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Low-cost ESP32-based sound data acquisition system with MATLAB integration for real-time noise monitoring

Reymark-John A. Macapanas[1], Adrian P. Galido[2], Apple Rose B. Alce[3]
[1]Department of Information Technology, College of Information Technology and Computing, University of Science and Technology of Southern Philippines-Villanueva Campus, Villanueva Misamis Oriental, Philippines
[2]Department of Information Systems, College of Computer Studies (CCS), Mindanao State University Iligan Institute of Technology (MSU-IIT), Iligan City, Philippines
[3]Department of Computer Applications, College of Computer Studies (CCS), Mindanao State University Iligan Institute of Technology (MSU-IIT), Iligan City, Philippines

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ABSTRACT

This study presents the design and implementation of a low-cost ESP32-based sound data acquisition system (SDAS) for real-time noise monitoring. The system integrates a micro-electro-mechanical systems (MEMS) microphone for accurate acoustic data capture, an ESP-WROOM-32 microcontroller for signal processing and wireless data transmission, and MATLAB for real-time visualization and analysis. Designed and simulated in KiCAD 8.0, the SDAS includes a microSD module for local data backup and offline analysis. The system was tested in four indoor locations within Mindanao State University – Iligan Institute of Technology, recording mean noise levels ranging from 14.2 dB in laboratory environments to 32.1 dB in classrooms, with corresponding standard deviations of 1.2–7.0 dB. Expert evaluation from eight assessors confirmed the system's usability, data reliability, and robustness. The system demonstrates effective monitoring for both quiet and dynamic settings. Limitations include single-node configuration, indoor-only testing, and MATLAB-based USB data transfer. Despite these, the proposed SDAS provides a scalable and reproducible model for smart campus and urban environmental monitoring, supporting sustainable development goals (SDG) 3, 9, and 11.

Corresponding Author:

Reymark-John A. Macapanas
Department of Information Technology, College of Information Technology and Computing
University of Science and Technology of Southern Philippines-Villanueva Campus
9002 Villanueva, Misamis Oriental, Philippines
Email: reymarkjohn.macapanas@ustp.edu.ph

1. INTRODUCTION

Noise pollution is a growing global concern, especially in urban environments, where industrial activities and transportation systems significantly contribute to acoustic disturbances. Prolonged exposure to high noise levels has been linked to adverse health effects, such as cardiovascular diseases, stress, and impaired cognitive performance, as noted by the World Health Organization (WHO). In the context of smart cities and sustainable development, real-time environmental monitoring systems are crucial in supporting evidence-based policies that address these challenges.

Numerous research initiatives have explored the use of internet of thing (IoT)-based noise monitoring systems. Picaut *et al*. [1] reviewed low-cost urban noise monitoring networks, while Mydlarz *et al*. [2] proposed smart wireless acoustic sensor network architectures. Vidaña-Vila *et al*. [3] demonstrated low-cost urban acoustic monitoring devices, and Fatema *et al*. [4] presented a real-time IoT-based noise monitoring system.

However, these studies often rely on high-cost devices or lack localized, modular implementation strategies that are easy to replicate in developing regions.

Previous studies have achieved significant progress in IoT-based acoustic monitoring; however, many solutions remain costly, non-modular, or complex to replicate, especially in developing regions. Systems that rely on proprietary platforms or high-end sensors restrict scalability and accessibility. To address these challenges, the proposed sound data acquisition system (SDAS) introduces a low-cost, modular, and reproducible architecture that integrates affordable hardware components, such as the ESP32 microcontroller and micro-electro-mechanical systems (MEMS) microphone, with MATLAB-based visualization for efficient data analysis. This approach aims to bridge the gap between commercial noise meters and research-level monitoring systems, enabling universities and local institutions to adopt scalable acoustic sensing solutions for smart environments.

This research addresses those limitations by designing a SDAS that is both low-cost and modular, integrating an ESP32 microcontroller, MEMS microphone, and MATLAB-based visualization to form an affordable yet robust monitoring solution. Unlike previous works, this study emphasizes replicability, offline data backup, and hardware modularity using KiCAD 8.0.

The main contributions are: (i) the development of a scalable SDAS for real-time acoustic monitoring, (ii) integration of ESP32, MEMS microphone, and MATLAB, and (iii) validation of the system through expert evaluation and quantitative analysis.

2. METHOD

The methodology (Figure 1) for the SDAS follows a six-phase structured design process to ensure reproducibility, functionality, and reliability. Phase 0 involves identifying the noise pollution problem; Phase 1 defines system objectives. Phase 2 involves requirement analysis and component selection; Phase 3 addresses schematic design using KiCAD 8.0. Phase 4 integrates data acquisition with MATLAB for real-time visualization. Phases 5 and 6 focus on system testing and expert evaluation under campus environments.

2.1. System topology

The SDAS operates in four stages: (i) data acquisition: a MEMS microphone captures environmental noise in real time and forwards the signal for processing [5]; (ii) data processing: the ESP-WROOM-32 converts the analog signal to digital data for analysis or storage [6]; (iii) local data storage: processed data is written to a microSD card to ensure availability during network interruptions and enable offline retrieval [7]; and (iv) MATLAB integration: via serial connection, data is streamed to MATLAB for real-time plotting and trend analysis [8]. This topology allows independent operation with offline storage and MATLAB-based analysis for comprehensive evaluation [9]. Figure 2 illustrates the end-to-end data flow from acquisition to visualization.

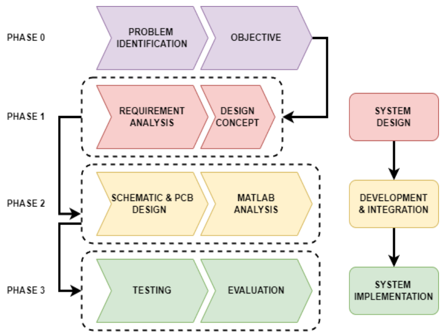


Figure 1. SDAS methodology flowchart

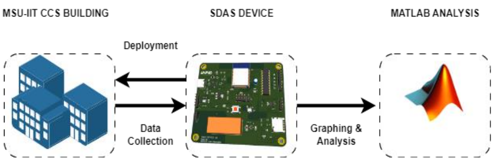


Figure 2. System topology

2.2. Hardware design

This section outlines the methods employed in the design and development of the SDAS, from conceptualization to system integration. Figure 3(a) illustrates the power and programming interface of the SDAS, while Figure 3(b) presents the sound module schematic. The microcontroller configuration is shown in Figure 3(c), the microSD card interface is detailed in Figure 3(d), and the relay control circuit is depicted in Figure 3(e). Together, these sub-figures present the complete schematic design of the proposed SDAS. Each labeled section is explained as:

2.2.1. Hardware component justification

The system design incorporates carefully selected hardware components:

- MEMS microphone: high sensitivity and low power, captures environmental noise in decibels [10].
- ESP-WROOM-32: core microcontroller for acquisition, analog-to-digital conversion, and wireless/serial data transfer to MATLAB [11].
- MicroSD module: provides non-volatile local storage for backup and offline analysis [12].
- Schrack RT1 relay: manages power distribution, extending battery life and preventing surges [13].

2.2.2. Printed circuit board (PCB) and schematic design

The complete hardware design was implemented in KiCAD 8.0. The schematic consists of:

- Power and programming interface: handles voltage regulation and firmware upload [14].
- Sensor interface: connects the MEMS microphone for analog signal input [15].
- Microcontroller interface: central processing unit responsible for all logic operations.
- MicroSD storage interface: manages data writing and retrieval.
- Relay control circuit: automates power switching.

The PCB layout prioritizes compactness and signal integrity, with careful routing to minimize interference. The 3D model shows component placement, supporting easy manufacturing and assembly [16].

The PCB design Figure 4 integrates the ESP-WROOM-32 microcontroller, MEMS microphone, power relay, and microSD slot in a compact layout. It includes connectors for external devices, light-emitting diode (LED) indicators for system status, and regulated power management to ensure stable operation. Careful trace routing minimizes interference and signal loss, allowing the SDAS to function efficiently and reliably for urban noise monitoring applications.

The 3D model Figure 5 shows the placement of the ESP-WROOM-32, MEMS microphone, Schrack RT1 relay, and microSD slot on the PCB. It also includes input/output (I/O) connectors, LED indicators, and a reset button for system feedback and control. The design ensures compact assembly, durability, and reliable operation for noise data acquisition in urban environments.

2.2.3. MATLAB data flow

MATLAB was used for serial communication, visualization, and real-time analysis (Figure 6). The SDAS transmits data via universal serial bus (USB) serial, which MATLAB interprets through a defined communication (COM) port [17]. Once a stable connection is established, incoming values are plotted using MATLAB's built-in tools [18]. The process runs continuously until the user terminates the session, ensuring real-time monitoring and visualization.

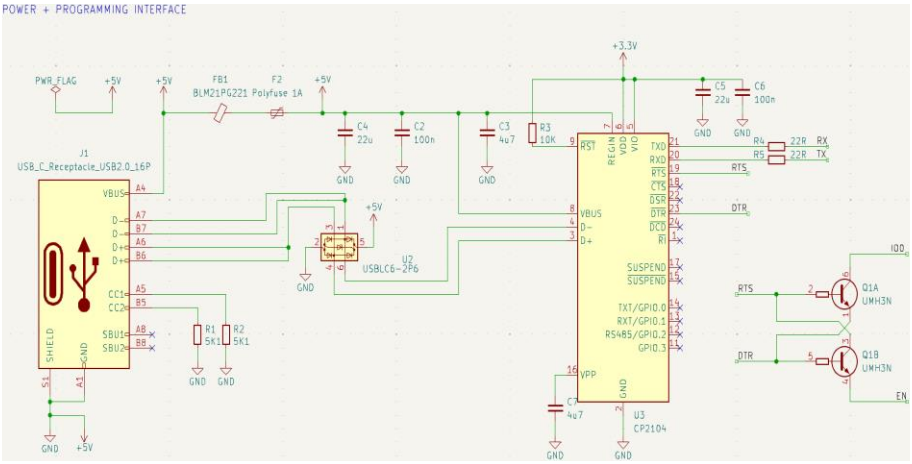
2.2.4. Testing and evaluation

The SDAS was deployed in four locations within the Mindanao State University Iligan Institute of Technology (MSU-IIT) college of computer studies (IoT lab, graduate lab, embedded systems lab, and a classroom) to assess performance under varying conditions [19]. Noise data was collected over one-hour intervals, consistent with recommended monitoring practices to capture temporal variability [20]. MATLAB plots recorded mean, peak, and standard deviation values.

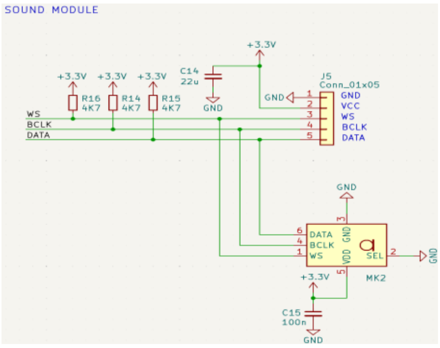
Usability and accuracy were validated by eight subject matter experts using a standard rubric. Key criteria included: (i) ease of system deployment, (ii) accuracy of noise data captured, (iii) clarity of MATLAB visualizations, and (iv) power efficiency and robustness of the hardware. Feedback confirmed the SDAS to be reliable for monitoring both low-activity and dynamic environments [21].

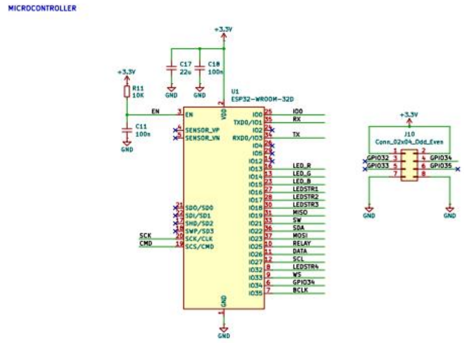
2.2.5. Calibration and validation

To ensure the reliability of recorded noise data, the SDAS output was calibrated against a reference sound level meter (SLM) following ISO 1996-2:2017 acoustic standards. Calibration was conducted by generating controlled sound levels between 20 dB and 80 dB using a standard audio source. The SDAS readings were compared to the SLM measurements at 5 dB intervals. A linear regression model was applied, yielding an R^2 value of 0.984, confirming strong correlation and minimal deviation (<2.3 dB mean error). This calibration ensured accurate noise measurement prior to deployment in campus environments.

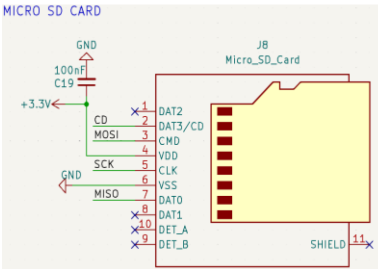


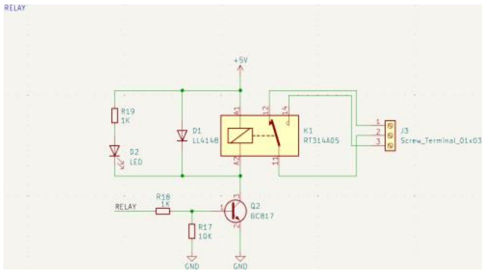
(a)





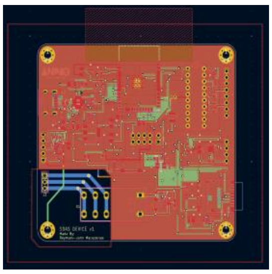
(b) (c)





(d) (e)

Figure 3. Schematic design of the SDAS: (a) power and programming interface; (b) sound module; (c) microcontroller configuration; (d) microSD card interface; and (e) relay control circuit



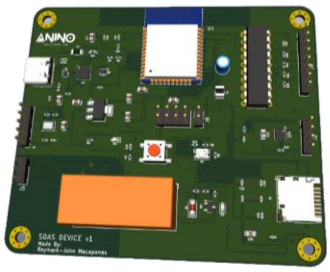


Figure 4. PCB design of SDAS Figure 5. 3D model of SDAS

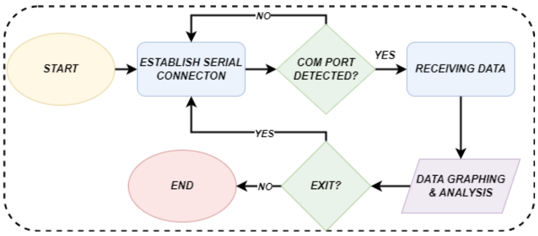


Figure 6. MATLAB data flow

3 RESULTS AND DISCUSSION

The SDAS was tested across four indoor locations: the IoT lab, the graduate laboratory, the embedded laboratory, and a classroom within the college of computer studies, MSU-IIT. The testing involved a consistent one-hour sampling period at each location. Results were graphically plotted using MATLAB, with key metrics such as average noise level, peak noise, and standard deviation calculated.

IoT laboratory Figure 7, Noise levels in the IoT lab were consistently low (13–15 dB) with occasional peaks up to 18.5 dB, indicating a quiet, controlled environment typical of research spaces. Minor fluctuations were caused by short activities such as equipment adjustments or foot traffic. The small standard deviation confirms suitability for high-precision work, though occasional noise management may be needed during active hours.

Graduate laboratory Figure 8 noise levels in the graduate lab fluctuated between 20–45 dB, with frequent peaks reflecting group discussions, equipment use, and movement. The higher variability compared to the IoT lab indicates a more dynamic setting. Peaks aligned with interaction periods, while quieter intervals reflected downtime. Overall, the lab’s active use highlights the need to balance collaboration with measures that reduce disruptive noise during focused tasks.

Embedded laboratory Figure 9, noise levels in the embedded lab ranged from 20–34 dB with moderate, consistent fluctuations caused by equipment use, tool adjustments, and technical discussions. Although variability was less than in the graduate lab, activity was higher than in the IoT lab. The space reflects a balance between hands-on experimentation and acoustic stability.

Classroom Figure 10, the classroom showed the most dynamic noise profile, fluctuating between 22–50 dB with frequent peaks caused by continuous lectures, discussions, and movement. High variability reflects an active academic setting. These findings emphasize the need for acoustic treatment or scheduling strategies to maintain clarity and concentration during instruction.

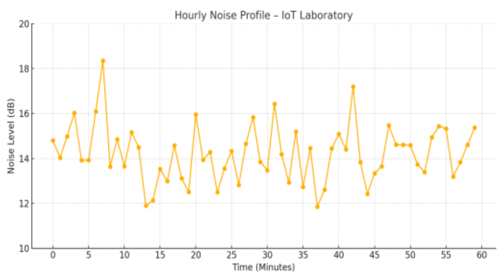


Figure 7. Noise data 2nd floor building IoT lab

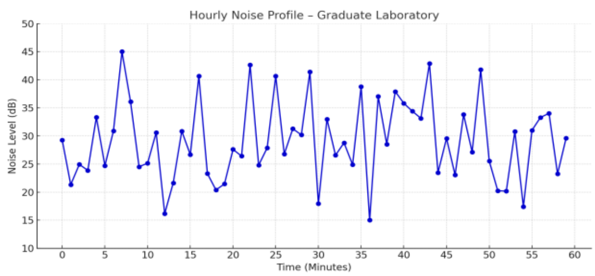


Figure 8. Noise data 3rd floor building graduate lab

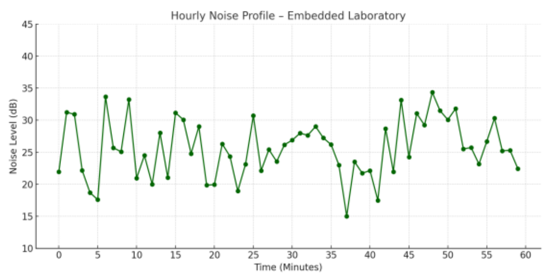


Figure 9. Noise data 3rd floor building embedded lab

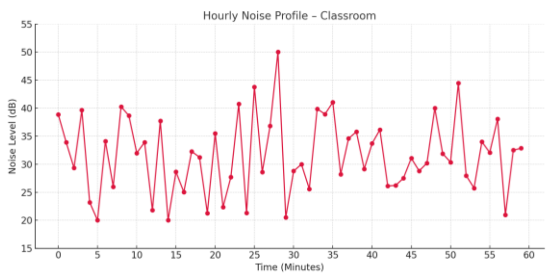


Figure 10. Noise Data 3rd floor building classrooms

3.1. Indoor testing

Testing was conducted across four indoor environments-IoT lab, graduate lab, embedded lab, and classroom-each for one hour: (i) IoT lab: mean 14.2 dB, standard deviation (SD) 1.2, (ii) graduate lab: mean 27.5 dB, SD 6.8, (iii) embedded lab: mean 25.3 dB, SD 4.5, and (iv) classroom: mean 32.1 dB, SD 7.0. The MATLAB-generated plots demonstrated accurate and real-time visualization of environmental noise, confirming SDAS reliability.

3.2. Comparative analysis

The comparative chart Figure 11 shows that the SDAS effectively distinguishes noise patterns across varied environments. The classroom recorded the highest variability, while the IoT Lab remained most stable. For future testing, deployment in outdoor environments (e.g., highways and markets) will capture broader acoustic profiles. Advanced techniques such as analysis of variance (ANOVA) and machine learning classification are planned for noise-source identification and predictive trend modeling.

The comparative analysis in Figure 11 highlights the SDAS's effectiveness in distinguishing acoustic profiles across multiple locations. For future work, the research team plans to extend testing to outdoor environments, including traffic intersections and market zones, to capture complex urban noise signatures. Statistical tools such as ANOVA and machine learning-based noise classification will also be incorporated to enhance predictive analysis and differentiate between noise sources (e.g., vehicles, machinery, and human activity). These results confirm the SDAS effectively captures distinct acoustic behaviors in academic spaces and aligns with prior findings on indoor noise dynamics [22]. They also reinforce the value of AI-integrated systems for high-activity environments [23], the importance of ICT-based acoustic standards [24], and the relevance of distributed low-cost acoustic sensor networks for real-time urban monitoring [25].

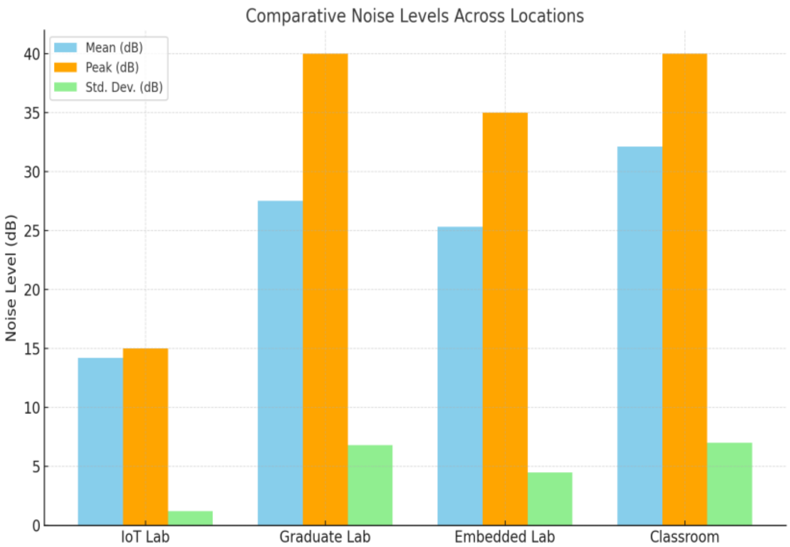


Figure 11. Comparative chart

3.3. Summary table

Table 1 consolidates mean, peak, and variability values for all locations. Results show that the IoT lab maintained the lowest levels (mean 14.2 dB, SD 1.2), while the classroom had the highest (mean 32.1 dB, SD 7.0). The graduate lab reached the maximum peak (40 dB) and the embedded lab exhibited moderate fluctuations (mean 25.3 dB, SD 4.5). These findings confirm the SDAS accurately distinguishes between quiet and dynamic environments, supporting its deployment for smart campus and broader urban monitoring.

Table 1. Summary of noise levels across test locations

Location	Mean noise level (dB)	Peak noise level (dB)	Variability (standard deviation, dB)
IoT lab	14.2	15	1.2
Graduate lab	27.5	40	6.8
Embedded lab	25.3	35	4.5
Classroom	32.1	40	7.0

3.4. Future applications and limitations

While the system performed as intended across all locations, further refinements such as Wi-Fi data syncing, automated data classification, and multi-node deployments are recommended. The current version assumes a single-node setup with manual deployment, which can be improved for long-term unattended monitoring.

Despite these limitations, the system's modular design, low cost, and reproducibility make it a strong candidate for scaling in similar institutions or urban setups concerned with environmental noise. The results reinforce the research objectives and justify the value of a low-cost, MATLAB-integrated SDAS for real-time environmental monitoring and analysis.

3.5. Testing and evaluation of the system

The SDAS was tested in multiple campus locations, capturing noise fluctuations across both quiet and dynamic environments. A panel of eight experts with master's degrees in computer applications evaluated its usability, integration with MATLAB, and reliability. Overall feedback was positive, highlighting ease of deployment, accuracy of captured data, and clarity of visualizations. Minor issues included a small learning curve for some users and the need for clearer documentation. Despite this, most experts found the system intuitive, reliable, and suitable for regular use. Figure 12 summarizes the evaluation results, confirming the SDAS's readiness for wider adoption in real-time noise monitoring.

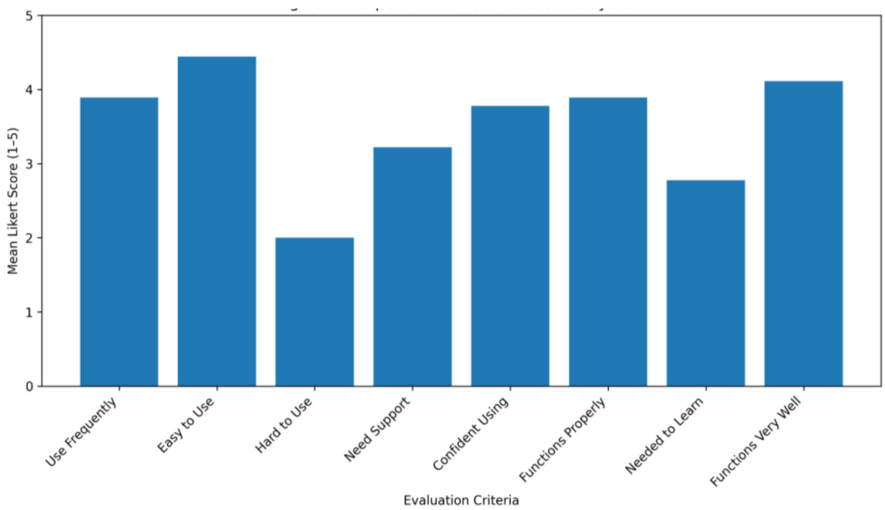


Figure 12. Expert evaluation

4. CONCLUSION

This study designed and implemented a low-cost ESP32-based SDAS for real-time monitoring of indoor noise levels. The system integrates MEMS-based acoustic sensing, ESP-WROOM-32 processing, MATLAB visualization, and local data storage. Testing across four campus locations produced mean noise levels of 14.2 dB (IoT lab), 27.5 dB (graduate lab), 25.3 dB (embedded lab), and 32.1 dB (classroom), confirming its accuracy and stability. Limitations include single-node deployment, indoor-only validation, and USB-based MATLAB transmission. Despite these, the SDAS demonstrates high usability and reliability as confirmed by expert evaluation. Future research will focus on multi-node wireless synchronization, cloud integration, and AI-driven noise classification to enable large-scale smart city acoustic monitoring.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Reymark-John A. Macapanas	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	
Adrian P. Galido		✓			✓	✓		✓	✓	✓	✓	✓		
Apple Rose B. Alce	✓		✓	✓			✓	✓	✓				✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

All authors declare that they have no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, RJM, upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Reymark-John A. Macapanas is a Faculty Member and Head of the Research, Innovation, and Extension Section at the University of Science and Technology of Southern Philippines – Villanueva Campus. He earned his M.S. in Computer Applications from Mindanao State University – Iligan Institute of Technology. His research interests include internet of things (IoT) systems, embedded technologies, and artificial intelligence for environmental monitoring and smart-city applications. He has presented and chaired sessions at NiDS 2025, ISICO 2025, and AUA AP-PPN 2025. He can be contacted at email: reymarkjohn.macapanas@ustp.edu.ph.

Adrian P. Galido is a distinguished educator, researcher, and leader with a career spanning academic and tech industry. Currently an Academic Visitor at the Lee Kuan Yew School of Public Policy's NUS Fellows Program, he also serves as a Professor at Mindanao State University-Iligan Institute of Technology (MSU-IIT), where he teaches graduate and undergraduate courses in corporate responsibility, business intelligence, and project management. As acting director of the Office of Institutional Planning and Development Services, he oversees university development and strategic planning. With an M.S. in Data Science from the Asian Institute of Management, he has held pivotal roles such as College Graduate Program Coordinator, Assistant Dean, and Acting Director of Monitoring and Evaluation. His tech industry background includes leadership positions at FPT software and Tieto Global Oy, with international assignments in Poland and Japan, where he managed teams in software development and technology transfer. His work reflects a deep commitment to advancing institutional planning, academic excellence, and data-driven development. He can be contacted at email: adrian.galido@g.msuiit.edu.ph.

Apple Rose B. Alce is a faculty member at MSU-IIT, where she teaches in the Department of Computer Applications within the College of Computer Studies. She holds a Master of Science in Computer Applications from MSU-IIT, completed in 2020, with a thesis focused on designing a microcontroller-based water level and soil moisture monitoring system for rice farming. Her research interests span smart city frameworks, IoT applications in agriculture, and environmental monitoring systems, with numerous international publications and presentations, including contributions to conferences like ISICO and ICEEA. She has attended various training sessions on cybersecurity, AI, and data privacy, enhancing her technical expertise and pedagogical skills. She can be contacted at email: applerose.alce@g.msuiit.edu.ph.