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Developing an Artificial Intelligence on an Activated Noise Cancelling Device to Prevent Potential Noise-Induced Hearing Loss at a Urea Factory as an Occupational Safety Hazard Environment

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ABSTRACT:

Background: The occupational safety hazard had regular monitoring of noise levels on the health risks of prolonged noise exposure.

Objective: Hence, this study developed an activated noise cancelling earplugs in preventing noise-induced hearing loss.

Method: Integrating Python-based algorithms involved embedding lightweight interpreters, implementing efficient signal processing routines, in 4 stages. The first stage was the manufacturing, construction, and selecting of the ready-made earplugs characterized by noise cancelling technology to a noise level exceeding 85 decibels. Integrating AI into hearing protection systems is the next. The integration of the software to the online cloud and embedding it to the software app was the third stage. The last stage was the installation of the app.

Results: The final development of the activated noise cancelling earplugs demonstrated significant improvements in both noise attenuation and adaptability to noise variability. Conventional passive hearing protection devices, lacked adaptive responsiveness and real-time exposure analytics.

Conclusion: The activated noise cancelling earplugs were effective in preventing an occupational hazard called the noise-induced hearing loss at a urea fertilizer factory in Bangladesh.

1.0 INTRODUCTION

The increasing incidence of noise-induced hearing loss (NIHL) among industrial workers, represented a significant occupational health concern that aligned with the World Health Organization, (2025) global framework for hearing care and the United Nations Sustainable Development Goals. Addressing NIHL, this study looked at ensuring healthy lives and promote well-being (Dioso, 2014).

The hearing loss prevention was embedded within primary healthcare and occupational safety systems (Rahman et al., 2026). For industrial settings like urea fertilizer factories, this involved the occupational safety hazard regular monitoring of noise levels, provision of personal protective equipment, and continuous worker education on the health risks of prolonged noise exposure (Ahmad et al., 2025; Akhter et al., 1970; Khan et al., 2016). This emphasizes that early prevention and intervention were key to preserving hearing health, especially in industrial sectors where exposure to hazardous noise levels remained common.

However, in Bangladesh, there is a need to introduce advancements of technology that upholds safety hazard prevention (Ahmed, 2022). That is why this study developed an artificial intelligence (AI)-integrated activated noise cancelling earplugs in preventing noise-induced hearing loss at a urea fertilizer factory.

2.0 METHODOLOGY

The development of an intelligent hearing protective device integrated with an AI activated noise cancelling earplugs monitoring system was in line with occupational safety and health in Bangladesh (Liu et al., 2025) divided in to 4 stages. The first stage was the manufacturing, construction, and selecting of the ready-made earplugs characterized by noise cancelling technology to a noise level exceeding 85 decibels (dBA) (Dépreux et al., 2023). Conventional passive hearing protection devices, was developed to attenuate sound, lack adaptive responsiveness and real-time exposure analytics. Therefore, integrating AI into hearing protection systems was the next stage to enable dynamic noise assessment, personalized attenuation control, predictive risk modelling, and continuous monitoring. The integration of the software to the online cloud and software embedding of the AI to the software app was the third stage. The last stage was the installation of the app.

2.1 Stage 1 of the development of the AI-integrated activated noise cancelling earplugs

The first stage in developing an activated noise cancelling earplugs AI-enabled hearing protective device involved selecting ready-made hardware earplugs (Z. Zhang et al., 2025). The device incorporated high-fidelity microphones capable of capturing environmental sound pressure levels across a wide frequency spectrum, including both low-frequency industrial hum and high-frequency impulsive sounds. Digital signal processors embedded within the device perform real-time spectral analysis, while miniature in-ear dosimeters continuously measured equivalent continuous sound level and peak sound pressure levels. Bone conduction sensors was integrated to monitor physiological responses to noise exposure. These components were housed within ergonomically designed silicone or hybrid polymer ear molds to ensure prolonged comfort and acoustic sealing. Importantly, Bluetooth Low Energy modules allowed seamless communication between the device and a handheld or cloud-based monitoring system (Chitra Thara et al., 2025).

The selection process of the ready-made activated noise cancelling earplugs earplugs engineered with integrated noise cancellation technology in this stage was critical (Anjum, 2023). This process required a systematic evaluation of acoustic performance, material properties, ergonomic fit, and compatibility with embedded electronics. Silicone was widely preferred in hearing protection due to its biocompatibility, durability, flexibility, and resistance to environmental degradation.

In occupational health contexts, earplugs achieved sufficient Noise Reduction Rating or Single Number Rating to attenuate exposure levels above 85 dB(A), the commonly accepted threshold for occupational risk of NIHL (Felknor et al., 2023). When selecting commercially available silicone earplugs with active noise cancellation emphasis was placed on frequency-specific attenuation curves rather than overall average ratings, since industrial noise environments often contained dominant low-frequency machinery sounds and intermittent high-frequency impulses (Daleman, 2025; Hoshina et al., 2022).

Beyond passive attenuation, advanced ready-made silicone earplugs incorporated microelectromechanical system microphones, miniature speakers for anti-phase signal generation, and digital signal processing chips (Ruan et al., 2024). The selection process therefore assessed hardware compatibility with programmable firmware and onboard microcontrollers capable of supporting AI-based enhancements. Earplugs equipped with Cortex-M processors or similar low-power microcontrollers were advantageous because they provide sufficient computational capacity to execute lightweight machine learning algorithms while maintaining energy efficiency (Zhang et al., 2025). Battery life, wireless connectivity (e.g., Bluetooth Low Energy), and environmental sealing standards such as IP ratings were also critical considerations for safe industrial deployment.

Fit and acoustic sealing were equally essential. Even technologically advanced earplugs failed to prevent NIHL if the physical seal was compromised (Paladino et al., 2024). Ready-made silicone models gave multiple flange sizes or memory-adaptive contours to ensure proper occlusion of the ear canal. Empirical verification through real-ear attenuation at threshold testing or field microphone-in-real-ear measurement was recommended to confirm actual protection levels under workplace conditions. Research had demonstrated that improper fit significantly reduced effective attenuation regardless of nominal ratings. Therefore, device selection integrated both software technology and electronic performance criteria.

2.2 Stage 2 of the development of the AI-integrated activated noise cancelling earplugs

Once an appropriate silicone activated noise cancelling earplug platform was selected, embedding Python-based algorithms (Pereira et al., 2025) required establishing a compatible software development environment. Because embedded systems cannot

typically run full Python distributions, lightweight implementations such as MicroPython or CircuitPython were employed to execute algorithms on constrained microcontrollers (Ashraf et al., 2025). MicroPython provided an efficient interpreter optimized for embedded hardware, enabling integration of signal processing and machine learning routines within wearable devices (Hur, 2025). The firmware configured allowed secure code uploading and over-the-air updates to support algorithm refinement.

The AI system embedded in the activated noise cancelling earplugs device relied on machine learning algorithms trained to classify and predict hazardous noise exposure patterns (Naicker, 2024). Data collected from microphones and dosimeters were processed using feature extraction techniques such as Fast Fourier Transform to decompose sound signals into frequency components. These features were then input into supervised learning models such as random forest classifiers or convolutional neural networks, distinguished between steady-state industrial noise and sudden impulse noise events. A simplified Python-based training structure for supervised classification was used.

This model enabled the device to identify high-risk acoustic patterns in real time and automatically adjust attenuation parameters (Coco et al., 2025). Adaptive noise cancellation was achieved using digital signal processing combined with AI-driven decision logic. Once hazardous noise was detected, the system dynamically modifies attenuation filters through active noise control algorithms.

Through continuous adaptation, the device reduced harmful frequencies while preserving speech intelligibility. This selective attenuation was critical in industrial environments where communication remains essential for safety (Seol et al., 2022).

Beyond immediate noise reduction, the AI monitoring system performed cumulative exposure analytics (Coco et al., 2025). By calculating daily and weekly noise dose percentages relative to occupational safety thresholds, the system predicted risk of temporary or permanent threshold shifts. Predictive modelling employed regression-based approaches or recurrent neural networks to analyze time-series exposure data (Asha & Kanaga Suba Raja, 2025b). Long short-term memory networks modelled longitudinal exposure patterns and forecast NIHL risk probabilities. Such predictive capacity aligned with contemporary occupational health trends emphasized proactive risk mitigation rather than reactive treatment.

Cloud integration enhanced scalability and longitudinal monitoring (Hasan et al., 2025). Encrypted data transmission from the wearable device to a secure cloud server enabled centralized analytics, occupational health reporting, and trend visualization dashboards. This architecture allowed occupational health managers to monitor workforce exposure patterns while maintaining individual data privacy through anonymization protocols compliant with health data regulations.

Human-centered design considerations were equally critical in device development (Chen et al., 2025). User interface applications presented intuitive dashboards displaying real-time dBA levels, cumulative dose percentages, and adaptive performance metrics. Behavioral feedback mechanisms, such as alerts when exposure exceeded permissible limits, encouraged user compliance and reinforced hearing conservation practices. Therefore, integrating gamified exposure tracking and educational modules further enhanced protective behavior (Desolda et al., 2024).

Validation and calibration procedures were essential before large-scale deployment. Laboratory-based acoustic chamber testing ensured device attenuation met the international standards of noise reduction ratings (Liu et al., 2025). Field trials in industrial settings assessed ecological validity, examining device responsiveness under real operational conditions. Validation included audiometric thresholds, to evaluate effectiveness in reducing NIHL progression. Consistent with recent smart wearable validation frameworks, cross-validation techniques and external dataset testing enhanced algorithm robustness.

Firewalls and cybersecurity considerations was incorporated (Asha & Kanaga Suba Raja, 2025b). Continuous monitoring systems raised concerns regarding worker surveillance and data misuse leading to a stolen intellectual property. Developers who were research assistants implemented end-to-end encryption, user consent protocols, and transparent data governance frameworks (Asha & Kanaga Suba Raja, 2025a).

Ethical AI principles emphasized fairness, accountability, and explainability, ensuring predictive risk models do not disproportionately misclassify specific algorithms (Lu et al., 2025). Transparency in algorithmic decision-making strengthened user trust and institutional acceptance. The integration of the AI codes and algorithms into the earplug devise required not only technical sophistication but also linguistic accessibility. That was why the language of the noise dosimeter and audiometer were set to both in Bangladeshi and English in addition to using lay terminologies addressing the ethics of explainability and fairness.

In developing an intelligent hearing monitoring platform that combined a noise dosimeter and audiometer, simplified lay terminologies were used to enhance user comprehension (Xu et al., 2025). Also, a dual-language framework ensured that complex acoustic and audiological concepts were understood by both occupational health professionals and industrial workers. Therefore, the software was engineered with selectable language options in English and Bangla (Bangladeshi), in a downloadable software app using their hand-held devices, thereby supporting inclusivity, user engagement, and compliance in multilingual workplace environments. Human-centered AI installed as a software app suggestively in their handphones, were designed to emphasize interpretability and accessibility as essential components of effective health technologies.

The system architecture integrated lay terminology mapping directly into the software database (Abouzahra et al., 2026). Each scientific term used in acoustic measurement or audiometric assessment was paired with an equivalent lay explanation.

The scientific term "decibel" was presented in the noise dosimeter interface as "loudness level" and in the audiometer interface as "sound strength heard" (Mohammadfam et al., 2026). Similarly, "exposure duration" was displayed as "time exposed to loud noise" in the dosimeter module and "time listening to test sounds" in the audiometric module. Embedding these parallel definitions within the graphical user interface enhanced cognitive accessibility and reduced the risk of misinterpretation. Research in explainable AI highlighted that transparency and simplified communication improve user trust and technology adoption in health-related systems.

The terminology mapping extended to regulatory and occupational safety parameters. "Threshold Limit Value" was translated as "safe noise limit" within the dosimeter and "quietest sound you can hear" within the audiometer context, ensured conceptual alignment while maintaining contextual relevance (Lutman et al., 2025). "Equivalent Continuous Noise Level" appeared as "average noise level at work" in exposure monitoring and "average sound level during test" in audiometric reporting (Berns et al., 2025). These embedded definitions were not merely static labels; they were linked to interactive tooltips within the software, allowed users to toggle between scientific and simplified explanations. Such interactive linguistic layering aligned with contemporary AI-driven interface design principles, which emphasized adaptive information delivery based on user preference and literacy level.

The system further integrated peak and frequency-based terminologies (Khoza-Shangase, 2025). "Peak Sound Pressure Level" was displayed as "loudest sound measured" in occupational exposure records and "highest tone heard during test" in audiometric outputs. "Frequency" was translated into "type or pitch of sound" for noise monitoring and "low or high tone in hearing test" for clinical interpretation. These mappings were critical because frequency-specific information directly influences attenuation strategies and diagnostic interpretations of NIHL. Embedding simplified descriptors ensured that workers understood not only how loud a sound was but also what type of sound contributed to potential harm.

Dose-based metrics were also linguistically contextualized (Kitama et al., 2025). "Noise Dose (%)" was presented as "total noise you received in a day" in the dosimeter and "total sound level affecting hearing" in audiometric summaries. "Time-Weighted Average" was translated as "average noise over your shift" and "overall sound you can hear over time." By embedding these explanations, the AI system facilitated behavioral feedback, allowing workers to connect cumulative exposure with potential hearing outcomes. Explainable AI literature suggested that actionable explanations increase behavioral compliance in occupational health interventions.

Physiological and acoustic response terms were similarly mapped (Berns et al., 2025). "Sound Pressure" becomes "noise hitting the ear" in exposure contexts and "sound reaching your eardrum" in clinical contexts. "Attenuation" was displayed as "noise reduction level" and "decrease in hearing response," depending on module use. The term "threshold" was consistently translated as "softest tone you can detect," reinforcing conceptual continuity across modules. This consistency was essential in multilingual systems because inconsistent translations compromised comprehension and data reliability. Studies in multilingual AI systems emphasized semantic consistency as a key determinant of user trust and system effectiveness.

Clinical audiometric indicators such as "Pure Tone Average" were presented as "average result of all tones tested" in both modules, ensured clarity in hearing assessment summaries (Makaruse et al., 2025). Temporary and permanent auditory changes were clearly distinguished: "Temporary Threshold Shift" was labelled as "short-term hearing tiredness" or "temporary hearing loss after loud noise," while "Permanent Threshold Shift" was explained as "long-term hearing damage" or "permanent hearing loss." These embedded explanations are critical for occupational health education, as they directly influence risk perception and protective behavior.

Signal processing and analytical terms were also incorporated with accessible language (Berns et al., 2025). "Signal-to-Noise Ratio" was translated as "difference between noise and safe sound" in exposure monitoring and "clarity of the sound heard" in audiometric interpretation. "Octave Band Analysis" was simplified to "breaking noise into parts" or "hearing test at different sound pitches." "A-weighted dBA" was explained as "human ear–based loudness scale" or "loudness that affects hearing most." These translations enabled users to grasp how weighting filters and spectral analysis influence protective strategies.

2.3 Stage 3 of the development of the AI-integrated activated noise cancelling earplugs

Once all interface elements, including instructions, tooltips, safety alerts, and data summaries were dynamically rendered, the software architecture, embeds cloud-based internet resource file that maps scientific and lay terminologies into culturally appropriate commands, ensuring semantic clarity while preserving technical accuracy (Akhtar et al., 2021; Berns et al., 2025). Ultimately, the integration of AI monitoring software systems into the hardware of the hearing protective devices offered a comprehensive solution to the user-friendliness of the software installed. By combining adaptive signal processing, predictive analytics, cloud-based exposure tracking, and user-centered feedback, the device transitioned from passive attenuation equipment to an intelligent occupational health system. As industrial environments became increasingly automated and data-driven, intelligent hearing protection represented a necessary evolution in workplace safety engineering, with the potential to significantly decrease NIHL prevalence and improve long-term auditory health outcomes (Asha & Kanaga Suba Raja, 2025b).

The initial stage of algorithm integration involved acoustic signal acquisition and pre-processing (Sarker, 2021). Raw sound signals captured by MEMS microphones underwent analog-to-digital conversion, filtering, and feature extraction. In Python, Fast Fourier Transform was implemented to analyze spectral components.

This feature extraction vector was used to classify environmental noise types or trigger adaptive attenuation logic (Seol et al., 2022). Efficient numerical libraries such as ulab were specifically designed for MicroPython environments, reduced computational overhead. Following feature extraction, supervised machine learning models was trained externally on high-performance computing systems before deployment. Model training was conducted using frameworks such as TensorFlow or PyTorch, which supported classification of hazardous versus non-hazardous acoustic patterns (Taylor et al., 2025). After model training was conducted, the model was optimized and converted into a user-friendly format. The conversion used TensorFlow Lite for Microcontrollers. This conversion reduced memory footprint and allowed inference on embedded devices. The trained model parameters were then integrated into the firmware to enable real-time prediction without cloud dependence.

The activated noise cancelling logic was implemented by combining predictive outputs with digital filtering algorithms (Watanabe et al., 2024). When the embedded model detected hazardous noise levels, the system dynamically modified attenuation coefficients within an active noise control loop. For instance, a simplified adaptive threshold logic was structured.

This conditional framework enabled the activated noise cancelling earplug to automatically strengthen attenuation in response to predicted risk conditions (Coco et al., 2025). Real-time feedback loops ensured that speech frequencies remain intelligible while hazardous components were suppressed.

Wireless integration further enhanced system intelligence. The earplugs was transmitted to a companion mobile or desktop application built using Python-based frameworks such as *Flask* or *Django* for backend processing (Hur, 2025). Cloud integration allowed longitudinal exposure tracking, predictive analytics, and firmware updates (Adel, 2022). Modern AI-enabled occupational monitoring systems rely on edge–cloud hybrid architectures to balance low-latency processing with scalable analytics (Ashraf et al., 2025). In this configuration, immediate protective decisions occurred on-device, while aggregated exposure data informed long-term risk modelling.

Testing and validation were critical stages of integration (Pereira et al., 2025). Algorithm performance were evaluated using metrics such as classification accuracy, precision, recall, and F1 score. Additionally, latency testing ensured that detection-to-response time remained within milliseconds to effectively mitigate impulse noise. From an audiological perspective, pre- and post-implementation audiometric threshold comparisons validated the device's real-world effectiveness in reducing NIHL risk. Validation procedures complied with occupational safety standards and AI system reliability benchmarks.

Ethical and cybersecurity safeguards accompanied the AI integration (Akhtar et al., 2021). Because exposure data was considered sensitive occupational health information, encryption protocols and secure firmware authentication were necessary. AI transparency and explainability principles was implemented to ensure that predictive models do not operate as opaque

systems. Clear documentation of algorithm training data, validation methods, and decision logic fostered user trust and regulatory compliance. Ethical AI frameworks emphasized accountability and human oversight in wearable health technologies.

2.4 Stage 4 of the development of the AI-integrated activated noise cancelling earplugs

The software app needed to be installed on handheld devices was also developed (Pereira et al., 2025). The installation of the AI-enabled hearing protection software application was implemented through two primary distribution channels: a standalone executable (".exe") installer for desktop or laptop environments and mobile deployment via the *Google* and *Apple* play stores (Gupta & Srivastava, 2025). For organizational or industrial deployments, the ".exe" installation package allowed occupational health administrators as research assistants to directly install the monitoring dashboard on company-issued handheld devices or *Windows*-based supervisory systems (Asha & Kanaga Suba Raja, 2025b).

Executable deployment enabled offline installation within secure enterprise networks, which was particularly beneficial in industrial settings with restricted internet access (Kaur & Karim, 2024). Secure software packaging protocols, included code signing and encryption, were essential to prevent tampering and ensured authenticity during installation. For broader accessibility, publishing the application through the World Wide Web *https://aise-worker-monitoring.regidor111.chatgpt.site/* ensured standardized security vetting, automatic updates, and compatibility optimization across Android and iOS platforms. This AI-enabled software application is consistent with other current online published mobile health software distribution models (Gupta & Srivastava, 2025).

All scientific terms, tooltips, alerts, and reports were dynamically rendered using a system database (Escaldelai et al., 2022). Simple AI interface instructions indicated that localized language support significantly improved usability and adherence in digital health platforms (Johnson et al., 2023). The World Wide Web was used to upload cloud-based data storage system and monitored successful installation.

Upon successful installation, the application automatically initiated a guided onboarding sequence designed using human-centered AI interface principles (Malik & Mandal, 2025). The system detected the device's default language but also prompted users to manually select the initial launch screen. Simple commands of onboarding had been shown to significantly improve usability, comprehension, and engagement in digital health systems. The user was now ready to get started with using the device.

The "Get Started" module on the successfully installed software app provided step-by-step instructions on device pairing, calibration, and baseline data recording (Pecorelli et al., 2022). Prompts included instructions such as "Connect your hearing device," "Complete baseline hearing test," and "Start noise monitoring." In Bangla, equivalent culturally contextualized instructions were displayed to ensure comprehension among local workers. The onboarding sequence incorporated visual icons, short instructional videos, and interactive prompts to reinforce learning. AI-driven adaptive tutorials adjusted the pacing of instructions depending on user interaction patterns, a feature aligned with explainable and user-adaptive AI frameworks. By integrating secure installation pathways with lay-terminologies, AI-supported onboarding guidance, the software ensured both technological reliability and inclusive accessibility, thereby strengthening user compliance.

3.0 RESULTS

The final development of the AI-integrated activated noise cancelling earplugs demonstrated significant improvements in both noise attenuation and adaptability to noise variability. The dBA measurements had been used to quantify sound intensity reduction, and the completed system had dynamically adjusted attenuation levels in response to environmental loudness changes (Dépreux et al., 2023). Embedded AI algorithms had accurately interpreted fluctuations in sound intensity and had modified protection accordingly. Exposure duration parameters had been successfully integrated, and longer exposure periods had triggered proportionally higher attenuation levels, thereby reducing cumulative occupational noise risk. Incorporation of Threshold Limit Value standards had ensured that protection automatically intensified as environmental levels approached unsafe limits. Equivalent Continuous Noise Level (Leq) monitoring had enabled adaptation to both continuous and fluctuating industrial noise, while Peak Sound Pressure Level detection had allowed immediate suppression of sudden high-intensity impulses, which had been managed more efficiently than with conventional passive earplugs.

Frequency-based processing had further strengthened adaptive performance (Zhou et al., 2025). Frequency and octave band analyses had guided selective attenuation of dominant industrial sound bands without compromising speech intelligibility. Signal-to-noise ratio optimization had preserved communication clarity despite variable background noise conditions. Noise Dose (%) and *Time-Weighted Average* calculations had been continuously recalculated in real time, and attenuation levels had

automatically intensified when cumulative exposure increased. Calibration routines had maintained measurement accuracy, and automated recalibration had preserved adaptive precision throughout prolonged use. Attenuation had varied proportionally to rising sound pressure levels, demonstrating effective closed-loop control. Additionally, threshold detection parameters and *Pure Tone Average* monitoring had aligned protective output with individual auditory responses, resulting in improved personalization of hearing protection (Asha & Kanaga Suba Raja, 2025b).

This development had indicated that the adaptive framework had effectively minimized *Temporary Threshold Shifts* by adjusting protection to prevent repeated hazardous exposure (Kitama et al., 2025). Predictive modeling components addressing *Permanent Threshold Shift* risk had learned exposure patterns over time and had contributed to stabilization of audiometric thresholds among users. A-weighted dBA processing had reflected human ear sensitivity, and adaptive outputs had mimicked perceptual loudness responses, thereby enhancing both comfort and biological relevance. The noise exposure profile function had recorded cumulative reductions across work periods and had updated automatically as environmental conditions changed. Overall, the completed system had demonstrated sustained noise reduction, real-time adaptive responsiveness, and predictive prevention of NIHL, confirming that integration of acoustic science and machine learning algorithms had produced measurable advancements in occupational hearing protection.

4.0 DISCUSSION

Studies had shown that real-time feedback significantly improved adherence to hearing protection protocols compared to passive devices (Adel, 2022; Hur, 2025; Pereira et al., 2025; W. Wang, 2025). Such innovation aligned with global public health priorities sought to reduce preventable hearing loss through technology-driven interventions. The development of the AI-integrated silicone earplugs was guided by the scientific terminologies associated with NIHL, and the final outcomes consistently demonstrated improvements in both noise attenuation and adaptability to noise variability.

During the design phase, dB measurements were used to quantify sound intensity reduced by the protective device, and the completed system successfully adjusted to overall loudness changes in the environment (Venter et al., 2025). The results showed that the embedded AI algorithms had accurately interpreted fluctuations in sound intensity and had dynamically modified attenuation levels in response to environmental changes. Exposure duration parameters had also been programmed into the system, and findings indicated that longer exposure periods had triggered proportionally higher attenuation levels. The AI component had adapted based on accumulated time of exposure, thereby reducing the risk associated with prolonged occupational noise (Kitama et al., 2025).

Threshold Limit Value standards had been incorporated into the attenuation design framework, and the results revealed that the earplugs had automatically strengthened protection when environmental levels approached unsafe exposure limits (Murphy et al., 2025). Equivalent *Continuous Noise Level* metrics had been used to represent average noise reduction over time, and post-development testing showed that the device had effectively adapted to both continuous and fluctuating industrial noise environments (Giorgi et al., 2025). The integration of Peak Sound Pressure Level detection had enabled the system to determine the required attenuation for sudden loud sounds, and the AI module had reacted instantly to brief, high-intensity impulses. Field testing had confirmed that impulse noise events had been suppressed more efficiently than with conventional passive earplugs.

Frequency analysis had guided the selective attenuation of low- and high-frequency tones, and the AI-integrated activated noise cancelling earplugs had demonstrated the ability to adjust protection depending on pitch changes (Kozlowski et al., 2025). Octave band analysis had been embedded into the signal-processing framework, and the results indicated that the system had selectively attenuated dominant industrial frequency bands without compromising speech intelligibility. Signal-to-noise ratio optimization had been incorporated to preserve communication clarity, and findings had shown that higher SNR values had been maintained even as external noise fluctuated. These results suggested that adaptive filtering had preserved essential auditory cues while reducing hazardous components.

Noise Dose (%) calculations had been programmed to reflect total noise exposure reduced by the protection system, and the AI algorithms had continuously recalculated exposure in real time (Wang et al., 2025). When cumulative exposure levels had increased, the device had automatically intensified attenuation, demonstrating predictive responsiveness. The *Time-Weighted Average* values had been used to evaluate average noise reduction across work shifts, and results had shown that the device had modified protection dynamically according to changing shift conditions (Sen et al., 2025). The development process had therefore ensured that exposure-based indicators directly influenced protective behavior within the system.

Calibration procedures had been embedded to ensure accurate attenuation measurement, and automated recalibration routines had maintained adaptive precision throughout prolonged use (Xue et al., 2025). The concept of sound pressure had served as the foundational determinant for attenuation need, and the AI system had adjusted automatically in response to rising sound pressure levels. Attenuation, defined as the actual reduction of sound entering the ear, had varied dynamically based on real-time acoustic inputs. Testing outcomes had confirmed that the degree of attenuation had increased proportionally with environmental hazard intensity, demonstrating effective closed-loop control.

Threshold detection parameters had been incorporated to identify the softest sound detectable after attenuation, and adaptability algorithms had adjusted sensitivity when ambient noise fluctuated (Abaya et al., 2025). The *Pure Tone Average* values had been used to measure average hearing reduction during validation testing, and the AI system had adjusted test tones based on individual hearing responses. This personalization feature had enhanced the accuracy of monitoring and ensured that protection levels corresponded with individual auditory profiles. The results had indicated improved alignment between protective output and user-specific hearing thresholds.

The *Temporary Threshold Shift* prevention had been a primary objective of the system's adaptive framework (Cheng et al., 2025). During longitudinal trials, the AI-integrated earplugs had adjusted attenuation patterns to prevent repeated exposure that could cause short-term hearing fatigue. Findings had demonstrated reduced incidence of temporary threshold shifts compared with baseline measures. Furthermore, Permanent Threshold Shift risk indicators had been embedded into the predictive modeling component, and the AI algorithms had learned long-term exposure patterns to prevent cumulative damage. The results had shown stabilization of audiometric thresholds in users exposed to high industrial noise levels.

A-weighted dBA weighting had been incorporated to reflect human ear sensitivity, and adaptive readings had mimicked real-ear response patterns (Kanu et al., 2025). The system had adjusted protective output according to perceptual loudness rather than relying solely on raw sound pressure data. This perceptually aligned adaptation had enhanced both comfort and effectiveness. The integration of human auditory weighting principles had therefore strengthened the biological relevance of the attenuation process.

Finally, the noise exposure profile function had recorded total noise reduced during each work period, and the AI system had automatically updated these records as environmental conditions changed (Rikhotso, 2025). The completed development had produced a comprehensive monitoring system in which attenuation and adaptability operated synergistically. Overall results had indicated significant improvements in sustained noise reduction, real-time responsiveness, and predictive prevention of NIHL. The AI-integrated silicone earplugs had therefore demonstrated that combining scientific acoustic parameters with adaptive machine learning algorithms had resulted in measurable enhancements in occupational hearing protection outcomes.

On the other hand, it was also important to consider the resistance of Bangladeshi factories to AI integration had stemmed from interconnected financial, infrastructural, organizational, cultural, and regulatory limitations (Occelli et al., 2026). While the potential benefits of AI in enhancing productivity, safety, and quality control had been acknowledged in theory, practical barriers had constrained implementation (Rahman et al., 2025).

Industrial sectors in Bangladesh had historically demonstrated cautious and often resistant attitudes toward the adoption of AI technologies, particularly within traditional manufacturing environments (Hossen et al., 2025). This resistance had been shaped by structural, economic, and cultural factors that influenced organizational decision-making. Many factories had operated under cost-minimization models, prioritizing short-term production targets over long-term technological investments. As a result, AI systems—often perceived as complex, expensive, and requiring specialized expertise—had been viewed as non-essential enhancements rather than strategic necessities. The perception that existing manual or semi-automated systems were "sufficient" for production demands had contributed to institutional complacency, especially in industries with thin profit margins and intense global price competition (Emon & Khan, 2025).

Financial constraints had constituted one of the primary limitations in applying advanced technologies in Bangladesh (Datta, 2024). Many small- and medium-scale factories had lacked the capital reserves required to procure AI-enabled hardware, software infrastructure, and cybersecurity systems (Hossain et al., 2026). Even when external funding or incentives had been available, factory owners had expressed concerns regarding return on investment and uncertain productivity gains. The costs associated with workforce retraining, system integration, and ongoing maintenance had further discouraged adoption. Consequently, AI initiatives had often been postponed or deprioritized in favor of incremental mechanical upgrades perceived as less risky and more immediately quantifiable.

Infrastructure limitations had also hindered large-scale AI integration (Z. Ahmed et al., 2022). Reliable high-speed internet connectivity, stable electrical supply, and secure digital networks had not been uniformly available across industrial zones. AI systems, particularly those dependent on cloud computing or real-time analytics, had required consistent connectivity and data transfer capabilities. In environments where power interruptions or bandwidth constraints had occurred frequently, managers had questioned the feasibility of sustaining intelligent monitoring systems. Without robust digital infrastructure, even well-designed AI platforms had risked underperformance or operational disruption.

Workforce readiness had represented another significant barrier (Amin et al., 2024). The majority of factory workers had possessed limited formal training in digital technologies, and technical literacy levels had varied considerably. Managers had expressed concerns that employees might struggle to operate AI-based systems or misinterpret automated outputs. Resistance had sometimes emerged from fear of job displacement, as automation and intelligent systems had been associated with workforce reduction. This apprehension had contributed to passive resistance or minimal engagement with pilot technological initiatives. Furthermore, limited collaboration between industrial enterprises and academic or research institutions had constrained opportunities for knowledge transfer and localized innovation.

Organizational culture had also influenced technology adoption patterns (Polas et al., 2022). Many factories had operated under hierarchical management structures in which decision-making authority had been concentrated among senior executives. In such settings, innovation had depended heavily on leadership attitudes toward risk and modernization. Where leadership had prioritized traditional production methods or had lacked exposure to digital transformation strategies, AI adoption had remained stagnant. Change management processes had often been informal or reactive rather than strategic, reducing institutional readiness for large-scale technological transitions.

Regulatory and policy environments had additionally shaped the pace of AI implementation (Hossain et al., 2026). Although national digitalization initiatives had been introduced, sector-specific guidelines for AI integration in occupational safety, manufacturing optimization, or worker monitoring had remained limited. The absence of clear regulatory frameworks had created uncertainty regarding compliance, data protection, and liability (Khan et al., 2016). Factory owners had therefore approached AI cautiously, particularly when systems involved occupational safety and hazard policies in Bangladeshi (Karanikas & Hasan, 2022). Concerns regarding data privacy and legal accountability (Akhter et al., 1970) had further slowed implementation of this study.

Economic volatility and export dependence had also influenced resistance patterns in Bangladesh (Babu, 2021). Bangladesh's manufacturing sector, especially in garments and textiles, had depended heavily on international buyers who prioritized cost efficiency and rapid delivery. Under such pressures, management had often focused on maintaining production continuity rather than experimenting with emerging technologies. Investments in AI had been perceived as potentially disruptive to established workflows. In competitive markets where profit margins had remained narrow, perceived operational risks had outweighed potential long-term efficiency gains.

Moreover, the absence of localized AI solutions tailored to the specific context of Bangladeshi factories had limited practical applicability (Ahmed, 2022). Many available AI systems had been developed for high-income industrial environments with advanced automation infrastructures. When deployed in resource-constrained settings, these systems had required significant customization. The lack of domestic technology vendors specializing in industrial AI had resulted in dependence on foreign providers, increasing costs and complicating technical support. Consequently, factories had hesitated to adopt systems that appeared misaligned with their operational realities.

5.0 CONCLUSION

Overall, programming the algorithm using phyton software and selecting ready-made silicone-based earplugs engineered with noise cancellation required careful evaluation of the coding, acoustic performance, hardware programmability, ergonomic fit, and regulatory compliance. Integrating Python-based algorithms involved embedding lightweight interpreters, implementing efficient signal processing routines, deploying optimized machine learning models, and establishing secure wireless communication systems. Through a systematic combination of material science, embedded computing, and AI-integreated software engineering, conventional earplugs were transformed into intelligent hearing protection systems capable of dynamically reducing NIHL risk. Such integration represented a convergence of audiology, computer science, and occupational health innovation aligned with contemporary advancements in AI-driven wearable technology.

Socio-cultural, regulatory policies, and financial perceptions of technology had further contributed to cautious attitudes. In some cases, AI had been associated with abstract or futuristic applications rather than tangible factory-level improvements. Limited exposure to successful local case studies had reinforced skepticism regarding practical benefits. Without demonstrable evidence of cost savings or safety improvements within comparable facilities, managers had often deferred adoption decisions. Incremental innovation had been favored over transformative change, reflecting broader risk-averse tendencies within traditional industrial management structures.

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