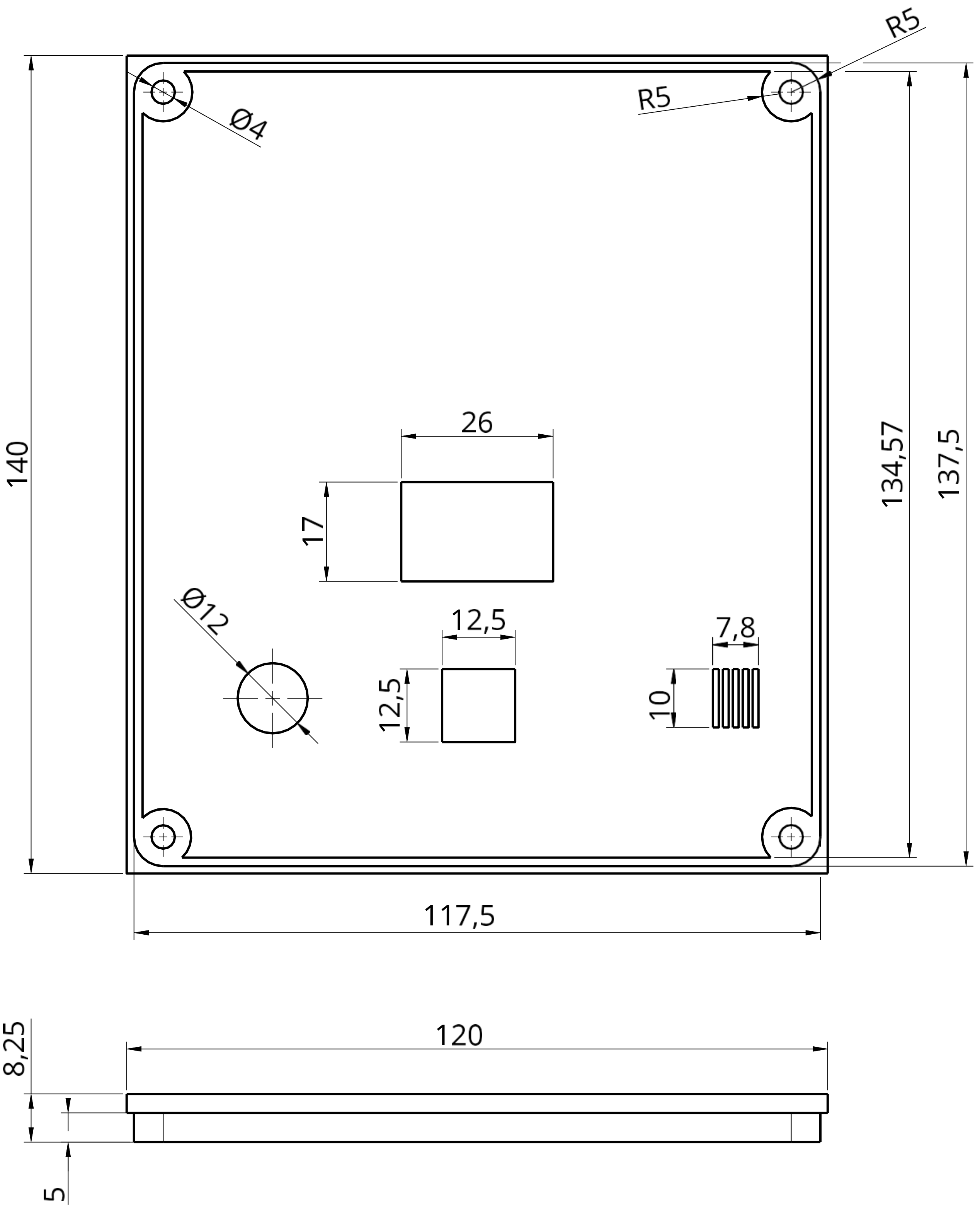
UNLESS OTHERWISE SPECIFIED, DIMENSIONS ARE IN MILLIMETERS
ANGULAR = ± °
SURFACE FINISH
DO NOT SCALE DRAWING
BREAK ALL SHARP EDGES AND REMOVE BURRS
FIRST ANGLE PROJECTION

	NAME	DATE
DRAWN	Jeferson dos Santos Vieira	2025-02-07
APPROVED	Jhoan Nicolás Ramos Niño	2025-02-07

MATERIAL
PLA (*Polímero ácido poliláctico*)

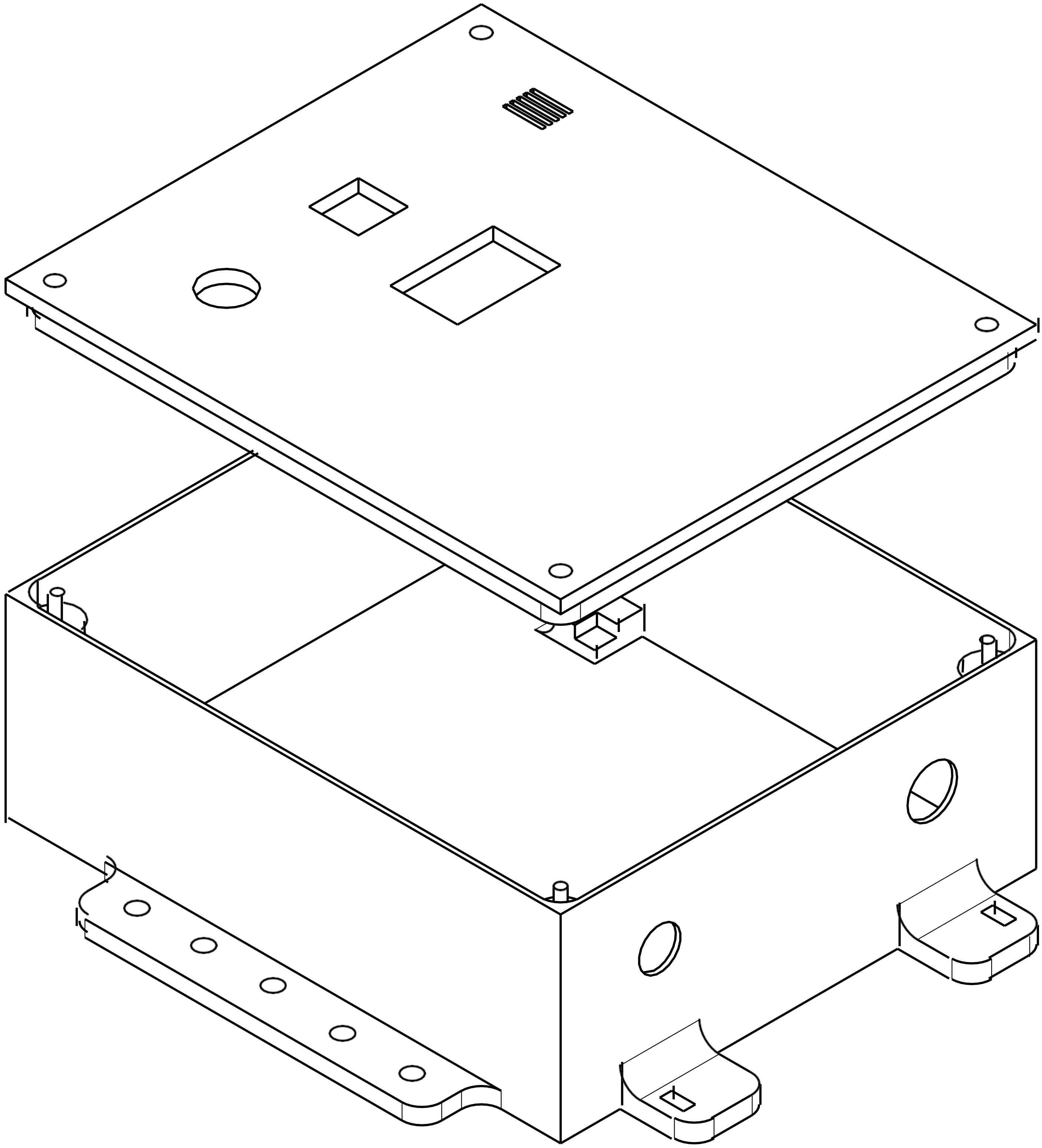
TITLE
BarnCare Tracker Box for 3D Printing
Box Right View

SIZE	SCALE	WEIGHT	SHEET
A4	1:1	86,23 g	2 of 4



UNLESS OTHERWISE SPECIFIED, DIMENSIONS ARE IN MILLIMETERS ANGULAR = ± ° SURFACE FINISH		NAME	DATE
	DRAWN	Jeferson dos Santos Vieira	2025-02-07
	APPROVED	Jhoan Nicolás Ramos Niño	2025-02-07
DO NOT SCALE DRAWING			
BREAK ALL SHARP EDGES AND REMOVE BURRS			
FIRST ANGLE PROJECTION	MATERIAL PLA (*Polímero ácido poliláctico*)		

TITLE			
BarnCare Tracker Box for 3D Printing Box cover			
SIZE A4	SCALE 1:1	WEIGHT 40,60 g	SHEET 3 of 4



UNLESS OTHERWISE SPECIFIED, DIMENSIONS ARE IN MILLIMETERS		NAME	DATE	TITLE
ANGULAR = ± °	DRAWN	Jeferson dos Santos Vieira	2025-02-07	BarnCare Tracker Box for 3D Printing
SURFACE FINISH	APPROVED	Jhoan Nicolás Ramos Niño	2025-02-07	Isometric assembly view
DO NOT SCALE DRAWING				
BREAK ALL SHARP EDGES AND REMOVE BURRS				
FIRST ANGLE PROJECTION	MATERIAL			
	PLA (*Polímero ácido poliláctico*)			

SIZE	SCALE	WEIGHT	SHEET
A4	1:1	126,83 g	4 of 4