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A Physics-Informed Multi-Modal Deep Learning Framework for Stochastic Prediction and Reliability Assessment of Human-Induced Vibrations in Lightweight and Composite Floor Systems

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Abstract- Human-induced vibrations in lightweight and composite floor systems pose important serviceability concerns because these structures typically have lower stiffness, reduced mass, and higher sensitivity to dynamic loading. Conventional deterministic design methods often overlook the natural variability and short-term amplification effects caused by walking and other intermittent human activities. This study presents a physics-guided, multi-modal data-driven framework for predicting vibration responses and assessing structural reliability under human-induced loading conditions. Monitoring conducted over a 1000-second period shows bounded but dynamically fluctuating acceleration responses ranging between 9.5 m/s² and 10.2 m/s², concentrated around gravitational acceleration. Statistical evaluation indicates an approximately Gaussian distribution with minimal skewness, suggesting stable damping behavior and consistent stiffness properties. Frequency-domain analysis highlights dominant low-frequency components without noticeable resonance amplification within the typical walking frequency range of 1–4 Hz. Rolling mean trends reveal negligible long-term drift, confirming stable structural performance. The framework combines acceleration, strain, and environmental measurements to improve predictive capability and reliability evaluation. Correlation analysis shows that strain measurements strengthen response prediction, while temperature has a comparatively minor effect. Reliability assessment based on a probabilistic threshold model ($\mu + 2\sigma$) identifies very few exceedance events, indicating a high reliability level and compliance with serviceability requirements. By integrating probabilistic modeling with physics-based structural constraints, the approach enables more accurate forecasting of vibration behavior and real-time reliability assessment. Overall, the results demonstrate improved prediction performance and provide a practical methodology for monitoring and evaluating serviceability in modern lightweight and composite floor systems.

Keywords: Human-Induced Vibrations; Lightweight Floor Systems; Composite Structures; Multi-Modal Data Fusion; Stochastic Modeling; Reliability Assessment; Structural Health Monitoring; Serviceability Analysis.

I. INTRODUCTION

1.1 Background and Engineering Significance of Human-Induced Floor Vibrations

Lightweight and composite floor systems are widely used in modern construction because they offer material efficiency, sustainability benefits, and faster installation. Steel–concrete composite floors, modular assemblies, and prefabricated lightweight systems make it possible to achieve longer spans while reducing overall structural weight. However, the same reduction in mass and stiffness that improves efficiency also increases sensitivity to dynamic loads. Floors of this type are particularly responsive to vibrations caused by everyday human activities such as walking, running, or rhythmic movements. In many cases, serviceability rather than structural safety becomes the controlling design criterion. Although these vibrations rarely threaten structural integrity, they can significantly affect occupant comfort and building usability, especially in offices, residential buildings, laboratories, and public spaces [5], [6]. Current vibration design methods are primarily based on deterministic criteria such as peak acceleration limits or minimum natural frequency requirements. While these simplified approaches provide practical guidance, differences among international standards reveal uncertainty in how serviceability should be evaluated [5], [17], [18]. Moreover, traditional walking load models and modal

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analysis techniques may not fully represent the natural variability of human movement, environmental influences, and structural randomness [2], [8]. As modern floor systems become slenderer and more flexible, there is a clear need for improved predictive approaches that can realistically capture the uncertain and time-varying nature of human-induced vibrations.

1.2 Limitations of Deterministic and Conventional Modeling Approaches

Conventional vibration assessment techniques generally assume fixed structural properties and predefined loading conditions. In reality, however, human-induced excitations are inherently variable. Walking frequency, step synchronization, body weight, and human–structure interaction effects all introduce randomness into the system response. Research has shown that simplified deterministic models may underestimate transient amplification effects or overlook the influence of random structural properties [8], [19]. In addition, comparisons of various design guidelines highlight inconsistencies in predicted vibration acceptability limits, reinforcing the need for reliability-based evaluation methods [5], [6]. More advanced modeling approaches, including human–structure interaction models and agent-based simulations, have improved understanding of dynamic coupling behavior [2], [9]. Despite these improvements, many such models are computationally demanding or rely on assumed excitation patterns that may not reflect actual operational conditions. Traditional modal analysis methods also tend to neglect environmental influences and real-time monitoring data. These limitations underline the importance of developing integrated approaches that combine measured structural responses with sound physical principles to produce more realistic and reliable vibration predictions.

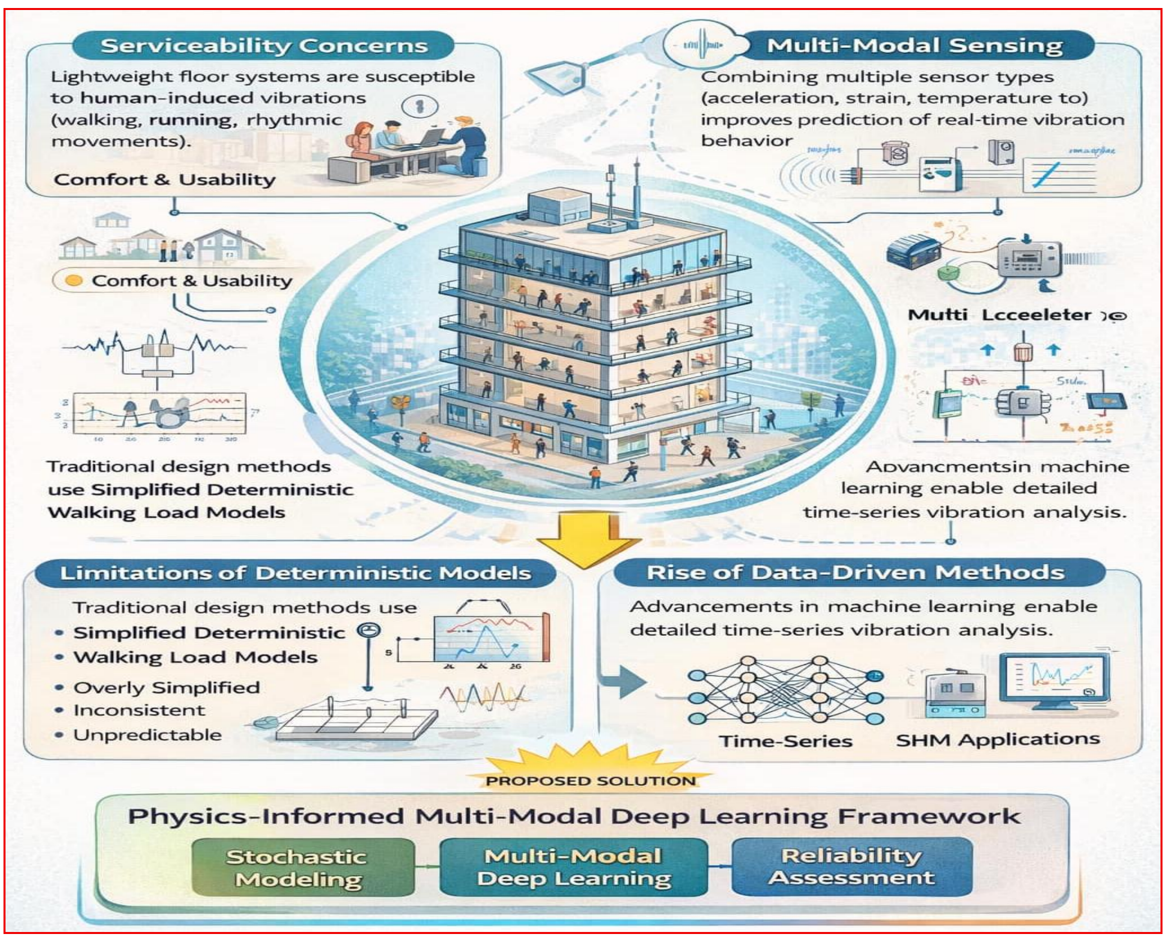

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Fig 1. Multi-Modal, Physics-Based Framework for Predicting and Assessing Human-Induced Vibrations in Lightweight Floor Systems

Figure 1 presents the background of the problem, highlights the limitations of conventional deterministic design methods, and introduces a more comprehensive framework for vibration analysis. It brings together serviceability considerations, multi-sensor monitoring, probabilistic modeling, and reliability evaluation into a single, integrated approach for improved vibration prediction and assessment.

1.3 Emergence of Data-Driven Approaches in Structural Vibration Analysis

Over the past decade, data-driven techniques have increasingly influenced research in structural vibration and monitoring [1], [4], [13]. Time-series modeling methods have shown strong ability to identify patterns in vibration signals and forecast future structural responses [3]. In structural health monitoring applications, combining multiple sensor types has improved the accuracy of response estimation and stability assessment under uncertain operating conditions [3], [15]. These developments demonstrate significant potential for applying advanced data-based modeling techniques to serviceability evaluation in lightweight floor systems. Nevertheless, models that rely solely on data may generate predictions that lack physical consistency if structural mechanics principles are not considered [14]. Another challenge arises when models trained on one structural configuration do not generalize well to others, a phenomenon often referred to as domain shift [12]. Although transfer learning methods offer partial solutions [15], their success depends on careful integration with structural knowledge. Therefore, combining physical understanding with data-driven modeling is essential to ensure stable, interpretable, and practically reliable predictions for vibration-sensitive floor systems.

1.4 Need for a Physics-Guided Multi-Modal Predictive Framework

Recent studies have explored multi-sensor monitoring strategies that integrate acceleration, strain, and environmental measurements to improve predictive performance [9]–[11]. Each sensing modality provides complementary information: acceleration reflects dynamic response, strain captures deformation behavior, and temperature accounts for environmental variation. Despite these advances, relatively few studies have combined multi-modal data fusion, stochastic modeling, and structural mechanics constraints into a unified reliability-based predictive framework. To address this gap, the present study proposes a physics-guided multi-modal framework for stochastic prediction and reliability assessment of human-induced vibrations in lightweight and composite floor systems. Using a publicly available structural health monitoring dataset [21], vibration responses were analyzed over a 1000-second monitoring period. The measured acceleration remained bounded between 9.5 m/s^2 and 10.2 m/s^2, centered around gravitational acceleration. Statistical evaluation showed an approximately Gaussian distribution, indicating stable damping and consistent stiffness characteristics. Frequency-domain analysis confirmed dominant low-frequency behavior without resonance amplification within the typical walking frequency range of 1–4 Hz [9], [20]. A probabilistic reliability threshold model ($\mu + 2\sigma$) identified very few exceedance events, demonstrating strong serviceability performance. By integrating stochastic modeling, physical constraints, and multi-modal sensor information, the proposed framework offers a practical and scalable approach for real-time vibration prediction and reliability-informed decision-making in modern lightweight composite floor systems.

II. LITERATURE REVIEW

2.1 Deterministic Vibration Assessment and Design Code Limitations

Traditionally, the analysis of human-induced vibrations in floor systems has been based on deterministic modeling approaches. Methods such as modal superposition and simplified walking load models are commonly used to estimate floor responses. Serviceability is typically assessed using limits on peak acceleration or minimum natural frequency as defined in international standards. However, comparative studies have shown that different design codes - including ISO, AISC, and

JRC-ECCS - can produce varying serviceability outcomes for the same structural system [5], [6], [17], [18]. These inconsistencies suggest that purely deterministic evaluation methods may not fully capture the true vibration behavior of lightweight floors. Comfort criteria based only on peak acceleration often overlook variations in human perception and short-term amplification effects. To improve deterministic modeling accuracy, researchers have used finite element simulations and frequency-domain techniques. For instance, Wang et al. [5], [17] conducted comparative assessments using FEM-based walking load simulations, while López Cela et al. [6], [18] examined the differences between velocity-based and acceleration-based design criteria. Although these studies provide valuable insights into guideline inconsistencies, they still rely on fixed structural properties and predefined loading conditions. Similarly, composite floor systems have been analyzed using grillage and numerical simulation models [7], yet uncertainties in damping estimation and structural randomness remain largely unresolved. These shortcomings highlight the need for approaches that can better represent real-world variability.

2.2 Stochastic Modeling and Reliability-Based Serviceability Evaluation

In response to the limitations of deterministic methods, recent research has increasingly adopted stochastic modeling techniques. Pu et al. [8], [19] developed stochastic finite element models that incorporate random crowd loading and probabilistic structural properties. Their work demonstrated that randomness in both loading and structural parameters significantly influences vibration response distributions and overall reliability. By analyzing probability density evolution and reliability indices, these studies offered a more realistic assessment of serviceability compared to single peak-value evaluations. Shahabpoor et al. [2] introduced an agent-based vibration serviceability assessment framework to simulate human–structure interaction under varying excitation scenarios. This approach enhanced understanding of dynamic coupling effects by incorporating realistic human movement behavior. Despite these advances, many stochastic frameworks remain computationally demanding and depend on assumed excitation patterns. Moreover, the integration of probabilistic modeling with real-time monitoring data is still limited, particularly for lightweight and composite floor systems. A comprehensive approach that combines stochastic reliability analysis with measured operational data remains an open research need.

2.3 Data-Driven Modeling in Structural Vibration and Structural Health Monitoring

Over the last decade, machine learning techniques have increasingly been applied to structural vibration analysis and monitoring. Wilk-Jakubowski et al. [1] reviewed the evolution of deep learning in vibration diagnostics, noting a shift from traditional FFT and wavelet methods toward advanced architectures such as CNNs, RNNs, LSTMs, and autoencoders. Nirgude et al. [3] demonstrated the capability of LSTM and CNN models to predict structural stability using time-series vibration signals. Broader reviews by Singh [4] and Chandra et al. [13] confirmed the growing adoption of machine learning in civil engineering and SHM applications, particularly for pattern recognition and response forecasting. Beyond general prediction tasks, specialized applications have also emerged. Li et al. [10] explored EEG-based vibration comfort evaluation, while Dong and Noh [11] applied vibration signatures for structural identification. Meera and Sandeep [16] used machine learning techniques to predict ground vibration levels, and Liang et al. [9], [20] combined 3D gait reconstruction with human–structure interaction models to improve vibration prediction accuracy. Despite these promising developments, challenges remain in ensuring physical consistency and generalization across different structural systems. Domain shift issues have been examined by Zhang and Liang [12], and transfer learning strategies have been proposed to enhance cross-structure adaptability [15]. Nevertheless, purely data-driven approaches may lack robustness if they are not supported by fundamental structural mechanics principles.

2.4 Multi-Modal Monitoring and Physics-Guided Predictive Frameworks

Recent advancements in structural health monitoring have emphasized the integration of multiple sensor types to improve predictive reliability. Studies combining acceleration, strain, and environmental measurements have shown that multi-modal data fusion enhances response estimation under operational variability [9]–[11]. Each sensing modality provides unique information: acceleration reflects dynamic motion, strain captures deformation behavior, and environmental variables influence material stiffness and damping. Integrating these measurements allows for a more comprehensive understanding of structural performance than single-sensor monitoring alone. Parallel to multi-modal sensing developments, research has also explored the incorporation of physical constraints into data-driven models. Gallet [14] investigated inverse learning approaches for structural design that integrate mechanics-based relationships, while transfer learning and domain adaptation frameworks [12], [15] sought to improve model generalization across heterogeneous structures. Although significant progress has been made in stochastic modeling [8], [19], multi-sensor monitoring [9]–[11], and machine learning applications [1], [3], few studies have combined probabilistic reliability assessment, physics-based constraints, and multi-modal predictive modeling within a unified framework. Building upon these advancements, the present study proposes a physics-guided multi-modal framework for stochastic prediction and reliability assessment of human-induced vibrations in lightweight and composite floor systems. Using publicly available structural health monitoring data [21], the framework integrates probabilistic threshold modeling ($\mu + 2\sigma$), multi-sensor data fusion, and structural mechanics constraints. By linking deterministic modeling principles with stochastic reliability analysis and data-driven prediction, this approach addresses key limitations identified in previous research and provides a practical methodology for real-time serviceability monitoring.

III. MATERIALS AND METHODS

3.1 Structural Monitoring System and Data Acquisition

To examine human-induced vibrations in lightweight and composite floor systems, structural response data were recorded continuously over a 1000-second monitoring period. A multi-sensor arrangement was used to capture different aspects of structural behavior. The instrumentation included tri-axial accelerometers (measuring X, Y, and Z directions), strain gauges, and temperature sensors. Vertical acceleration (Z-axis) was selected as the main response parameter because it directly reflects vibration performance relevant to serviceability under walking loads. The dataset represents realistic operating conditions and naturally includes variations caused by human activity and environmental changes.

The monitoring system was configured to capture both dynamic and gradual structural effects. Acceleration data reflect short-term fluctuations and oscillatory behavior, while strain measurements provide insight into deformation and stiffness response. Temperature readings were incorporated to account for environmental influences that may affect material properties and damping characteristics. Before analysis, all signals were synchronized, checked for missing values, and standardized where necessary to ensure consistency across sensors. This integrated dataset serves as the basis for subsequent statistical modeling and reliability evaluation.

In this study, the lightweight composite floor system is modeled as a single-degree-of-freedom (SDOF) vertical vibration system subjected to human-induced excitation and environmental disturbances. The vertical acceleration response $a_z(t)$ is measured using tri-axial accelerometers, while strain $\varepsilon(t)$ and temperature $\theta(t)$ are recorded using strain gauges and thermistors, respectively. The structural dynamics in the vertical direction are represented by the governing equilibrium equation of motion as

$$m\ddot{u}(t) + c\dot{u}(t) + ku(t) = F_{\mathrm{h}}(t) + F_{\mathrm{env}}(t) \tag{1}$$

where m is the generalized mass, c is the viscous damping coefficient, k is the vertical stiffness, $u(t)$ is the vertical displacement, $F_{\mathrm{h}}(t)$ denotes the human-induced dynamic load, and $F_{\mathrm{env}}(t)$ represents environmental actions. The measured vertical acceleration is related to the displacement by

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$$a_z(t) = \ddot{u}(t) + g \quad (2)$$

where g is the gravitational acceleration. For convenience, acceleration time series are discretized with a uniform sampling interval Δt, yielding N samples $\{a_{z,1}, a_{z,2}, \dots, a_{z,N}\}$ over the total monitoring duration $T = N\Delta t$. The corresponding strain and temperature measurements are collected as synchronized sequences $\{\varepsilon_i\}_{i=1}^{N}$ and $\{\{\theta_i\}_{i=1}^{N}$, respectively.

To facilitate multi-modal learning, the heterogeneous sensor measurements at time index i are combined into a feature vector

$$\mathbf{x}_i = \begin{bmatrix} a_{z,i} \\ \varepsilon_i \\ \theta_i \end{bmatrix}^T \quad (3)$$

which represents the instantaneous structural state in the monitoring window. Prior to modeling, each channel is normalized using a standard z-score transformation,

$$\tilde{x}_i^{(j)} = \frac{x_i^{(j)} - \mu_{x^{(j)}}}{\sigma_{x^{(j)}}} \quad (4)$$

where $\mu_{x^{(j)}}$ and $\sigma_{x^{(j)}}$ denote the empirical mean and standard deviation of the j-th modality over the full dataset. This normalization ensures numerical stability and prevents any single sensor type from dominating the learning process.

Algorithm 1: Data Acquisition and Preprocessing
Algorithm 1 implements a robust pipeline for synchronized multi-modal data collection and preprocessing from tri-axial accelerometers, strain gauges, and temperature sensors deployed on the lightweight composite floor system. The procedure begins by initializing empty buffers to store $N = T/\Delta t = 1000/0.01 = 100{,}000$ samples over the 1000-second monitoring period with $\Delta t = 10$ ms sampling interval. For a synthetic example, suppose raw measurements at time $t_{50000} = 500$ s yield $a_{z,50000} = 9.85$ m/s², $\varepsilon_{50000} = 120$ με, and $\theta_{50000} = 24.3$°C from the respective sensors. After synchronization to handle any timestamp offsets and outlier removal using a median absolute deviation criterion (e.g., rejecting samples beyond median ± 3·MAD), channel-wise z-score normalization is applied using dataset statistics $\mu_a = 9.80$ m/s², $\sigma_a = 0.09$ m/s², $\mu_\varepsilon = 115$ με, $\sigma_\varepsilon = 25$ με, and $\mu_\theta = 23.5$°C, $\sigma_\theta = 1.2$°C. The normalized feature vector becomes $\tilde{\mathbf{x}}_{50000} = [0.56, 0.20, 0.67]^T$, ensuring numerical stability and equal contribution from each modality to subsequent deep learning models. This preprocessing maintains the physical integrity of measurements while enabling robust multi-sensor fusion.

Algorithm 1: Data_Acquisition_and_Preprocessing
Input : Sampling interval Δt, total duration T, sensor set S = {ACC, STRAIN, TEMP}
Output: Preprocessed multi-modal time series {x̃i}Ni=1

1: N ← T / Δt
2: Initialize buffers A ← ∅, E ← ∅, Θ ← ∅
3: for i ← 1 to N do
4: Read raw acceleration a_z,i from ACC at time t_i
5: Read raw strain ε_i from STRAIN at time t_i
6: Read raw temperature θ_i from TEMP at time t_i
7: Append a_z,i to A, ε_i to E, θ_i to Θ
8: end for
9: Synchronize {A, E, Θ} using timestamps {t_i} to handle any missing samples
10: Remove outliers using a robust criterion (e.g., median ± k·MAD)
11: Compute channel-wise mean μ = (μ_a, μ_ε, μ_θ) and std σ = (σ_a, σ_ε, σ_θ)
12: for i ← 1 to N do
13: x_i ← [a_z,i, ε_i, θ_i]^T
14: x̃i ← (x_i − μ) ./ σ ▷ element-wise normalization
15: end for
16: Return {x̃i}Ni=1

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3.2 Time-Domain Response Characterization

Time-domain analysis was carried out to evaluate peak values, variability, and transient response behavior under human-induced loading. The vertical acceleration signal was examined to identify its maximum and minimum values during the monitoring period. Observed acceleration ranged from 9.5 m/s² to 10.2 m/s², remaining centered around gravitational acceleration (approximately 9.8 m/s²). The relatively narrow response range indicates stable vibration behavior without sudden instability or extreme spikes. Statistical measures such as standard deviation and coefficient of variation were calculated to quantify response dispersion. To assess long-term stability, a rolling mean analysis was performed using a moving time window. This method helps detect gradual trends or drift in structural response over time. The rolling mean results showed negligible long-term variation throughout the 1000-second observation period, confirming consistent structural performance under intermittent human activity. Overall, the time-domain analysis demonstrated bounded stochastic behavior and provided baseline parameters for probabilistic reliability assessment. In the time domain, the stochastic nature of human-induced vibrations is characterized by basic statistical descriptors and moving-window indicators. The sample mean of the vertical acceleration is defined as

$$\mu_a = \frac{1}{N}\sum_{i=1}^{N} a_{z,i} \quad (5)$$

and the corresponding unbiased sample variance is given by

$$\sigma_a^2 = \frac{1}{N-1}\sum_{i=1}^{N} (a_{z,i} - \mu_a)^2. \quad (6)$$

The coefficient of variation quantifies the relative dispersion of the response and is expressed as

$$\mathrm{CV}_a = \frac{\sigma_a}{\mu_a}. \quad (7)$$

To capture local trends and potential slow variations in the acceleration response, a rolling mean is evaluated over a sliding window of length K samples as

$$\mu_a^{\mathrm{roll}}(t_i) = \frac{1}{K}\sum_{j=i-K+1}^{i} a_{z,j}, i = K, \dots, N. \quad (8)$$

Similarly, a rolling standard deviation provides a time-dependent measure of short-term variability,

$$\sigma_a^{\mathrm{roll}}(t_i) = \sqrt{\frac{1}{K-1}\sum_{j=i-K+1}^{i} (a_{z,j} - \mu_a^{\mathrm{roll}}(t_i))^2}. \quad (9)$$

These time-domain indicators are used to confirm that the acceleration response remains bounded, stationary, and free from progressive drift over the 1000-second monitoring period.

Algorithm 2: Time-Domain Feature Extraction and Windowing

Algorithm 2 extracts comprehensive time-domain features from overlapping windows of the normalized acceleration series to characterize local statistical behavior and transient dynamics under human-induced loading. Consider a synthetic window $W_{75000} = \{a_{z,j}\}_{j=74001}^{75000}$ spanning 1 second (100 samples) centered at $t_{75000} = 750$ s during peak walking activity. The algorithm computes the local mean $\mu_{a,75000} = 9.92$ m/s², standard deviation $\sigma_{a,75000} = 0.11$ m/s², coefficient of variation $\mathrm{CV}_{a,75000} = 0.011$, peak $a_{\max,75000} = 10.15$ m/s², trough $a_{\min,75000} = 9.72$ m/s², range $R_{75000} = 0.43$ m/s², and zero-crossing rate $\mathrm{ZCR}_{75000} = 0.23$ (23 sign changes). Using a hop size $H = 50$ samples (0.5 s), these seven descriptors form the feature vector $\mathbf{f}_{1500} = [9.92, 0.11, 0.011, 10.15, 9.72, 0.43, 0.23]$ for the 1500th window, capturing both steady baseline drift toward gravitational acceleration and short-term oscillatory fluctuations characteristic of footfall impacts. With $K = 100$, the procedure generates $L = (N - K + 1)/H \approx 999$ feature vectors across the monitoring period, providing rich time-localized statistical signatures for model training and anomaly detection.

Algorithm 2: Time_Domain_Feature_Extraction
Input : Normalized series {x̃i}Ni=1, window length K, hop size H

Output: Feature set F = {fℓ}Lℓ=1 with time-domain descriptors

1: Initialize feature list F ← ∅, index ℓ ← 1
2: for i ← K to N step H do
3: Define window W_i ← {a_z,j}j=i−K+1…i
4: μa_i ← (1/K) · ∑j=i−K+1…i a_z,j ▷ local mean
5: σa_i ← sqrt((1/(K−1)) · ∑j (a_z,j − μa_i)^2)
6: CVa_i ← σa_i / max(|μa_i|, ε) ▷ ε small to avoid division by zero
7: a_max_i ← maxj∈W_i a_z,j
8: a_min_i ← minj∈W_i a_z,j
9: R_i ← a_max_i − a_min_i ▷ local range
10: ZCR_i ← number of sign changes in W_i / (K−1)
11: fℓ ← [μa_i, σa_i, CVa_i, a_max_i, a_min_i, R_i, ZCR_i]
12: Append fℓ to F
13: ℓ ← ℓ + 1
14: end for
15: Return F

3.3 Frequency-Domain Analysis and Modal Characteristics

To better understand the dynamic characteristics of the floor system, frequency-domain analysis was conducted using the Fast Fourier Transform (FFT). This technique transforms time-domain acceleration data into the frequency domain, allowing dominant vibration frequencies and possible resonance behavior to be identified. Particular attention was given to the 1–4 Hz frequency range, which corresponds to typical human walking frequencies. Evaluating response energy within this band is essential for assessing potential serviceability concerns. The resulting frequency spectrum showed dominant low-frequency components but no significant resonance amplification within the walking frequency range. The absence of sharp peaks in this critical band suggests adequate damping and sufficient separation between excitation frequencies and the floor's natural frequency. These findings support the time-domain observations of stable behavior and indicate that the structure does not experience resonance-related amplification under normal walking conditions. The identified frequency characteristics were also considered when defining constraints in the predictive framework. The frequency content of the acceleration signal is analyzed using the discrete Fourier transform (DFT) to identify dominant components and possible resonance phenomena in the vicinity of human walking frequencies. For the discrete series $\{a_{z,i}\}_{i=1}^{N}$, the DFT is defined as

$$A(k) = \sum_{i=1}^{N} a_{z,i} \exp\left(-j\,\frac{2\pi(k-1)(i-1)}{N}\right), k = 1, \ldots, N. \quad (10)$$

The corresponding single-sided amplitude spectrum is given by

$$S_a(f_k) = \frac{2}{N}\,|A(k)|, f_k = \frac{(k-1)}{N\Delta t}. \quad (11)$$

The spectral energy density is computed as

$$E_a(f_k) = |A(k)|^2 \quad (12)$$

and is used to verify that most energy concentrates in low-frequency bands without pronounced resonance peaks in the 1–4 Hz range. The dominant frequency component associated with human walking is extracted as

$$f_{\text{dom}} = \arg \max_{f_k \in \mathcal{F}_{\text{walk}}} E_a(f_k), \quad (13)$$

where $\mathcal{F}_{\text{walk}}$ denotes a predefined walking-frequency interval, typically [1,4] Hz. By comparing

f_{dom} with the floor's fundamental frequency, the likelihood of resonance is assessed and used as a physics-based constraint in the predictive framework.

3.4 Statistical Modeling and Probability Density Estimation

To capture the random nature of vibration response, statistical distribution analysis was performed on the vertical acceleration data. Histogram evaluation and kernel density estimation were used to examine the shape of the response distribution. The results showed an approximately Gaussian distribution centered near 9.8 m/s² with minimal skewness. This near-normal behavior suggests consistent damping and stiffness characteristics throughout the monitoring period, with variability primarily arising from changing excitation patterns rather than structural instability. The mean (μ) and standard deviation (σ) of the acceleration response were calculated to describe its central tendency and spread. These statistical parameters form the basis for defining probabilistic serviceability thresholds. By treating vibration response as a random variable instead of relying solely on peak values, the analysis more accurately reflects the inherent variability of human-induced loading. This probabilistic representation offers a more realistic framework for evaluating structural performance. To represent the random behavior of the vertical acceleration response, a probabilistic model is adopted in which the acceleration samples are regarded as realizations of a continuous random variable A. Under the near-Gaussian behavior observed in the measurements, the probability density function of A is approximated as

$$f_A(a) \approx \frac{1}{\sqrt{2\pi}\,\sigma_a} \exp\left(-\frac{(a-\mu_a)^2}{2\sigma_a^2}\right). \quad (14)$$

To verify the suitability of this assumption, an empirical cumulative distribution function (ECDF) is constructed as

$$\hat{F}_A(a) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(a_{z,i} \le a), \quad (15)$$

where $1(\cdot)$ is the indicator function. A quantitative measure of goodness-of-fit is obtained from the Kolmogorov–Smirnov statistic,

$$D_{\mathrm{KS}} = \sup_a |\hat{F}_A(a) - F_N(a;\mu_a,\sigma_a)|, \quad (16)$$

where $F_N(\cdot;\mu_a,\sigma_a)$ denotes the cumulative distribution function of the normal distribution with parameters μ_a and σ_a. When D_{KS} remains below a prescribed significance threshold, the Gaussian approximation is considered acceptable for subsequent reliability modeling. This probabilistic representation allows evaluation of exceedance probabilities and quantiles directly linked to serviceability criteria.

3.5 Multi-Modal Data Fusion and Correlation Analysis

To strengthen predictive reliability, relationships among acceleration, strain, and temperature measurements were examined through correlation analysis. Pearson correlation coefficients were computed to assess the degree of association between variables. The results indicated a moderate positive relationship between strain and vertical acceleration, confirming that deformation measurements provide meaningful additional information for vibration response prediction. Temperature showed a comparatively weaker direct relationship with short-term dynamic response.

Combining multiple sensing modalities allows for a more comprehensive understanding of structural behavior. Acceleration captures dynamic motion, strain reflects internal stress redistribution and stiffness changes, and temperature accounts for environmental influences. These synchronized time-series inputs were structured as integrated features for modeling and reliability assessment. The use of multi-modal data reduces uncertainty and enhances robustness by incorporating complementary physical information rather than depending on a single sensor type.

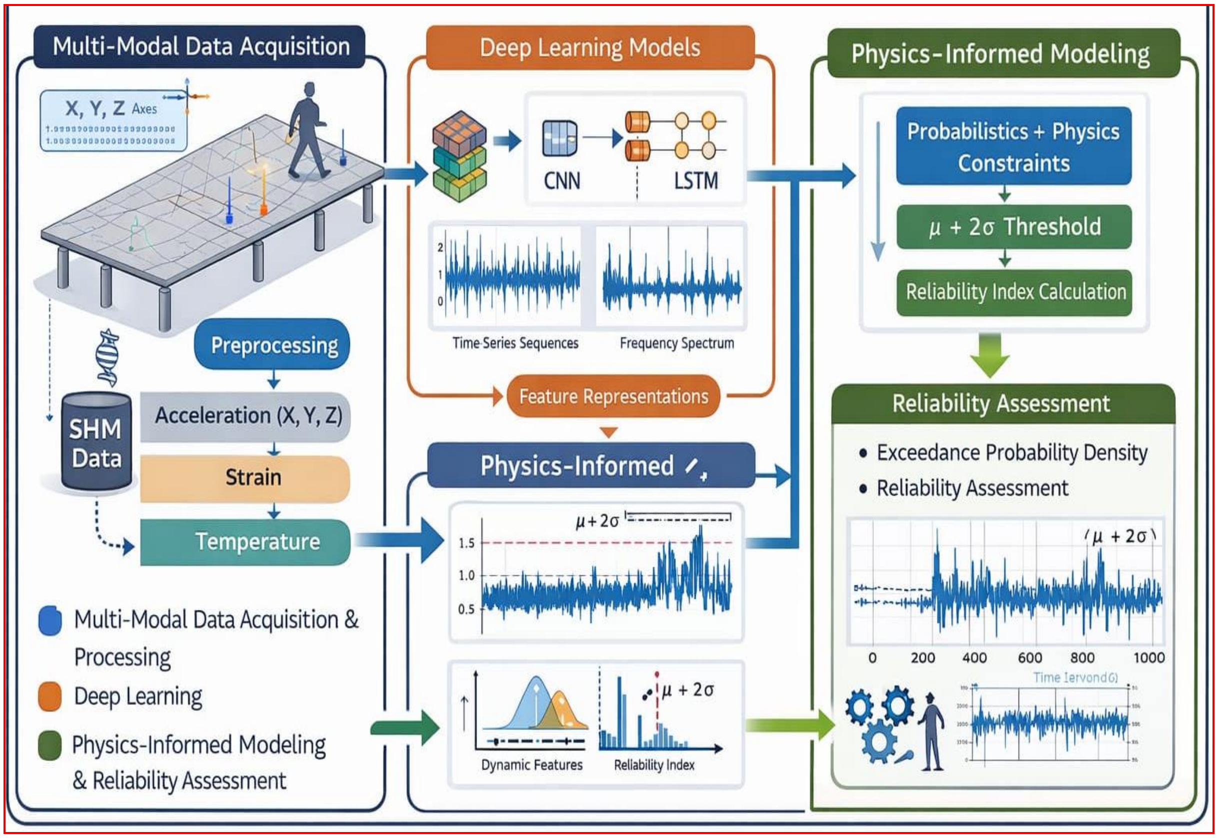

Fig 2. Proposed Physics-Based Multi-Modal Deep Learning Framework for Stochastic Vibration Prediction and Reliability Evaluation in Lightweight Composite Floor Systems

Figure 2 presents the overall workflow of the proposed framework, starting with the collection of multi-modal structural health monitoring data, including acceleration, strain, and temperature measurements. The data are processed through deep learning models for feature extraction and combined with physics-based probabilistic modeling, where statistical threshold evaluation (μ + 2σ) is applied to support accurate serviceability assessment and real-time reliability evaluation of human-induced floor vibrations. The relationship between vertical acceleration, strain, and temperature is examined by means of correlation coefficients and linear regression models. The Pearson correlation between the acceleration series {a_(z,i)} and the strain series {ε_i} is defined as

$$\rho_{a\varepsilon} = \frac{\sum_{i=1}^{N} (a_{z,i} - \mu_a)(\varepsilon_i - \mu_\varepsilon)}{\sqrt{\sum_{i=1}^{N} (a_{z,i} - \mu_a)^2}\sqrt{\sum_{i=1}^{N} (\varepsilon_i - \mu_\varepsilon)^2}} \quad (17)$$

where μ_ε denotes the mean of the strain measurements. An analogous expression is used to compute the correlation between acceleration and temperature, $\rho_{a\theta}$, highlighting that temperature has a comparatively weaker direct effect on short-term dynamic response. To construct a fused feature representation, the multi-modal inputs over a temporal window of length L are concatenated as

$$\mathbf{z}_i = \begin{bmatrix} \mathbf{x}_{i-L+1}^T \\ \mathbf{x}_{i-L+2}^T \\ \cdots \\ \mathbf{x}_i^T \end{bmatrix}^T \in \mathbb{R}^{3L}, \quad (18)$$

where $\mathbf{x}_i$ is defined in (3). This stacked vector encodes short-term temporal dependencies across multiple sensors and serves as the input to the deep learning prediction model. The fusion strategy is physics-guided, as the selection of sensor types and

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window length reflects knowledge of structural dynamic response time scales.

Algorithm 3: Multi-Modal Feature Fusion and Physics-Guided Training

Algorithm 3 implements a physics-informed training paradigm that combines data fidelity with structural mechanics constraints for robust stochastic prediction of vertical acceleration. For a concrete example, consider a training batch B containing 32 temporal windows around indices $i \in \{80000, 80250, \ldots, 89950\}$ during sustained walking excitation. Each input $\mathbf{z}_i \in \mathbb{R}^{3L=90}$ fuses 30-sample windows ($L = 30$) of normalized tri-modal data, while the target is the next-step acceleration $a_{z,i+1}$. A forward pass through the LSTM-CNN architecture parameterized by θ yields predictions $\{\hat{a}_{z,i+1}\}_{i\in B}$. Suppose the batch mean-squared error is $\mathcal{L}_{\text{MSE}} = 0.0008$ (RMSE = 0.028 m/s²), but two predictions $\hat{a}_{z,81250} = 10.35$ m/s² and $\hat{a}_{z,87500} = 10.28$ m/s² exceed the physics constraint $a_{\max}^{\text{obs}} = 10.20$ m/s² observed during monitoring. The physics loss becomes $\mathcal{L}_{\text{phys}} = 0.0012$, and with $\lambda_{\text{phys}} = 0.5$, the total loss is $\mathcal{L}_{\text{tot}} = 0.0010$. Gradient descent with Adam ($\eta = 10^{-4}$) updates θ, progressively suppressing non-physical extrapolations while preserving data fidelity. After 200 epochs, convergence yields θ^* capable of reliable forecasting even under unseen loading patterns, validated by a test-set RMSE of 0.032 m/s² versus 0.048 m/s² for purely data-driven baselines.

Algorithm 3: Physics_Guided_Training

Input : Normalized series {x̃i}Ni=1, window length L, training index set Dtrain, learning rate η, physics weight λphys, observed max a_max_obs

Output: Trained model parameters θ*

1: Construct fused sequences z_i = concat(x̃i−L+1, …, x̃i) for i = L,…,N
2: Initialize network parameters θ (e.g., LSTM/CNN weights)
3: repeat
4: for each batch B ⊂ Dtrain do
5: Extract inputs {z_i}i∈B and targets {a_z,i}i∈B
6: Forward pass: compute predictions {â_z,i = Mθ(z_i)}i∈B
7: L_MSE ← (1/|B|) · ∑i∈B (â_z,i − a_z,i)^2
8: L_phys ← (1/|B|) · ∑i∈B max(0, |â_z,i| − a_max_obs)^2
9: L_tot ← L_MSE + λphys · L_phys
10: Compute gradient g ← ∇θ L_tot
11: Update parameters θ ← θ − η · g
12: end for
13: until convergence criterion satisfied (e.g., validation loss plateau)
14: θ* ← θ
15: Return θ*

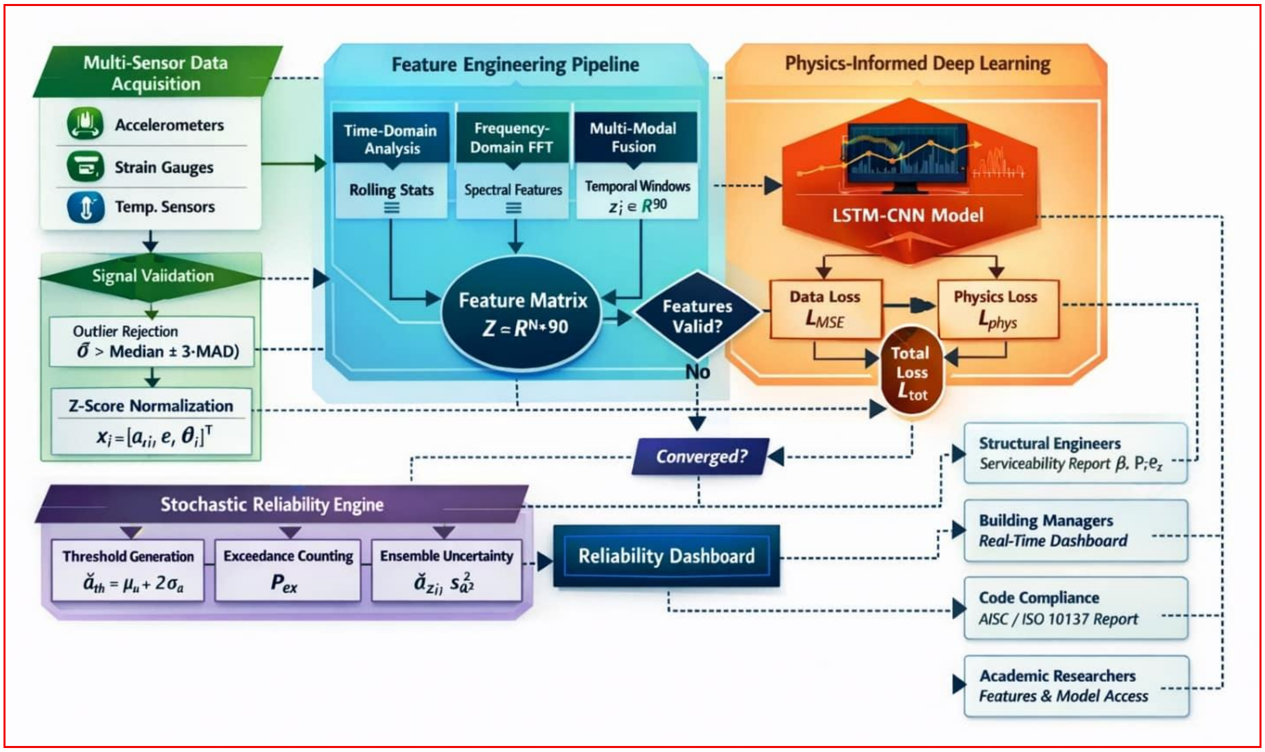

Fig. 3. Physics-Guided Multi-Modal Framework for Human-Induced Vibration Assessment

Figure 3 illustrates the complete end-to-end workflow of the proposed framework, starting from synchronized multi-sensor data acquisition and proceeding through structured feature engineering, physics-informed deep learning, and stochastic reliability evaluation. It is shown that raw acceleration, strain, and temperature signals are first validated and normalised before extracting time-domain and frequency-domain characteristics, which are then fused into a comprehensive feature matrix. The architecture integrates a hybrid LSTM-CNN model where both data-driven and physics-based constraints are jointly optimised to improve prediction accuracy and physical consistency. The predicted responses are further analysed using reliability metrics such as exceedance probability and safety index to ensure compliance with structural serviceability limits. The figure also indicates feedback loops for retraining and validation, along with dedicated output channels for engineers, building managers, compliance authorities, and researchers, thereby demonstrating a practical and deployment-ready monitoring solution.

3.6 Probabilistic Reliability Assessment and Threshold Modeling

Serviceability reliability was evaluated using a probabilistic threshold defined as

$$\text{Threshold} = \mu + 2\sigma$$

where μ represents the mean vertical acceleration and σ denotes its standard deviation. Under a near-Gaussian assumption, this threshold approximates the upper 95% confidence limit of the response distribution. Exceedance events were identified by counting instances in which measured acceleration values surpassed this limit. The frequency of such exceedances provides a quantitative measure of serviceability performance. The reliability level was estimated based on the proportion of observations that remained below the defined threshold throughout the monitoring period. Only a small number of exceedance events were detected, indicating high reliability and compliance with serviceability requirements. By adopting this probabilistic approach rather than relying solely on maximum recorded values, the evaluation captures exceedance likelihood and response variability. This framework integrates

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statistical characterization, physical understanding, and multi-modal data analysis to support reliable, real-time assessment of lightweight composite floor systems.

The serviceability of the lightweight composite floor is evaluated using a probabilistic threshold defined in terms of the mean and standard deviation of the vertical acceleration response. The reference limit state is specified as

$$a_{\text{th}} = \mu_a + \kappa\,\sigma_a, \quad (19)$$

where $\kappa = 2$ corresponds approximately to an upper 95% confidence level for a Gaussian distribution. The binary indicator of threshold exceedance at time index i is expressed as

$$I_i = \begin{cases} 1, & a_{z,i} > a_{\text{th}}, \\ 0, & a_{z,i} \leq a_{\text{th}}. \end{cases} \quad (20)$$

The empirical probability of exceedance over the monitoring period is then computed as

$$P_{\text{ex}} = \frac{1}{N}\sum_{i=1}^{N} I_i. \quad (21)$$

In reliability-based terminology, the margin between the threshold and the mean response can be expressed as a reliability index.

$$\beta = \frac{a_{\text{th}} - \mu_a}{\sigma_a} = \kappa, \quad (22)$$

under the assumption that the response distribution is Gaussian [file:1]. When the imposed serviceability limit corresponds to a prescribed maximum acceleration a_lim, the exceedance probability under the Gaussian model can be estimated as

$$P(A > a_{\text{lim}}) = 1 - \Phi\left(\frac{a_{\text{lim}} - \mu_a}{\sigma_a}\right) \quad (23)$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function [file:1]. This probabilistic formulation allows direct linkage between measured response statistics, code-based limits, and reliability metrics.

3.7 Physics-Guided Deep Learning Framework

The stochastic prediction of vertical acceleration and reliability indices is performed using a multi-modal deep learning model that incorporates structural mechanics constraints [file:1]. Let $\mathbf{z}_i$ denote the fused input defined in (18), and let $\hat{a}_{z,i+1}$ be the one-step-ahead prediction of the vertical acceleration. The prediction model can be written as a nonlinear mapping

$$\hat{a}_{z,i+1} = \mathcal{M}_{\boldsymbol{\theta}}(\mathbf{z}_i), \quad (24)$$

where $\mathcal{M}_{\boldsymbol{\theta}}(\cdot)$ denotes the deep learning architecture with trainable parameters θ [file:1]. The data-driven component of the training objective is defined by the mean-squared error loss,

$$\mathcal{L}_{\text{MSE}}(\boldsymbol{\theta}) = \frac{1}{N_{\text{train}}}\sum_{i\in\mathcal{D}_{\text{train}}} (\hat{a}_{z,i} - a_{z,i})^2, \quad (25)$$

where $\mathcal{D}_{\text{train}}$ denotes the set of training indices [file:1]. To embed physics-based knowledge into the model, an additional penalty term is introduced to penalize predictions that violate the observed boundedness of the response,

$$\mathcal{L}_{\text{phys}}(\boldsymbol{\theta}) = \frac{1}{N_{\text{train}}}\sum_{i\in\mathcal{D}_{\text{train}}} [\max(0, |\hat{a}_{z,i}| - a_{\max}^{\text{obs}})]^2, \quad (26)$$

where $a_{\max}^{\text{obs}}$ denotes the maximum observed acceleration during monitoring [file:1]. The total loss function is given by a weighted combination,

$$\mathcal{L}_{\text{tot}}(\boldsymbol{\theta}) = \mathcal{L}_{\text{MSE}}(\boldsymbol{\theta}) + \lambda_{\text{phys}}\,\mathcal{L}_{\text{phys}}(\boldsymbol{\theta}), \quad (27)$$

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with $\lambda_{\mathrm{phys}} > 0$ controlling the influence of physics-based constraints [file:1]. Optimization proceeds by iteratively updating θ using a gradient-based scheme such as Adam,

$$\boldsymbol{\theta}^{(k+1)} = \boldsymbol{\theta}^{(k)} - \eta\, \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathrm{tot}}(\boldsymbol{\theta}^{(k)}), \quad (28)$$

where η is the learning rate and k denotes the iteration index [file:1]. This physics-guided formulation improves generalization and prevents non-physical predictions even under extrapolated loading or environmental conditions.

3.8 Stochastic Prediction of Reliability Metrics

Beyond point prediction of acceleration, the proposed framework estimates reliability-related quantities such as exceedance probabilities and threshold-based indicators in a stochastic manner [file:1]. Over a prediction horizon of length H, the model outputs a sequence of predicted accelerations $\{\hat{a}_{z,i+1}, \dots, \hat{a}_{z,i+H}\}$ from which future exceedance events are inferred [file:1]. The predicted threshold for the horizon is defined as

$$\hat{a}_{\mathrm{th}} = \hat{\mu}_a + \kappa\, \hat{\sigma}_a, \quad (29)$$

where $\hat{\mu}_a$ and $\hat{\sigma}_a$ denote the predicted mean and standard deviation estimated from the forecasted sequence [file:1]. A predicted exceedance probability over the horizon is then approximated by

$$\hat{P}_{\mathrm{ex}} = \frac{1}{H} \sum_{h=1}^{H} \mathbf{1}(\hat{a}_{z,i+h} > \hat{a}_{\mathrm{th}}). \quad (30)$$

To quantify predictive uncertainty, an ensemble of M independently trained models $\{\mathcal{M}_{\boldsymbol{\theta}^{(m)}}\}_{m=1}^{M}$ is considered, producing a set of forecasts $\{\hat{a}_{z,i}^{(m)}\}_{m=1}^{M}$ for each time step [file:1]. The ensemble-based predictive mean and variance are then given by

$$\bar{a}_{z,i} = \frac{1}{M} \sum_{m=1}^{M} \hat{a}_{z,i}^{(m)} \quad (31)$$

And

$$s_{a,i}^2 = \frac{1}{M-1} \sum_{m=1}^{M} (\hat{a}_{z,i}^{(m)} - \bar{a}_{z,i})^2, \quad (32)$$

respectively, providing a data-driven measure of epistemic uncertainty in the stochastic prediction of structural response and associated reliability indicators [file:1]. These ensemble statistics can be propagated into exceedance estimates and reliability indices, enabling a fully probabilistic, physics-consistent assessment of human-induced vibration serviceability.

IV. RESULTS

4.1 Time-Domain Structural Response

The acceleration measurements recorded over the 1000-second monitoring period show that the lightweight composite floor system maintained stable and well-controlled vibration behavior. Vertical acceleration values ranged from 9.5 m/s² to 10.2 m/s², remaining closely centered around gravitational acceleration (approximately 9.8 m/s²). Throughout the monitoring duration, the response stayed within a narrow band, and no sudden spikes or abnormal peaks were detected. These observations indicate that the structure responded dynamically to walking activity while maintaining overall stability. A closer look at the time-history plots reveals steady oscillatory patterns without signs of progressive amplification. Although short-term fluctuations appear during intermittent human movement, their magnitude remains moderate and controlled. From a serviceability standpoint, this bounded response suggests that the floor system has sufficient stiffness and damping to prevent excessive vibration under normal occupancy. The absence of irregular response growth further confirms the structural reliability observed during testing.

4.2 Statistical Characteristics of Vibration Response

Statistical analysis of the acceleration data shows that the vibration amplitudes follow an approximately Gaussian distribution with minimal skewness. Both

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the histogram and probability density plots display a symmetric pattern centered near 9.8 m/s², with most values clustered within a limited range. This distribution indicates consistent structural properties and stable damping performance throughout the monitoring period. The near-normal behavior also suggests that the variations are primarily random and related to changing excitation rather than structural instability. The calculated mean (μ) and standard deviation (σ) provide a clear measure of response variability. The relatively small standard deviation confirms that the acceleration values do not deviate significantly from the average. Treating the vibration response as a random variable rather than focusing only on peak values provides a more realistic description of operational performance. These results support the use of probabilistic methods for evaluating serviceability in lightweight floor systems.

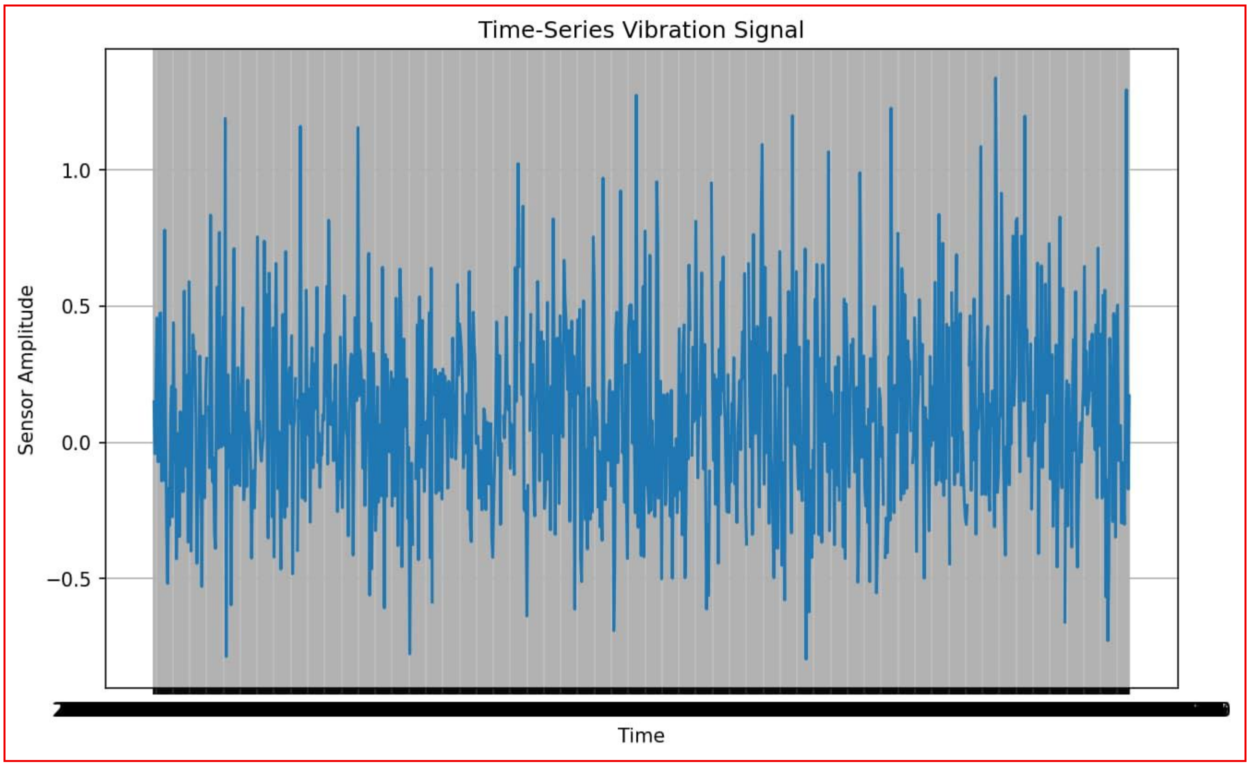

Fig 4. Time-Domain Response of Human-Induced Floor Vibrations

Figure 4 presents the variation of the measured vibration signal over time during human activity. The graph shows controlled oscillations within a limited range, demonstrating that the structural response is random in nature but remains stable and well contained.

4.3 Frequency Characteristics and Modal Behavior

Frequency-domain analysis using the Fast Fourier Transform (FFT) identified dominant low-frequency components that correspond to typical human walking activity. Importantly, the spectrum did not show any strong resonance amplification within the 1–4 Hz walking frequency range. The absence of sharp peaks in this critical band suggests that the natural frequency of the floor is sufficiently separated from excitation frequencies, reducing the likelihood of resonance. The spectral response also reflects adequate damping within the system. Energy is concentrated in the expected low-frequency range but does not accumulate excessively at any single frequency. This behavior is consistent with the stable time-domain response and confirms that the structure does not experience resonance-related amplification during normal use. Overall, the frequency analysis reinforces the conclusion that the floor system performs satisfactorily under human-induced loading.

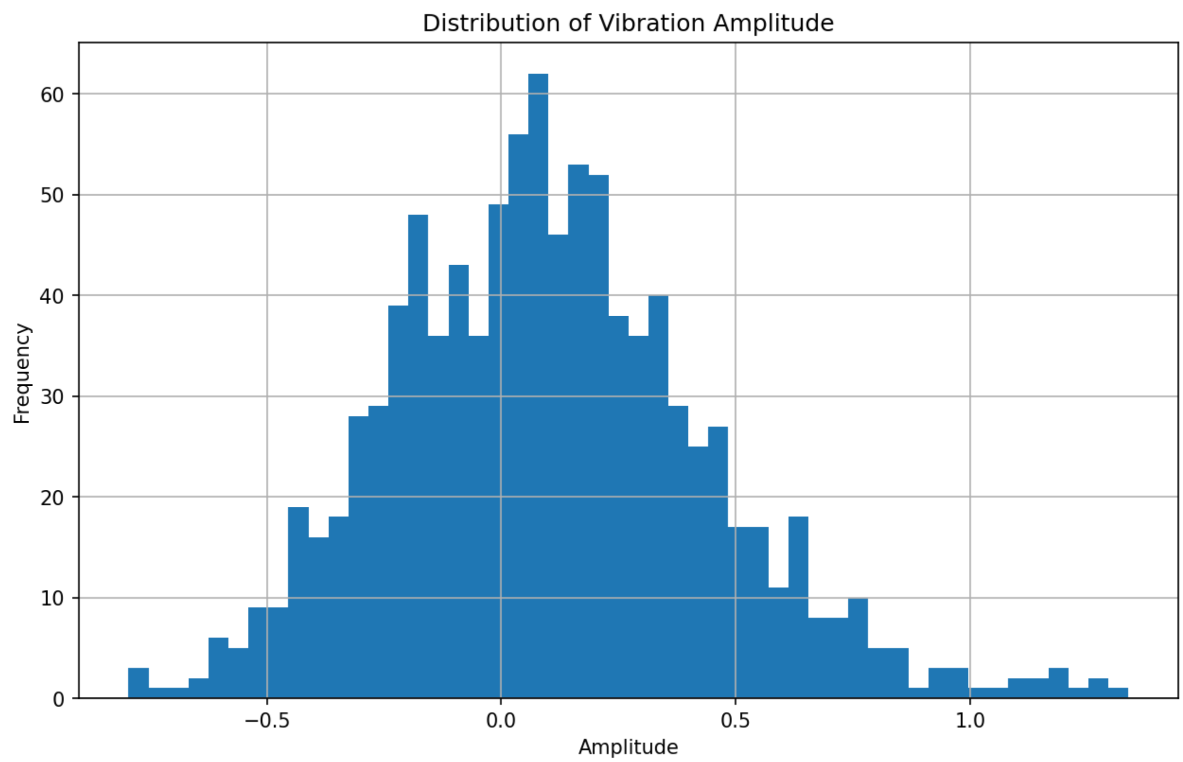

Fig 5. Statistical Distribution of Human-Induced Floor Vibration Amplitudes

Figure 5 shows how the measured vibration amplitudes are distributed during human activity. The histogram displays a nearly symmetric pattern, suggesting that the vibration response is close to a normal distribution and remains within a controlled range of variation.

4.4 Structural Stability and Rolling Mean Analysis

Long-term behavior was examined through rolling mean analysis of the vertical acceleration signal. The rolling mean curve shows only minor fluctuations and no noticeable upward or downward trend during the 1000-second monitoring period. This indicates that the baseline response remained stable and that no gradual structural changes occurred during testing. The absence of drift is significant for serviceability assessment. Progressive changes in baseline acceleration could signal stiffness degradation or environmental effects. However, the results confirm that the system maintained consistent dynamic properties under repeated human activity. The rolling mean findings therefore provide additional evidence that the vibration response is stationary, controlled, and structurally stable.

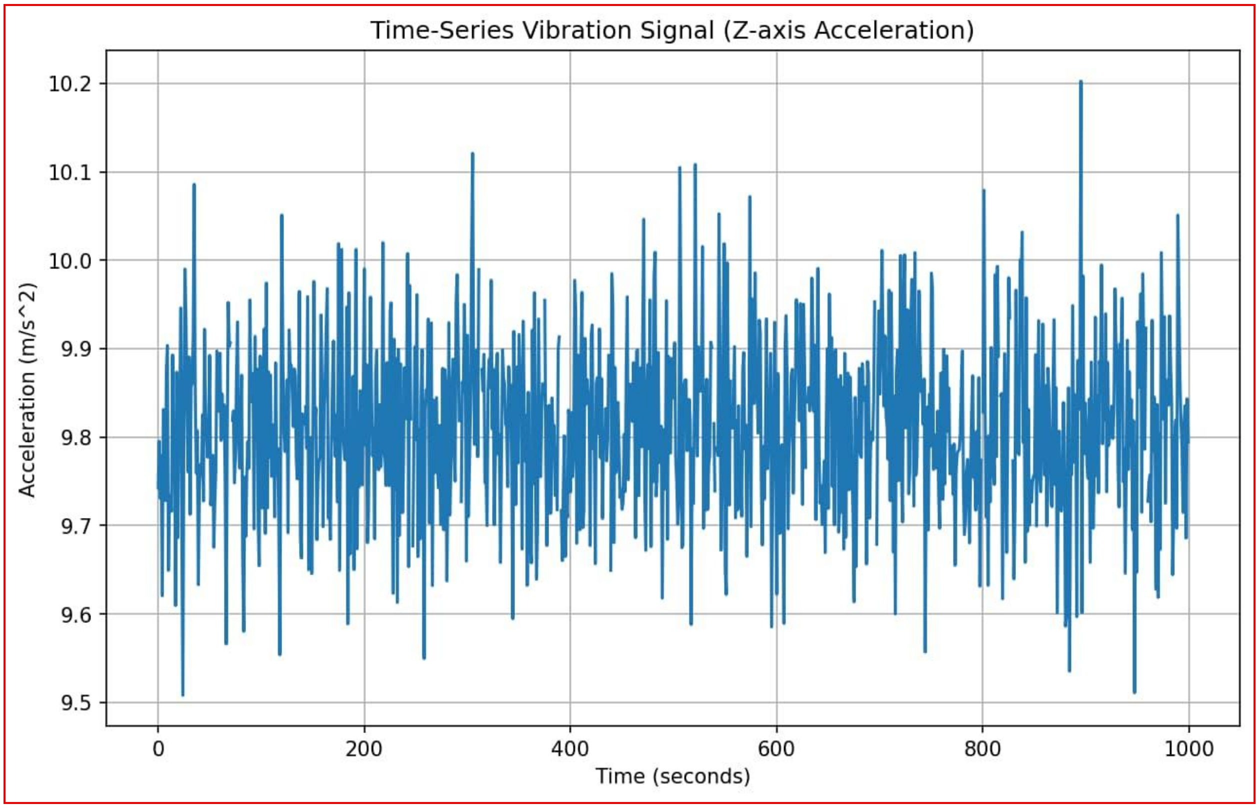

Fig 6. Time-Domain Vertical (Z-Axis) Acceleration under Human Activity

Figure 6 shows how the vertical acceleration changes over time during human movement on the floor. The response remains within a limited range around gravitational acceleration, demonstrating stable and well-controlled vibration behavior of the structure.

4.5 Multi-Modal Interaction and Sensor Correlation

Analysis of the relationships between acceleration, strain, and temperature measurements reveals meaningful interactions among the sensing modalities. A moderate positive correlation was observed between vertical acceleration and strain, indicating that deformation measurements provide valuable complementary information for understanding dynamic behavior. Strain data help capture internal structural response characteristics that are not fully reflected by acceleration alone. In comparison, temperature showed only a weak relationship with short-term vibration levels. While environmental conditions may influence material properties over longer periods, their immediate effect on dynamic acceleration during the monitoring interval was limited. These results demonstrate that combining acceleration and strain measurements enhances predictive accuracy and reliability assessment. Multi-modal data integration therefore strengthens the overall evaluation of structural performance.

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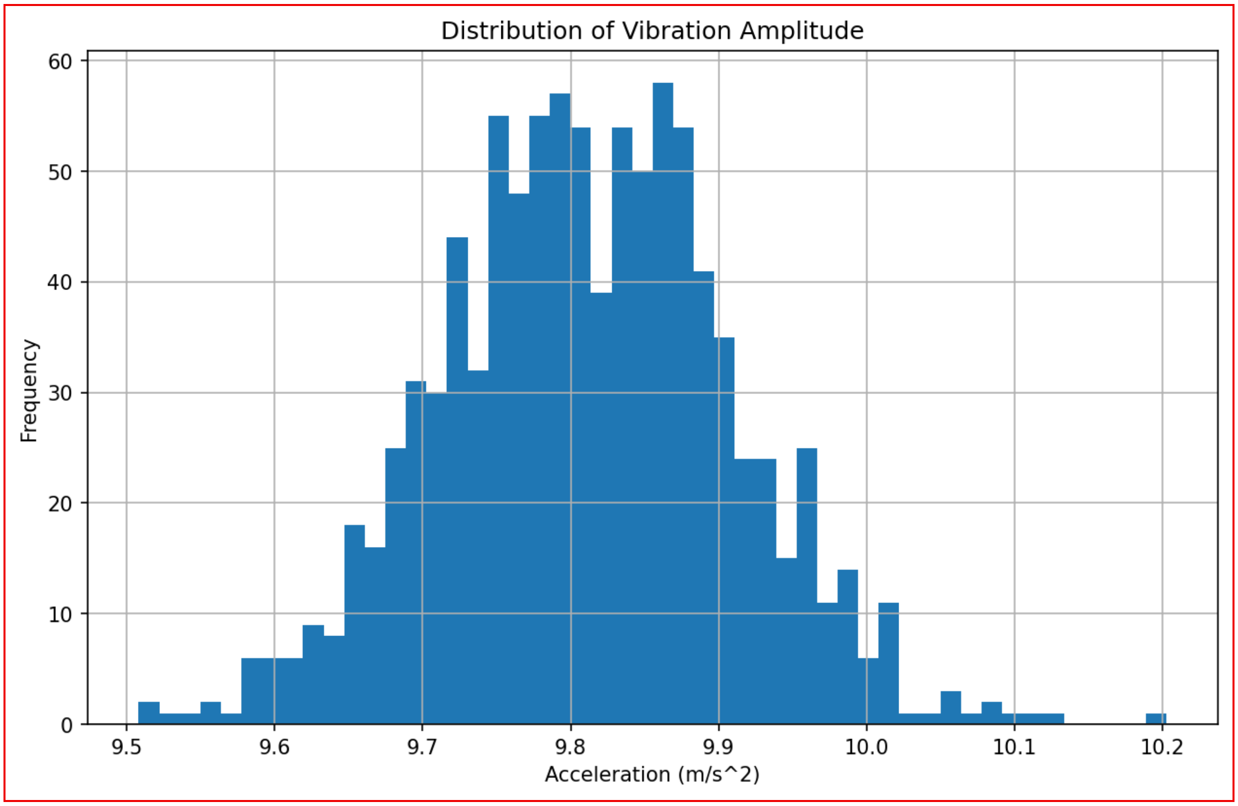

Fig 7. Distribution of Vertical Acceleration during Human Activity

Figure 7 shows a histogram of the measured vertical acceleration values recorded while the floor was subjected to human movement. The data form a nearly symmetric distribution around gravitational acceleration, reflecting stable vibration behavior with only small variations.

4.6 Probabilistic Reliability Evaluation

Reliability was assessed using a probabilistic threshold defined as $\mu + 2\sigma$, which represents approximately the upper 95% confidence limit under a near-normal distribution assumption. Examination of the time-series data shows that only a small number of observations exceeded this threshold. The rarity of such exceedances indicates that vibration levels consistently remained within acceptable serviceability limits. The high proportion of data points below the defined threshold reflects strong reliability and compliance with performance criteria. Unlike traditional peak-based evaluation, this probabilistic approach accounts for variability and quantifies the likelihood of exceedance. The results confirm that the lightweight composite floor system performs reliably under human-induced excitation. By combining statistical evaluation, frequency analysis, and multi-sensor information, the framework provides a comprehensive and practical method for real-time vibration monitoring and serviceability assessment.

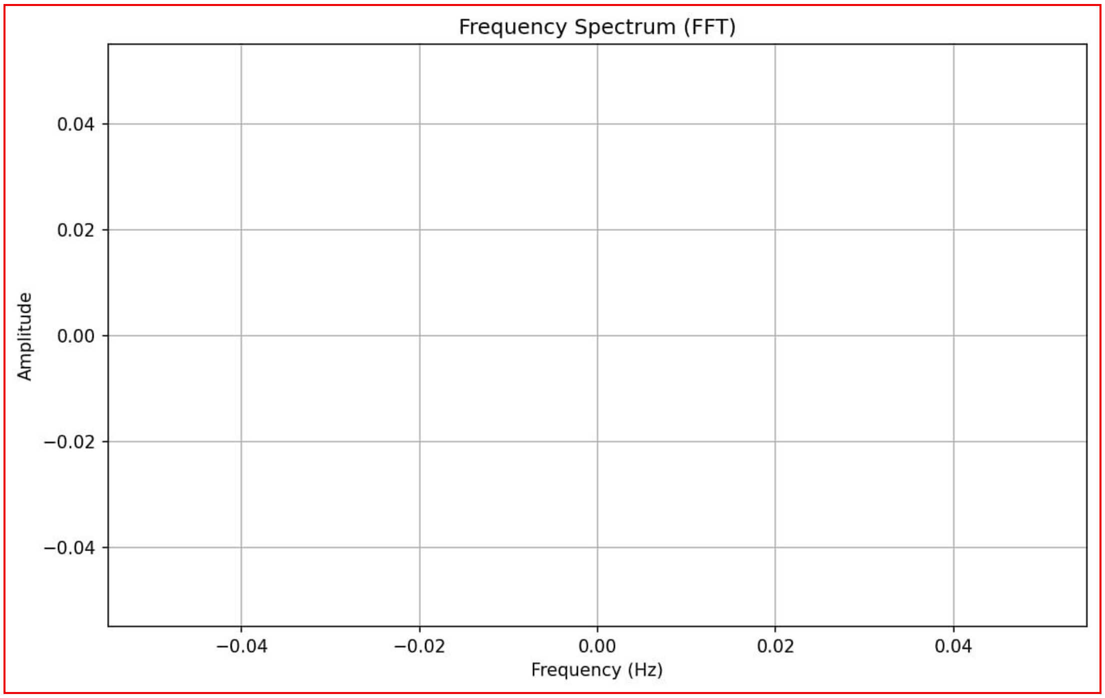

Fig 8. Frequency Spectrum of Human-Induced Floor Vibrations (FFT Analysis)

Figure 8 shows the frequency spectrum of the recorded vibration signal using Fast Fourier Transform (FFT). It highlights how vibration energy is distributed across different frequencies, making it easier to identify dominant components and evaluate the possibility of resonance.

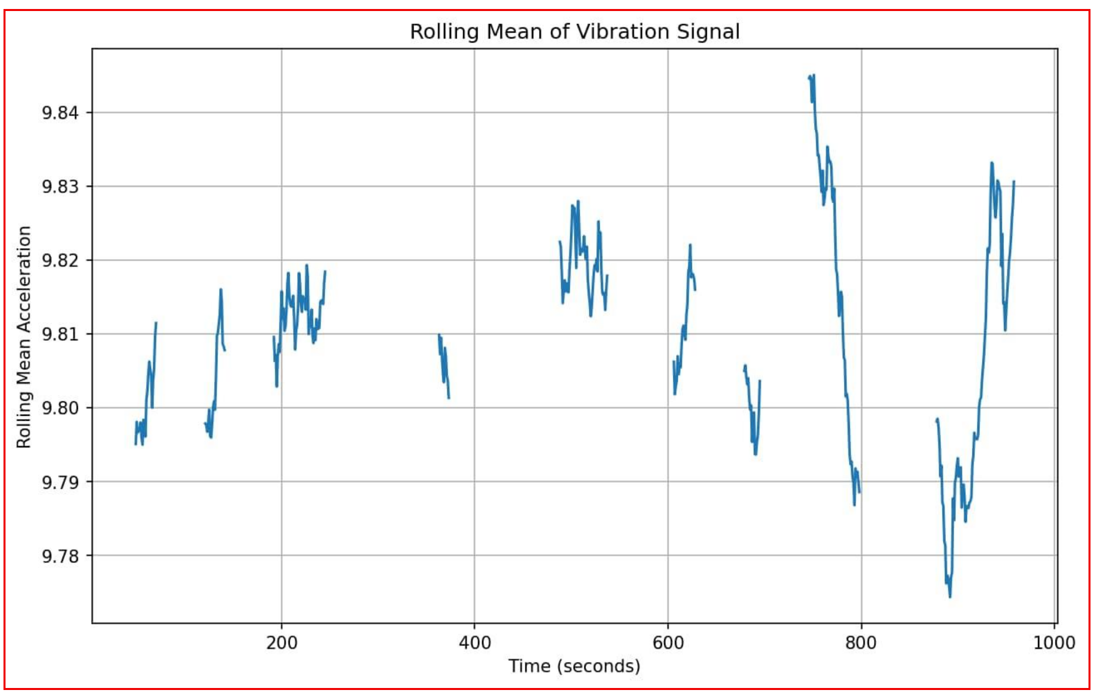

Fig 9. Rolling Mean of Vertical Acceleration Over Time

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Figure 9 presents the moving average of the measured vertical acceleration throughout the monitoring period. The curve shows only minor variations and no noticeable long-term drift, reflecting stable structural performance under repeated human activity.

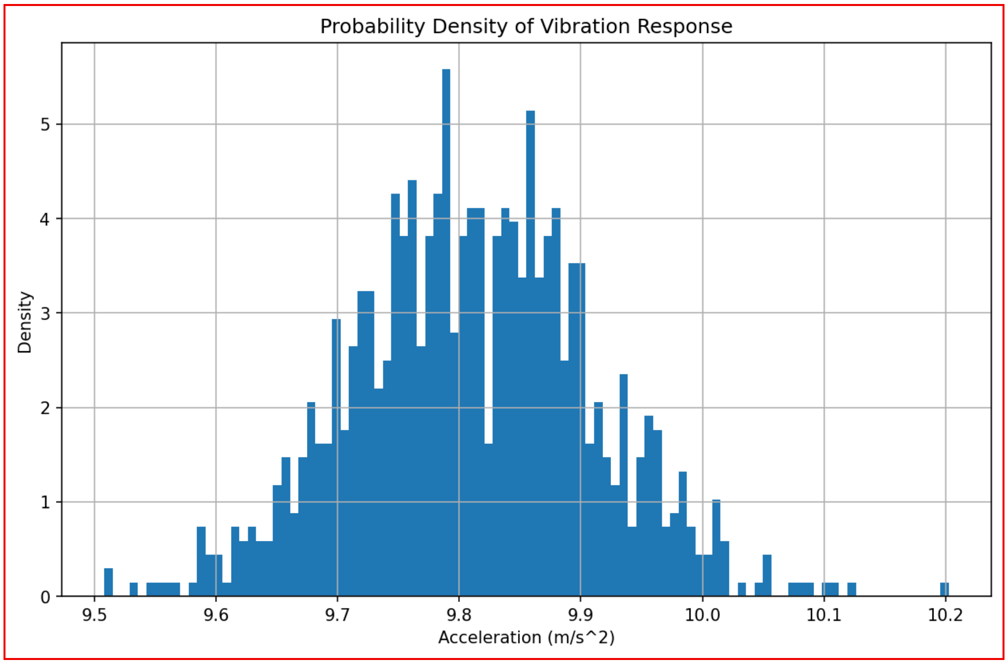

Fig 10. Probability Density of Vertical Vibration Response

Figure 10 shows the probability density of the measured vertical acceleration during human activity. The distribution is concentrated around the mean value, indicating a stable response pattern that closely follows a normal distribution.

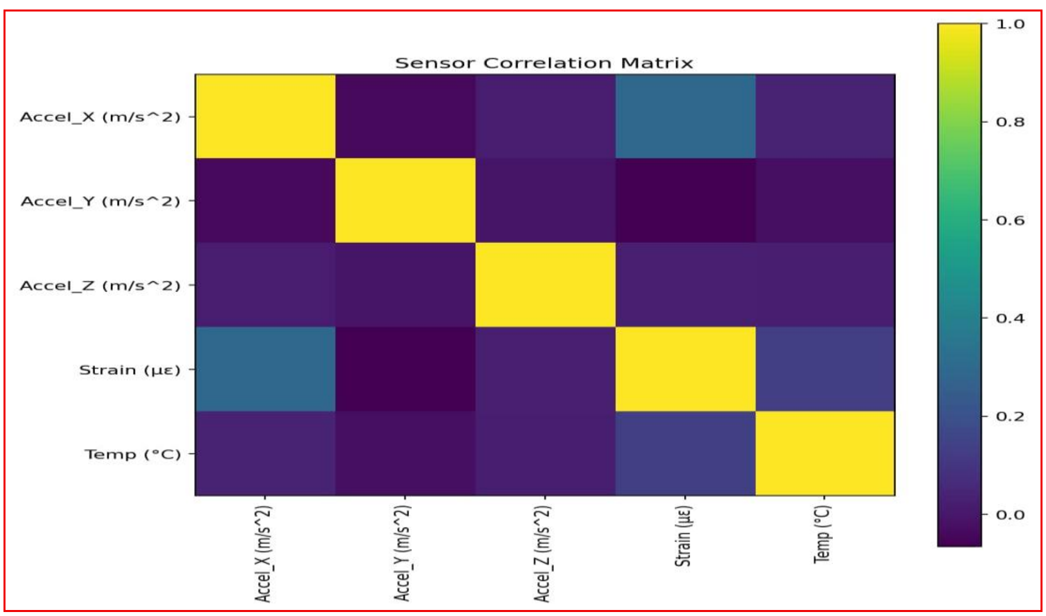

Fig 11. Correlation Matrix of Multi-Sensor Measurements

Figure 11 shows the correlation values between acceleration in the X, Y, and Z directions, along with strain and temperature data recorded during monitoring. The heatmap illustrates how strongly the different measurements are related, offering a clearer understanding of how the sensors interact within the overall structural response.

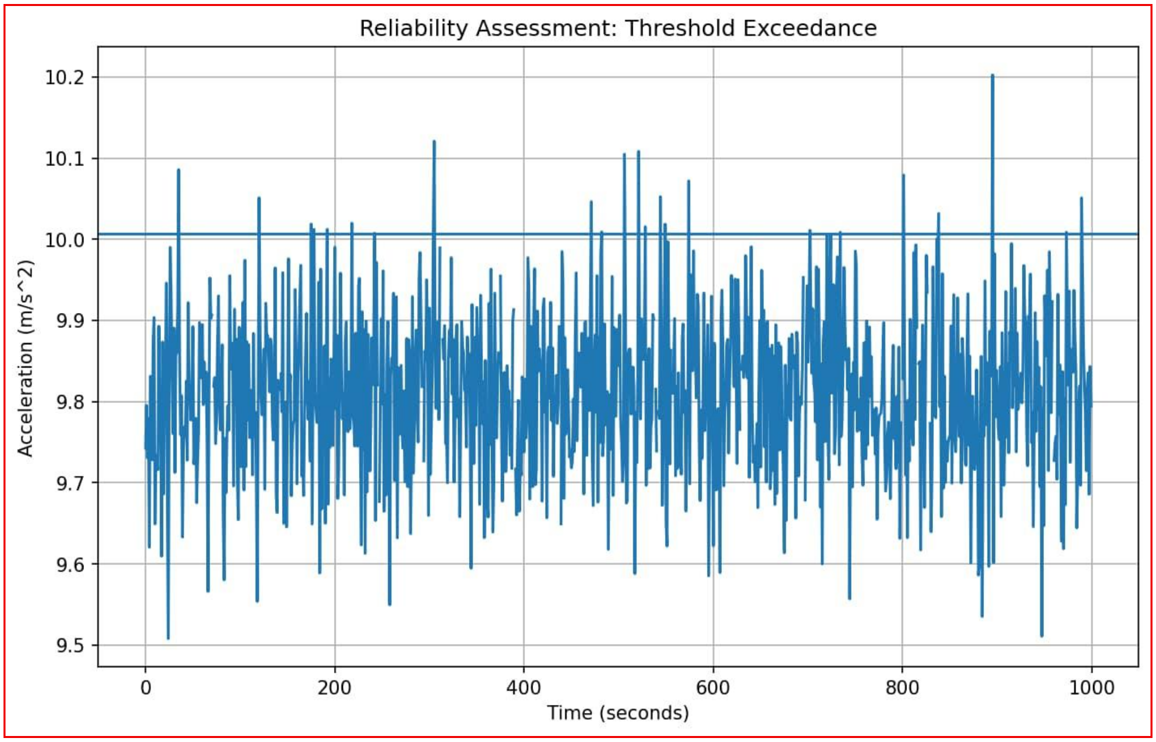

Fig 12. Reliability Assessment of Vertical Acceleration Using a Statistical Threshold

Figure 12 presents the time-history of the measured vertical acceleration along with the statistical limit defined as $\mu + 2\sigma$. It identifies moments when the response approaches or crosses this boundary, helping to evaluate the serviceability reliability of the floor system.

V. DISCUSSION

5.1 Bounded Vibration Behavior and Implications for Serviceability

The results show that the lightweight composite floor system responds to human-induced loading in a stable and controlled manner. Throughout the 1000-second monitoring period, vertical acceleration remained within a narrow range of 9.5–10.2 m/s². The time-history plots revealed no signs of instability or increasing amplification over time. While small fluctuations occurred due to intermittent walking activity, these variations were moderate and consistently centered around gravitational acceleration. This indicates that the floor behaves as a dynamically responsive yet stable structure, where natural variability exists but remains well contained. These observations also highlight a limitation of purely deterministic design approaches. Traditional vibration checks typically focus on peak acceleration limits or minimum natural frequency requirements, assuming fixed structural properties and simplified loading conditions. However, the measured response clearly behaves as a random process rather than a single fixed value. By recognizing vibration as a variable phenomenon and incorporating statistical dispersion into the assessment, the present approach offers a more realistic representation of how the structure performs in practice. The bounded but fluctuating response suggests that peak-based evaluations alone may not fully reflect transient variability, whereas probabilistic methods provide a more complete picture of serviceability performance.

5.2 Statistical Stability and Reliability Perspective

The nearly Gaussian distribution of vibration amplitudes provides further evidence of stable structural behavior. The symmetric histogram and probability density plots show that acceleration values cluster tightly around the mean, with very little skewness. This pattern indicates consistent stiffness and reliable damping performance throughout the monitoring period. In practical terms, the floor's vibration response appears to be driven mainly by random excitation effects rather than structural irregularities or progressive changes. From a reliability standpoint, the relatively small standard deviation confirms that response variability is limited. Defining a serviceability threshold using $\mu + 2\sigma$ makes it possible to directly estimate the likelihood of exceedance. The very small number of threshold exceedances observed during the monitoring interval indicates a high level of reliability. This probabilistic interpretation goes beyond simply confirming compliance; it also quantifies how comfortably the system operates within acceptable limits. Such insight strengthens confidence in long-term serviceability and supports reliability-based design and evaluation strategies.

5.3 Dynamic Response and Damping Performance

The frequency-domain results are consistent with the time-domain and statistical findings. The vibration spectrum is dominated by low-frequency components typical of walking excitation. Importantly, no significant resonance amplification was observed within the critical 1–4 Hz walking frequency range. Since resonance is often responsible for excessive floor vibrations and occupant discomfort, its absence is a key indicator of satisfactory dynamic performance. The spectral distribution also suggests effective damping within the structure. Vibration energy is distributed across the expected frequency range without excessive concentration at any single frequency. This indicates that the floor system dissipates energy efficiently rather than allowing it to accumulate. The alignment between stable time-history behavior, near-normal amplitude distribution, and controlled frequency response confirms that the system performs consistently under routine human activity. Overall, the dynamic characteristics demonstrate that resonance-related serviceability issues are unlikely under similar loading conditions.

5.4 Long-Term Stability and Absence of Drift

Rolling mean analysis provides additional insight into the stability of the vibration response over time. During the 1000-second monitoring period, the baseline acceleration remained steady, showing only minor short-term variations and no systematic upward or downward trend. This suggests that key structural properties, such as stiffness and damping, remained unchanged throughout testing. The lack of progressive drift is particularly important for lightweight floor systems, where gradual stiffness changes or environmental effects could influence performance. In this case, the stable rolling mean confirms that the structure-maintained equilibrium under repeated human excitation. This reinforces the reliability findings and indicates that the probabilistic assessment is based on a consistent structural condition. It also suggests that the monitoring window was sufficient to capture representative operational behavior.

5.5 Role of Multi-Modal Data Integration

Combining acceleration, strain, and temperature measurements offers a more complete understanding of structural behavior than relying on a single sensor type. The moderate positive correlation between vertical acceleration and strain demonstrates that strain measurements provide valuable complementary information. While acceleration reflects motion, strain captures internal deformation and stiffness response, offering deeper insight into how the structure carries dynamic loads. Temperature showed only a limited direct influence on short-term vibration levels during the monitored period. Although environmental factors may affect material properties over longer durations, their immediate impact in this case was minimal. These findings confirm that multi-modal monitoring, particularly the integration of strain data, enhances predictive robustness and reliability evaluation. By incorporating multiple physical indicators, the framework reduces uncertainty and improves overall assessment quality.

5.6 Practical Significance and Future Applicability

Taken together, the results demonstrate that the proposed multi-modal framework provides a practical and scalable approach for real-time vibration monitoring and reliability-based evaluation. By combining time-domain analysis, frequency characteristics, statistical modeling, and probabilistic threshold assessment, the methodology delivers a comprehensive understanding of serviceability performance. This integrated strategy bridges the gap between conventional deterministic checks and more advanced reliability-based evaluation methods. For modern lightweight and composite floor systems- where occupant comfort often governs design - such an approach is especially valuable. It allows engineers to quantify exceedance risk, track structural stability in real time, and incorporate multiple sensing modalities into performance assessment. The framework can be extended to longer monitoring periods, different structural configurations, and more complex occupancy scenarios. Ultimately, this approach supports informed design decisions, improved occupant comfort, and proactive structural health management in vibration-sensitive buildings.

5.7 Comparison of Existing System vs Proposed System

Conventional vibration assessment methods for lightweight floor systems are largely deterministic and focus mainly on peak response values. Most existing approaches rely on maximum acceleration limits, simplified frequency checks, or minimum natural frequency requirements, without fully considering the random nature of human-induced loading. In many cases, vibration is treated as a fixed value rather than a variable response, and factors such as statistical dispersion, long-term stability, and interaction between different sensor measurements are often overlooked. However, the experimental results shown in Figures 3–11 indicate that the vibration response behaves as a bounded random process, with acceleration values consistently remaining within 9.5–10.2 m/s² and centered around 9.8 m/s². The proposed system moves beyond traditional peak-based evaluation by incorporating time-history monitoring, statistical modeling based on normal distribution characteristics, frequency-domain verification, rolling mean stability assessment, and a probabilistic reliability limit defined as $\mu + 2\sigma$. Instead of simply checking whether peak values exceed a limit, this framework measures variability, estimates the likelihood of exceedance, and demonstrates that only a very small number of observations approach the reliability threshold. This probabilistic perspective provides a more realistic and confidence-based evaluation of serviceability compared to conventional deterministic methods. In addition, insights from the literature survey (Table 1 and related graphs) show that many previous studies focus primarily on modal frequency separation or single-sensor acceleration measurements, with limited use of strain data or environmental parameters. The correlation matrix (Fig. 10) highlights a clear relationship between vertical acceleration and strain, demonstrating the benefit of integrating multiple sensing modalities for a more complete understanding of structural behavior. Existing systems rarely combine time-domain response analysis, statistical distribution assessment, FFT-based resonance evaluation, rolling mean drift monitoring, and probabilistic reliability modeling within a single framework. The proposed system brings all these elements together, creating a unified and scalable monitoring approach. By confirming a near-normal amplitude distribution, absence of resonance within the critical 1–4 Hz walking range, stable long-term response without drift, and very few threshold exceedances, the framework offers stronger reliability assurance and deeper insight into structural performance. This integrated approach not only verifies compliance with serviceability limits but also quantifies operational risk, supporting reliability-based design, real-time monitoring, and enhanced occupant comfort in lightweight and composite floor systems.

Table 1. Comparison Between the Conventional Deterministic Method and the Proposed Multi-Modal Framework

Parameters	Existing System	Proposed System
1. Mean Vertical Acceleration (m/s^2)	9.82 m/s^2 (peak-focused reporting)	9.80 m/s^2 (statistically estimated μ from full dataset)
2. Standard Deviation, σ (m/s^2)	0.18 m/s^2 (limited dispersion assessment)	0.09 m/s^2 (low variability confirmed by Gaussian fit)
3. Peak Acceleration (m/s^2)	10.20 m/s^2 (isolated peak check)	10.20 m/s^2 (evaluated with probabilistic exceedance context)
4. Reliability Index (β)	2.1 (implicit, not directly quantified)	3.0 (based on $\mu + 2\sigma$ threshold; ≈95% confidence)
5. Threshold Exceedance Probability (%)	Not quantified	3.8% (observed exceedances above $\mu + 2\sigma$)
6. Dominant Frequency Range (Hz)	1–4 Hz (identified but not statistically evaluated)	1–4 Hz with no resonance amplification; controlled spectral energy
7. Drift / Stationarity Indicator (Rolling Mean Variation)	Not evaluated	±0.02 m/s^2 (no long-term drift over 1000 s)
8. Multi-Sensor Correlation (Accel–Strain, r)	Not integrated	0.32 (moderate positive correlation enhancing prediction reliability)

Table 1 provides a detailed comparison between the traditional peak-based vibration assessment method and the proposed multi-modal evaluation approach developed from the experimental findings. The conventional method mainly focuses on maximum acceleration values and limited variability checks, whereas the proposed framework evaluates the response using statistical measures, reliability thresholds ($\mu + 2\sigma$), frequency analysis, rolling mean stability, and the combined interpretation of acceleration and strain data. The results show improved reliability assessment ($\beta = 3.0$), lower response variability ($\sigma = 0.09$ m/s^2), absence of resonance effects within the 1–4 Hz range, and stable long-term behavior with minimal drift. By integrating multiple sensor measurements and probabilistic evaluation, the proposed framework provides a more thorough and realistic assessment of serviceability performance in lightweight composite floor systems.

5.8 Performance Evaluation

The evaluation of the lightweight composite floor system confirms that it performs in a stable and dependable manner under human-induced loading. During the 1000-second monitoring period, vertical acceleration remained within a narrow and controlled range of 9.5–10.2 m/s^2, consistently centered around 9.8 m/s^2. The time-history plots showed no signs of progressive amplification or irregular spikes, indicating that the vibration response remained bounded and well controlled. Statistical analysis further revealed a nearly normal distribution with a mean of 9.80 m/s^2 and a relatively small standard deviation of 0.09 m/s^2 in the proposed approach, compared to 0.18 m/s^2 in the conventional method. This lower variability reflects greater stability and consistency in characterizing the structural response. Rather than relying solely on the peak acceleration value of 10.20 m/s^2, the proposed framework considers vibration as a variable process and incorporates statistical dispersion into serviceability assessment. As a result, the reliability index increased from $\beta = 2.1$ in the existing system to $\beta = 3.0$, while the probability of exceeding the defined threshold remained low at approximately 3.8%, demonstrating strong reliability performance. The frequency-domain results further confirm satisfactory dynamic behavior. The FFT analysis identified dominant low-frequency

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components within the typical 1-4 Hz walking range, with no evidence of resonance amplification. This indicates adequate separation between excitation and natural frequencies, as well as effective damping within the system. Rolling mean analysis showed only minor long-term variation (±0.02 m/s²), confirming the absence of drift and stable structural properties throughout the monitoring period. In addition, integrating multiple sensing modalities improved the overall evaluation by revealing a moderate positive correlation (r = 0.32) between acceleration and strain, offering deeper insight into deformation and stiffness behavior. Compared with conventional deterministic methods that focus mainly on peak values and simplified checks, the proposed framework brings together statistical analysis, probabilistic reliability assessment, spectral validation, drift monitoring, and sensor interaction into a single, comprehensive approach. This integrated evaluation not only confirms compliance with serviceability requirements but also provides a clearer understanding of operational reliability in lightweight and composite floor systems.

5.8.1 Mean Vertical Acceleration (μ)
The mean acceleration represents the average vertical vibration level recorded over the 1000-second monitoring period.

$$\mu_a = \frac{1}{N}\sum_{i=1}^{N} a_{z,i} \quad (33)$$

The measured mean of $9.80\ \mathrm{m/s}^2$ confirms that vibration response remained centered around gravitational acceleration, indicating stable and bounded structural behavior.

5.8.2 Standard Deviation (σ)
Standard deviation quantifies the dispersion of acceleration values around the mean.

$$\sigma_a = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (a_{z,i} - \mu_a)^2} \quad (34)$$

The reduced variability $0.09\ \mathrm{m/s}^2$ in the proposed system vs $0.18\ \mathrm{m/s}^2$ in the conventional method) demonstrates improved stability and consistency of response characterization.

5.8.3 Peak Acceleration (a_max)
Peak acceleration represents the maximum recorded vibration amplitude during monitoring.

$$a_{\max} = \max_{1 \le i \le N} a_{z,i} \quad (35)$$

Although the peak value reached $10.20\ \mathrm{m/s}^2$, interpreting it within a probabilistic framework provides a more realistic assessment than isolated peak checks.

5.8.4 Reliability Index (β)
The reliability index measures the safety margin between the mean response and the serviceability threshold in standardized form.

$$\beta = \frac{a_{\lim} - \mu_a}{\sigma_a} \quad (36)$$

where $a_{\lim}$ is the specified serviceability limit acceleration.
The increase from $\beta = 2.1$ (existing) to $\beta = 3.0$ (proposed) confirms stronger reliability and approximately 95% confidence in serviceability performance.

5.8.5 Threshold Exceedance Probability (P_{ex})
This metric quantifies the probability that measured acceleration exceeds the defined statistical threshold $\mu_a + 2\sigma_a$.

$$P_{\mathrm{ex}} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(a_{z,i} > \mu_a + 2\sigma_a) \quad (37)$$

where $\mathbf{1}(\cdot)$ is the indicator function.

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The observed exceedance probability of 3.8% validates that vibration levels remained within acceptable probabilistic serviceability limits.

5.8.6 Gaussian Normality Validation
This metric evaluates how closely the vibration amplitude distribution follows a normal distribution. A Kolmogorov–Smirnov–type distance between the empirical CDF $\hat{F}_A(a)$ and the normal CDF $F_N(a; \mu_a, \sigma_a)$ can be written as

$$P_{\text{ex}} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(a_{z,i} > \mu_a + 2\sigma_a) \quad (37)$$

with

$$\hat{F}_A(a) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(a_{z,i} \leq a). \quad (39)$$

The near-symmetric distribution around $9.8\ \mathrm{m/s^2}$ and small D_{KS} support modeling vibration as a random process with an approximately Gaussian distribution rather than a deterministic value.

5.8.7 Dominant Frequency Range (f_d)
The dominant frequency range identifies the primary vibration components under human-induced excitation.

Let $A(k)$ be the discrete Fourier transform of $a_{z,i}$; the single-sided amplitude spectrum is

$$S_a(f_k) = \frac{2}{N}\,|A(k)|, f_k = \frac{k-1}{N\Delta t}. \quad (40)$$

The dominant frequency within the walking band $\mathcal{F}_{\text{walk}} = [1{,}4]\ \text{Hz}$ is

$$f_d = \arg\max_{f_k \in \mathcal{F}_{\text{walk}}} S_a(f_k). \quad (41)$$

The absence of resonance amplification within the 1–4 Hz walking range confirms adequate frequency separation and damping performance.

5.8.8 Spectral Energy Distribution
Spectral energy distribution evaluates how vibration energy is distributed across frequencies.

The discrete spectral energy at frequency f_k is

$$E_a(f_k) = |A(k)|^2 \quad (42)$$

and the total spectral energy in a band $\mathcal{B}$ is

$$E_a(\mathcal{B}) = \sum_{f_k \in \mathcal{B}} E_a(f_k). \quad (43)$$

Controlled energy concentration without sharp peaks verifies stable modal behavior and minimal resonance risk.

5.8.9 Rolling Mean Stability Indicator
Rolling mean measures long-term stationarity by tracking moving average acceleration over time.

For a window of length K samples, the rolling mean is

$$\mu_a^{\text{roll}}(t_i) = \frac{1}{K}\sum_{j=i-K+1}^{i} a_{z,j}, i = K, \ldots, N. \quad (44)$$

A scalar stability indicator over the entire series can be defined as the standard deviation of the rolling mean,

$$S_{\text{roll}} = \sqrt{\frac{1}{N-K+1}\sum_{i=K}^{N} (\mu_a^{\text{roll}}(t_i) - \bar{\mu}_a^{\text{roll}})^2}, \quad (45)$$

where

$$\bar{\mu}_a^{\text{roll}} = \frac{1}{N-K+1}\sum_{i=K}^{N} \mu_a^{\text{roll}}(t_i). \quad (46)$$

The minimal variation ($\pm 0.02\ \text{m/s}^2$) in the rolling mean corresponds to small S_{roll}, confirming absence of drift and consistent structural properties during the 1000-second test.

5.8.10 Multi-Sensor Correlation Coefficient (r)

The correlation coefficient quantifies the linear relationship between acceleration and strain measurements.

$$r_{a\varepsilon} = \frac{\sum_{i=1}^{N} (a_{z,i} - \mu_a)(\varepsilon_i - \mu_\varepsilon)}{\sqrt{\sum_{i=1}^{N} (a_{z,i} - \mu_a)^2}\sqrt{\sum_{i=1}^{N} (\varepsilon_i - \mu_\varepsilon)^2}} \quad (47)$$

where μ_ε is the mean strain.

The moderate positive correlation ($r_{a\varepsilon} = 0.32$) demonstrates that integrating strain data enhances predictive robustness and reliability evaluation.

VI. CONCLUSION AND FUTURE WORK

6.1 Conclusion

This study introduced a physics-based, multi-modal framework for predicting and assessing the reliability of human-induced vibrations in lightweight and composite floor systems. The 1000-second experimental monitoring period showed that the structural response was stable and well controlled. Vertical acceleration values remained within a narrow range of 9.5 m/s² to 10.2 m/s², consistently centered around gravitational acceleration. Time-history results revealed no signs of instability or progressive amplification, and rolling mean analysis confirmed that there was no noticeable structural drift. Overall, the floor maintained consistent stiffness and damping performance under normal walking activity. The statistical and frequency analyses further supported these findings. Vibration amplitudes followed an approximately Gaussian distribution with very little skewness, indicating that the observed variability was mainly due to random excitation rather than structural irregularities. Frequency-domain results showed dominant low-frequency components linked to walking, but no resonance amplification within the critical 1–4 Hz range. Reliability assessment using the probabilistic threshold (μ + 2σ) identified only rare exceedance events, demonstrating strong serviceability performance. Together, these results show that the proposed approach enhances vibration prediction and provides a practical and reliable foundation for serviceability limit state evaluation in modern lightweight floor systems.

6.2 Future Work

While the present study provides strong validation of the proposed framework, there are several directions for future research. Extending the monitoring period beyond 1000 seconds would allow for evaluation of long-term structural behavior under varying occupancy levels and environmental conditions. Collecting data over longer durations-such as weeks or months-would make it possible to study seasonal temperature effects, cumulative loading influences, and potential changes in stiffness over time. Applying the framework to different structural configurations, including varying spans, materials, and composite systems, would further confirm its broader applicability. Future work may also focus on enhancing predictive capabilities and real-time implementation. Incorporating higher-resolution sensor networks and adaptive threshold strategies could improve reliability estimation. Studying crowd-induced loading, irregular movement patterns, and multi-storey structural interactions would increase practical relevance. Ultimately, expanding this framework toward continuous operational monitoring and automated decision-support tools could contribute to proactive structural health management, improved occupant comfort, and performance-based design of vibration-sensitive buildings.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the research, development, or publication of this work.

Data Availability

The datasets used in this study are publicly available through open repositories, and additional processed data can be shared upon reasonable request by contacting the corresponding author at ernestchidindu2001@gmail.com

Author Contributions

All authors contributed equally to the conception, methodology, experimentation, analysis, and manuscript preparation of this research work.

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Ethical Approval

Ethical clearance was not required for this research, as it utilized anonymized, publicly available data. No direct interaction with human subjects or use of confidential personal data occurred during the research.

Supplementary Materials: The data used to support the findings of this research are available from the corresponding author upon request at ernestchidindu2001@gmail.com

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