Estimating the performance of heavy impact sound insulation using empirical approaches

Jongwoo Cho\textsuperscript{a}, Hyun-Soo Lee\textsuperscript{b}, Moonseo Park\textsuperscript{c}, Kwonsik Song\textsuperscript{d}, Jaegon Kim\textsuperscript{e} and Nahyun Kwon\textsuperscript{f}

\textsuperscript{a}Department of Architecture and Architectural Engineering, Seoul National University, Seoul, Republic of Korea; \textsuperscript{b}Dept. Of Architecture and Architectural Engineering, Institute of Construction and Environmental Engineering, Seoul National University, Seoul, Republic of Korea; \textsuperscript{c}Department of Architecture and Architectural Engineering, Institute of Construction and Environmental Engineering, Seoul National University, Seoul, Republic of Korea; \textsuperscript{d}Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, MI, USA; \textsuperscript{e}Department of Architecture and Architectural Engineering, Seoul National Univ., Seoul, Republic of Korea; \textsuperscript{f}Department of Architecture and Architectural Engineering, Hanyang University, Ansan, Republic of Korea

ABSTRACT

With an increasing demand for quieter residential environments, impact sound insulation for floating floors is gaining importance. However, existing methods for estimating the performance of heavy impact sound insulation are limited by their inability to comprehensively analyze various types of floating floors, as well as difficulties mathematically determining the input force of the reference source for heavy impacts. To overcome these limitations, this study proposes empirical models for estimating the sound insulation performance of floating floors under heavy impacts. The proposed models are then validated; the model with the highest accuracy exhibits an average estimation error of 2.73 dB at 50–60 Hz. The proposed models exhibit better accuracies than existing analytical models for frequencies below 100 Hz, where the estimation errors of the analytical models were large. Thus, the proposed models may help reduce errors in analytical estimates or when estimating a single numerical quantity for sound insulation rating during the design stage of multifamily housing.

1. Introduction

The acoustic performance of residential buildings has recently become a prominent issue due to recognition of the adverse effects of noise on the health and lives of residents (e.g., speech interference, hearing impairment, sleep disturbance, annoyance) (Berglund, Lindvall, and Schwela 1999; Secchi et al. 2016; Schiavi 2018; NECRC 2016; Haron, Yahya, and Mohamad 2009; Kwon et al. 2018). Specifically, floor impact sounds cause a number of noise-related problems in high occupancy areas with multifamily housing (e.g., apartment buildings) as they are inevitably transmitted through the floors and walls (Eom and Paek 2009; Kim et al. 2009; K-eco 2018; Ho and Yoon 2019). Such sounds are generally termed neighbor noise. According to the World Health Organization, neighbor noise is the second major cause of noise annoyance after road traffic in many European countries (WHO-
Europe 2004). Moreover, the noise dispute resolution authority (K-eco) in Korea, where approximately 75.7% of the population lives in multifamily housing, received an average of 22,099 acoustic discomfort consultations pertaining to neighbor noise over the past five years (2014–2018); approximately 82.8% of all acoustic annoyance cases stemmed from floor impacts (e.g., footsteps, children running/jumping, and moving furniture) (K-eco 2018, Statistics Korea 2018). Therefore, floor impact noise should be effectively managed in residential buildings with shared floors and walls.

As a way to manage floor impact sounds in multifamily housing, floating floor structures are widely used (Kim et al. 2009; Vér 1971; Cremer, Heckl, and Petersson 2005; Park et al. 2015). Floating floors, which comprise rigid walking surfaces decoupled from the surrounding structure by resilient layers, have high potential for reducing disturbances due to impact noises in dwellings (Schiavi 2018; Caniato et al. 2017). Accordingly, considerable attention has been given to estimating the impact sound insulation performance of floating floors (Vér 1971; Gerretsen 1999; Stewart and Craik 2000; Schiavi, Belli, and Russo 2005; e Sousa and Gibbs 2014). These studies have primarily aimed to derive estimation models based on the theoretical analysis of sound transmission when a certain impact is input into a given system (i.e., a schematic model reflecting the shape of the floating floor). In previous theoretical studies, experiments were performed to verify the accuracy of the estimated insulation performance of floating floors (Má  and Wang 2015). Floating floors can be categorized into three types based on the connection state between the walking surface and the base slab (Hopkins 2014; Rindel 2018). For floor types in which the walking surface covers the entire base via resilient layers, the insulation performance is considerably influenced by the mass of the walking surface and the dynamic stiffness of the resilient material (Gerretsen 1999; Schiavi, Belli, and Russo 2005; e Sousa and Gibbs 2014; Schiavi et al. 2007; e Sousa and Gibbs 2011). However, for other floor types, the estimation accuracy is poor for practical applications, even when more factors are considered (e.g., the quasi-longitudinal phase velocity, loss factor, or surface area of the subsystem) (Vér 1971; Stewart and Craik 2000; Hopkins 2014; Dickow, Brunskog, and Ohrich 2013).

Notably, previous analytical approaches for estimating sound insulation performance are limited because the input force is merely assumed as the impact of a tapping machine. Footsteps, which are the main cause of complaints regarding sound insulation in multifamily housing, can be categorized as either light impacts (e.g., those produced by footsteps in hard-heeled shoes) or heavy impacts (e.g., those generated by barefoot walking or running and jumping) (Hopkins 2014; Tachibana and Tanaka 1996; Grimwood 1997). Heavy impact sounds are a particular cause of nuisance for residents, especially in dwellings where people do not wear hard-heeled shoes (K-eco 2018; Inoue, Yasuoka, and Tachibana 2000; Schoenwald, Zeital, and Nightingale 2011, Oh 2014). To quantify the poor sound insulation caused by heavy impacts, the International Organization for Standardization (ISO) provides two reference impact sources as a tool for evaluating sound insulation performance: a tapping machine and a rubber ball (ISO 10140-3 2010; ISO 10140-5 2010; ISO 16283-2 2018). The tapping machine consists of five equally spaced hammers that generate a series of constant impacts, which allows the accurate measurement of continuous signals. However, the tapping machine, which is acoustically equivalent to walking with hard-heeled shoes, cannot adequately reflect the characteristics of heavy impacts (Schoenwald, Zeital, and Nightingale 2011). On the contrary, the rubber ball, which takes the form of a silicone rubber spherical shell, is more appropriate for representing heavy impacts because the sound response induced by its impact corresponds relatively well to that of an adult jumping (Tachibana and Tanaka 1996; Inoue, Yasuoka, and Tachibana 2000). Nevertheless, the input force of the rubber ball approach is inadequate for the analytical estimation of sound insulation performance because the rubber ball generates a single free-fall impact and the measurement of such a transient impact is typically based on the maximum value over a short time period (Hopkins 2014). To overcome these limitations, many studies have analyzed the deformation and impact force spectrum of the rubber ball approach (Park, Jeon, and Park 2010) and performed mathematical modeling of the rubber ball impacting a rigid surface (Schoenwald, Zeital, and Nightingale 2011). Despite these efforts, there are still limitations to estimating the sound insulation performance of floating floors due to the unique characteristics of the rubber ball (Robinson and Hopkins 2015).

Therefore, this research aims to develop empirical models for estimating the sound insulation performance of various types of floating floor upon heavy impacts. One of the advantages of an empirical methodology, which derives models from observations or experiments, is that it can provide convincing solutions even when the causal relationships among variables are ambiguous (Flood and Issa 2009). Accordingly, this advantage eliminates the need for impact force calculations and allows the assessment of various types of floating floor during the model development process. However, adequate explanatory variables that sufficiently explain the comprehensive estimation models should be carefully considered. Hence, this research utilizes several superficial variables as input variables (e.g., surface density, structure thickness, contact area,...
on the walking/resilient layer, etc.) that can be commonly derived from each type of floor during the design phase. This approach enables more flexibility when optimizing sound insulation structures due to its compatibility and applicability; however, validation is required to confirm the effectiveness of the developed models.

The steps performed in this study are as follows. (1) Preliminary research is conducted on floating floor types, their impact on sound insulation performance, and the reference impact sources used as a premise for the estimation in order to determine the limitations of conventional approaches. (2) Considering the characteristics of three types of floating floor and the variables used in analytical estimation approaches, explanatory variables are selected for empirical estimation modeling. Simultaneously, a total of 45 sample floating floors are prepared to collect data related to each variable. Subsequently, the sound reduction level of each sample floor is measured using the rubber ball method. Based on the measured values and the explanatory variables derived from the sample floating floors, several estimation models are proposed through empirical approaches such as multivariate regression and principal component regression. (3) Additional experiments are conducted using a validation sample to compare the estimation error between the developed models. Based on the explanatory variables derived from the validation sample, the estimation results of each developed model are obtained. Then, the applicability of the developed models is validated through an analysis of the absolute differences and absolute error rate (AER) in the estimated and measured results.

2. Related works

2.1. Estimating sound insulation performance according to floating floor type

According to the classification of Hopkins (Hopkins 2014) and Rindel (Rindel 2018), the shapes of walking surfaces that can float on base slabs were divided into three main types, as shown in Figure 1. For the first type, labeled “A,” the walking surface and base are connected via resilient materials at individual points. This form resembles what is often called a raised floor consisting of pedestals and panels KS F 4760 (2008). For the second type, labeled “B,” the walking surface is coupled along lines. For the third type, labeled “C,” the walking surface continuously covers the entire base slab. Many researchers (Schiavi 2018; Kim et al. 2009; Gerretsen 1999; e Sousa and Gibbs 2014; Cho 2013) have limited the scope of their investigations to Type C floating floors because they do not contain any bars or coupling, unlike the other two types. Due to its simple composition, analytical estimation models are relatively well established for this floor type based on sound and vibration transmission theories.

Based on the results of Cremer et al. (Cremer, Heckl, and Petersson 2005), the improvement in the sound pressure level, \( \Delta L \), of a Type C floor under tapping machine impacts can be obtained using Equation (1):

\[
\Delta L = 40 \log \frac{f}{f_0} \text{ (dB)},
\]

where \( f \) is the octave or 1/3-octave band center frequency (unit: Hz) to be observed and \( f_0 \) is the resonance frequency of the system (Hz), which is dominated by the mass per unit area of the walking surface \( (\rho_s, \text{ unit: kg/m}^2) \) and the dynamic stiffness per unit area of the resilient layer \( (s', \text{ unit: MN/m}^3) \).

\[
f_0 = \frac{1}{2\pi} \sqrt{\frac{s'}{\rho_s}} \text{ (Hz)}.
\]

Equations (1 and 2) indicate that such a structure is usually effective at high-frequency bands, but the sound reduction decreases toward lower frequencies (Gudmundsson 1984). In contrast to Type C, Types A and B require structural coupling. Thus, many factors affect the sound insulation performance and it is difficult to estimate \( \Delta L \). In the case of Type A, an approximate estimation equation for \( \Delta L \) under tapping machine impacts can be derived using the statistical energy analysis model proposed by Vér (Vér 1971) (Equation 3):

\[
\Delta L \approx 10 \log \frac{2.3 s_i^2 \rho_s c_i h \eta \omega^3}{N k^2} \text{ (dB)}
\]

where \( N \) is the number of mounts, \( k \) is the dynamic stiffness of each resilient mount (N/m), the subscript 1 represents the properties of subsystem 1, which represents a Type A floating structure, \( \rho_s \) is the mass per unit area (=surface density, kg/m²), \( c_i \) is the quasi-longitudinal phase velocity (m/s), \( h \) is the plate thickness, \( \eta \) is the loss factor, \( S \) is the area (m²), and \( \omega \) is the angular frequency (=2\( \pi f \)).

Although some researchers (Hopkins 2014; Maysenhölder and Horvatic 1998; Rindel 1994) have evaluated \( c_i \) and \( \eta \) for homogenous materials by assuming a finite plate, these values are difficult to determine in the design stage because they differ according to the material composition and shape of the floating structure. Thus, in addition to the relatively large number of variables, this aspect hinders the accuracy of \( \Delta L \) estimates for this floor type (Rindel...
2.2. Reference sources for heavy impacts

The analytical models discussed above are commonly derived using the impact force of the tapping machine as an input variable. A tapping machine generates continuous impacts by dropping five steel hammers through an electrically operated lifting shaft from a height of 4 cm (ISO 10140-3 2010; ISO 10140-5 2010). Its force spectrum is constant in intervals of 10 Hz and resembles a human wearing hard-heeled shoes walking on a heavy concrete floor. Tapping machines have commonly been used due to the convenience of signal processing (e.g., averaging and normalization), which stems from their signal characteristics (Schoenwald, Zeitler, and Nightingale 2011). However, the sounds generated by barefoot impacts or jumping children peak in the low-frequency range, unlike those of the tapping machine, and are dominated by floor-structure vibration characteristics (Inoue, Yasuoka, and Tachibana 2000). Therefore, to represent the sound characteristics of such impacts, a rubber ball has been suggested as an alternative. In this method, a hollow spherical shell composed of 30-mm-thick silicone rubber with an external diameter of 180 mm is dropped from a height of 1 m (Tachibana and Tanaka 1996).

As the forces of heavy impacts tend to be concentrated in the low-frequency band, Sousa and Gibbs (Sousa and Gibbs 2014, 2011) investigated the parameters influencing low-frequency impact sounds under in-situ conditions for Type C floating floors. These parameters included descriptions of the surrounding elements rather than the floating floor, such as the material properties of the base slab, walking surface dimensions, and edge conditions, in order to reduce the prediction uncertainty at low frequencies. Some researchers (Kim et al. 2009; Park et al. 2015) also used rubber balls as reference impact sources in their experiments. These works also focused on resilient materials and their composites for Type C floors.

However, compared with the force generated by a tapping machine, the force produced when a rubber ball transiently contacts a solid surface is difficult to determine mathematically as the rubber ball does not generate a constant impact over a long period. Therefore, the observation involves measuring the maximum sound pressure level within a short time period of 25 ms (Hopkins 2014). Some researchers have modeled the force spectrum by considering morphological changes (Schoenwald, Zeitler, and Nightingale 2011) or using observational approaches (Park, Jeon, and Park 2010). The force characteristics are modeled to predict the sound insulation performance of the structure by using the force as the input parameter of an analytical model. By employing this method, Robinson and Hopkins (Robinson and Hopkins 2015) estimated the sound pressure level when a rubber ball impacted a homogeneous structure. However, the limitation of this approach is that it cannot be used to evaluate the sound insulation performance of floating floors because they are commonly composed of heterogeneous materials. Some important studies on the sound insulation performance of floating floors are summarized in Table 1. In contrast to these studies, the approach proposed in this study estimates the improvement in the sound pressure level (ΔL) under rubber ball impacts for a diverse range of floating floor types utilizing the empirical methodologies described in Section 2.3.

2.3. Empirical modeling methodologies

Mathematical models can be simply classified into either empirical or analytical models. An empirical model is developed based on the observed responses of a specific system. In contrast, a model derived by considering the fundamental laws or principles that govern the system is called an analytical model (Flood and Issa 2009). Although empirical models do not provide sufficient explanations of their outputs, they can help to yield appropriate solutions for areas in which relevant input variables have not been comprehensively established (Flood and Issa 2009). After reviewing the studies mentioned in Table 1, it is clear that it is still difficult to determine the input variables (e.g., impact force of the rubber ball and variables related to floating floor composition) required to model heavy impact sound insulation using analytical approaches. Thus, empirical modeling is applied in this study to estimate the sound insulation performance of floating floors. Regression analysis and principal component regression (PCR) are the primary methodologies.

Regression analysis, which is a widely used empirical modeling approach, attempts to model the relationship between explanatory and response variables by fitting a linear equation to the observed data. An approach using two or more explanatory variables is termed multivariate regression (MR) (Pires et al. 2008).
Table 1. Literature review on impact sound insulation of floating floors.

| Authors | Research contents | Highlighted factors | Estimating methods | Reference impact | Subject structure |
|---------|-------------------|---------------------|-------------------|------------------|------------------|
| Geretsen (1999) | Validation of Cremer’s ΔL estimation model through the properties of various materials | Material properties | Analytical | Tapping | machine |
| Type C floating floor | Research on the change in acoustic performance of resilient materials under floating floors over time | Material properties (resilient layer) | Analytical | Tapping | machine |
| Vér (1971) | Derivation of the ΔL estimation model for point-supported floating floors based on analytical approach | Estimation model development | Analytical | Tapping | machine |
| Type A floating floor | Research on the phase velocity of various concrete affecting the vibration transmission | Material properties | – | – | Type A floating floor |
| Rindel (1994) | Research on ΔL estimation for batten-supported floating floor based on proposed wave transmission model | Vibration transmission modeling | – | Rubber | ball |
| Stewart and Craik (2000) | Development of a rubber ball as a standard impact source representing heavy impact | Reference impact source development | Impact force spectrum modeling | – | Rubber |
| – | – | – | Rubber | ball |
| Scoenwald et al. (2011) | Research on modeling the time-dependent impact force of rubber balls considering their deformation of shape | Reference impact source development | Impact force spectrum modeling | – | Rubber |
| Robinson and Hopkins (2015) | Research on estimation of sound pressure level upon transient rubber ball impact in homogenous structure | Validation of analytical estimation | Analytical | Rubber | ball |
| Kim et al. (2009) | Research on the relation between the dynamic stiffness and the heavy impact sound pressure level | Material properties (resilient layer) | Empirical | Bang | Homogenous concrete structure |
| Type C floating floor | Research on sound pressure level comparisons between analytical estimates and in situ measurements | Observation focused on 63 Hz octave band | Analytical | Bang | machine |
| Cho (2013) | – | – | – | – | – |

Principal component analysis (PCA) is a powerful multivariate technique not only for analyzing the structures of variables or compressing data sets while preserving important information but also for dealing with the multicollinearity problem which causes inappropriate regression estimates in MR (Abdi and Williams 2010; Rencher 2002). PCA is a mathematical method that utilizes orthogonal linear transformation to convert correlated variables into a set of uncorrelated variables (Ji, Park, and Lee 2012). Gathering the highly correlated variances of the given data set, PCA creates new variables called principal components (PCs) that are orthogonal and uncorrelated. As shown in Equation (4), $PC_j$, one of the created PCs, is presented as a linear function of all standardized original variables $X_i$:

$$PC_j = \sum_{i=1}^{p} c_{ij}X_i$$  \hspace{1cm} (4)

Here, $c_{ij}$ is the eigenvector corresponding to the $j$th PC and $i$th explanatory variable (Li et al. 2015). In PCA, the first PC ($PC_1$) demonstrates the greatest variance in the data. Also, the contribution of converted PCs for the original variance can be prioritized by the subscript values of the PCs. (Kwan 2008).

PCR, which is used in this research as an empirical modeling technique, utilizes the PCs selected through PCA as explanatory variables in MR; that is, this approach is a combination of PCA and MR (Pires et al. 2008). PCR establishes the relationship between the output variable, $y$, and the selected PCs derived from the standardized input variables $X_i$. As shown in Equation (5), the standardized PCR equation for estimating the response variable, $\hat{y}$, using the selected PCs and their regression coefficients is

$$\hat{y} = \sum_{j=1}^{p} b_jPC_j$$ \hspace{1cm} (5)

where $\hat{y}$ is the estimated PCR value, $b_j$ is the $j$th standardized partial regression coefficient of $PC_j$, and $p$ is the selected number of PCs. Consequently, the final form of this PCR process resembles a general linear regression (Li et al. 2015).

3. Model for estimating heavy impact sound insulation performance

This study developed empirical models for estimating the improvement in sound pressure level (Δ$L$) achieved by floating floors under rubber ball impacts. The model development process consists of (1) data collection and (2) empirical modeling (Figure 2). In the data collection phase, the explanatory variables for the empirical modeling are selected, including the variables whose correlation to Δ$L$ has been verified analytically in previous research (Vér 1971; Cremer, Heckl, and Petersson 2005; Stewart and Craik 2000; Schiavi, Belli, and Russo 2005). Then, data for the explanatory and response variable Δ$L$ are collected for different floating floor samples. In the empirical modeling phase, correlations between the quantitative explanatory variables are examined because their multicollinearity can lead to an adverse effect on estimation.
3.1.1. Explanatory Data

3.1. Data collection

3.1.1. Explanatory variable selection

A floating floor commonly has a resilient layer and a walking surface on the base slab. Because types of floating floor are distinguished by the connection state of the middle part between the resilient layer and the walking surface, the variables used in the estimations should be able to explain the information regarding (1) the connection state of the floor, (2) the damping properties of the resilient layer, and (3) the physical form of the walking surface, as shown in Figure 3.

Therefore, for MR modeling, one qualitative variable (i.e., the floor type) and two quantitative variables (i.e., the surface density of the walking surface $\rho$, and the dynamic stiffness of the resilient layer ($s'$)) are used as explanatory variables to estimate $\Delta L$ considering the analytical equations (Equations (1–3)). For PCR modeling, the floor type variable is substituted for four quantitative variables because the purpose of PCR is to propose empirical estimation models that are universally applicable regardless of the floor type. The four variables that contain information regarding the connection state and are identifiable in the design stage are the structure thickness, $h$, the contact surface area of the walking layer, $S_{\text{top}}$, the contact surface area of the resilient layer per unit area, $S_{\text{bottom}}$, and the ratio between the two contact surface areas, $C_{\text{ratio}}$. These variables can be expressed in values per unit area. As the floor type affects the sound insulation performance (Vér 1971; Cremer, Heckl, and Petersson 2005; Stewart and Craik 2000; Hopkins 2014), it is assumed that the four variables are also correlated to $\Delta L$; however, the estimation results of an empirical model using these variables must be further validated.

Figure 4 illustrates the four variables in detail, using Type B as an example. If the middle part with an area of $0.4 \times 3 \, \text{m}^2$ is in contact with a total walking surface area of $6 \, \text{m}^2$, $S_{\text{top}}$ is 0.2. Similarly, if the bottom of the middle part has an area of $0.45 \times 2 \, \text{m}^2$, $S_{\text{bottom}}$ becomes $0.9 \div 6 = 0.15$, where $C_{\text{ratio}}$ is $0.2 \div 0.15 = 1.3$ (i.e., $S_{\text{top}}/S_{\text{bottom}}$). If the same walking surface is supported by nine pedestals which have the same top and bottom side area of 0.06 (i.e., the middle part of Type A in Figure 3), $S_{\text{top}}$ and $S_{\text{bottom}}$ are equally $(0.06 \times 9) \div 6 = 0.09$, where $C_{\text{ratio}}$ is 1. If the walking surface is directly supported by a resilient layer (i.e., Type C), $S_{\text{top}}$, $S_{\text{bottom}}$, and $C_{\text{ratio}}$ become 1. Also, the vertical form information of floating floors is expressed by $h$, the height from the upper side of the resilient layer to the walking surface. Table 2 summarizes the explanatory variables used in the empirical modeling.

3.1.2. Data acquisition

To obtain data corresponding to the selected explanatory variables, floating floor samples were prepared by varying the three components. First, the three sample floor types include raised floors using cement panels with a joint compound (i.e., Type A), battens/joists incorporating polypropylene (i.e., Type B), and a continuous layer of cement boards (i.e., Type C). Second, the resilient layer of samples consists of either a 12-mm-thick layer of polyurethane (PU), a 24-mm-thick PU layer, or a 24-mm-thick ethylene-vinyl acetate compound. The purpose of changing the resilient layer is to obtain several different $s'$ values. Thus, the $s'$ values of each resilient layer are measured according to ISO 9052–1 (ISO 9052-1 1989). Finally, the walking surface of samples consists of five thicknesses of

Figure 2. Framework of empirical sound insulation estimation model for heavy impact.

Figure 3. Factors that distinguish the type of floating floors.

Figure 4. Derivation of explanatory variables describing middle-part connection state.
cement board by varying the number of 12-mm-thick cement board stacks from zero to eight. Each cement board has a mass of 16.3 kg/m². Therefore, the total sample size is 45 (composition of three floor types × three resilient layers × five walking surfaces). For each of these samples, the variables presented in Section 3.1.1 are derived and used to develop the estimation models. Figure 5 illustrates different floating floor samples depending on the substructure shape, resilient layer, and laminated mass.

To obtain the response variable data, ΔL, 2.5 × 2.5-m-dimension floating floor samples with each detail level element of the three components illustrated in Figure 5 were sequentially installed in the center of impact source room of an experimental laboratory and impacted by a rubber ball. Figure 6 shows laboratory specifications with the sample installation location, its impact positions in the source room, and the microphone positions in the receiving room. The samples were constructed by placing a resilient layer first, substructure on it, and laminating several cement boards over the substructure. The laboratory, which has a 210-mm-thick concrete base slab, is a two-story reinforced concrete structure; its second floor was used as the impact source room, and the first floor was used as the receiving room. To reflect the general characteristics of multifamily housing in Korea, the base slab thickness of the laboratory was set considering the floor thickness guidelines for multifamily housing structures in Korea (MOLIT 2013).

As shown in Figure 6, five evenly distributed impact positions were employed, with one point near the center and the other four points 0.5 m from the edges of the installed samples. To avoid measuring outliers that can occur when the microphone is too close to the room edge, the microphones were installed at four evenly distributed measurement points located 0.7 m from the receiving room wall at a height of 1 m. When using a rubber ball as the impact source, the measured fast time-weighted maximum sound pressure level, \(L_{i,Fmax}\), is generally in the frequency range of 50–630 Hz (ISO 10140-3 2010; ISO 16283-2 2018). The sound pressure level for each impact was obtained from microphone positions M1–M4, as illustrated in Figure 6. The measurements obtained from each microphone through a 1/3 octave band filter were then averaged using Equation (6):

\[
L_{i,Fmax} = 10 \log \frac{1}{n} \sum_{k=1}^{n} 10^{\frac{L_{i,Fmax,k}}{10}} (\text{dB}).
\]  

(6)

In addition, for each \(L_{i,Fmax}\) value of the 1/3-octave band, the response variable is \(\Delta L\) for the floating floors when exposed to the impact of the rubber ball:

\[
\Delta L = L_{\text{slab}} - L_{\text{specimen}} (\text{dB})
\]  

(7)

Here, \(L_{\text{slab}}\) is the value of \(L_{i,Fmax}\) when the bare slab of the impact source room is impacted by the ball and \(L_{\text{specimen}}\) is the value of \(L_{i,Fmax}\) when the impact source room slab is impacted with a given sample installed. Consequently, the measurement dataset for each impact consists of 12 \(\Delta L\) values in the 50–630 Hz frequency band, expressed as \(\Delta L_{50}, \Delta L_{63}, \cdots, \Delta L_{630}\).

| Notation | Unit | Description | Applied approach |
|----------|------|-------------|------------------|
| \(\rho_s\) | kg/m³ | Surface density | MR, PCR |
| \(s'\) | MN/m³ | Dynamic stiffness of the resilient layers | MR, PCR |
| \(h\) | m | Structure thickness | PCR |
| \(S_{\text{top}}\) | m² | Contact area on the walking layer (per unit area) | PCR |
| \(S_{\text{bottom}}\) | m² | Contact area on the resilient layer (per unit area) | PCR |
| \(C_{\text{ratio}}\) | - | - | PCR |

| Component | Density (mass of slab: 560 kg/m²) | Type A | Type B | Type C |
|-----------|-----------------------------------|--------|--------|--------|
| Substructure shape | Resilient layers | 12 mm | 24 mm | 24 mm |
| Number of stacked boards | PU | PU | EVA | PU |
| Density (mass of slab: 298 kg/m²) | Type B | 12 mm | 24 mm | 24 mm |
| Number of stacked boards | PU | PU | EVA | PU |
| Density (mass of slab: 527 kg/m²) | Type C | 28 mm | 24 mm | 24 mm |
| Number of stacked boards | PU | PU | EVA | PU |

Figure 5. Description of sample structures.

Figure 6. Laboratory specifications, with impact and microphone positions.
3.1.3. Measurement results

As described above, each sample was impacted at five points, and each impact provided $\Delta L$ values in the 50–630 Hz frequency range. For a more precise investigation of $\Delta L$ differences according to the respective detail levels illustrated in Figure 5, the $\Delta L$ measurements obtained from common detail levels were clustered and averaged. Figure 7 shows the mean measured values of the respective levels within the observed frequency range at 95% confidence intervals. In other words, the black rectangular points in Figure 7(a) represent the averages of measured $\Delta L$ obtained from samples with “Type A” as a common denominator; this group consists of 15 samples containing each of the three different levels of resilient layers and five different levels of stacked boards, respectively.

As can be deduced from Equation (1), $\Delta L$ tends to increase as the observation frequency increases. Among the three graphs in Figure 7, and Figure 7(a), which compares the structure type, shows the most distinctive results. As presented in Figure 7(a), the average $\Delta L$ is largest for Type A and smallest for Type C over almost the entire observed frequency range (i.e., Type C shows the least improvement in the sound pressure level). The sound insulation effects of the floating floor types can, therefore, be ranked in descending order as follows: Type A > B > C. Type C shows a significant difference to the other types in that the noise is somewhat amplified in the 50–80 Hz band. However, according to Figure 7(b), there is no notable difference in the average value of $\Delta L$ due to the change of resilient material when compared to the differences caused by a change in the floor type or walking surface. This result could be misunderstood as indicating that the damping of an impact force has no effect on the sound control. Thus, more detailed analysis of this result will be addressed in Section 5. In Figure 7(c), $\Delta L$ seems to improve as the mass of the walking surface increases. In a series of experiments, the number of stacked boards ($N$) was controlled at regular intervals, but the reduction effect due to the increase in $\rho_s$ seemed to decrease gradually. This result implies that the relationship between $\rho_s$ and $\Delta L$ is not linear. Therefore, considering the results shown in Figure 7(c) and Equations (1 and 2), it seems appropriate to apply logarithmic transformation to the explanatory variables in the empirical modeling.

3.2. Empirical modeling

3.2.1. Multicollinearity between explanatory variables

Although the explanatory variables in Table 2 are common elements of the three floor types, it is unreasonable to regard them as mutually exclusive. Accordingly, it is necessary to confirm the correlations among them prior to deriving the estimation models based on the collected data. If the correlation is significant and high, the linear model derived from the regression analysis cannot provide appropriate estimates. Thus, a correlation analysis matrix for the explanatory variables is presented in Figure 8. The correlation calculations and subsequent model development were performed using the R language and environment (R Core Team 2019). When the six variables were separated into three categories; that is, rigid body traits ($\rho_s$, $h$), connection states ($S_{\text{top}}$, $S_{\text{bottom}}$, $C_{\text{ratio}}$), and resilient properties ($s'$), remarkably high correlations were found within each category. With a large frame, there was almost no correlation between the resilient properties and those in the other two categories; however, the rigid body traits and connection states exhibited close correlations. These results imply that the multicollinearity problem cannot be avoided if all explanatory variables are applied to the MR. Thus, the
influence of multicollinearity should be minimized through variable extraction or suppression methods (Li et al. 2015). The following two sections describe the generation of empirical models using these two approaches.

### 3.2.2. Multivariate regression

In regression analysis, one of the fundamental empirical modeling approaches, the simplest method of minimizing the influence of multicollinearity is to use only those variables exhibiting no correlation (Rencher 2002). As shown in Figure 8, ρₚ and s’ are not significantly correlated. Furthermore, considering Equation (2) regarding Type C floors, which are not coupled to the surrounding structure, it is expected that a highly appropriate linear equation could be derived from these two variables. For the other floor types, these two variables can also be regarded as significant explanatory variables for estimating ΔL under heavy impacts. In addition, considering the measurement results and the fact that the response variable ΔL was obtained in units of decibels, a logarithmic transformation was applied for the quantitative variables s₀ and s’. Therefore, the regression equations for each type were first derived using the qualitative variable; i.e., the floating floor types, in addition to the two logarithmically transformed quantitative variables. In total, 12 multivariate regressions were performed to construct a model to estimate ΔL of each 1/3 octave band frequency. As qualitative data were applied as explanatory variables in the multivariate regression, corresponding to three different structure types, three regression equations were derived from each regression analysis. In this research, the derived set of regression equations in the 50–630 Hz frequency range is termed the MR model. Figures 9–11 show the MR

**Figure 8.** Correlation matrix of quantitative explanatory variables.

**Figure 9.** Regression equations and graphs for relation between ΔL–s’–s (Type A).

**Figure 10.** Regression equations and graphs for relation between ΔL–ρₚ–s’ (Type B).
results, which illustrate the relationships among $\rho_i$, $\Delta L$, and $\rho_i$ for each frequency band and their regression equations for Type A, B, and C floors, respectively.

In the regression results for the 50-Hz frequency band, it is difficult to judge whether the results are significant due to the low coefficient of determination ($R^2 = 0.37$). However, the results for other frequency bands are applicable because they have $R^2$ values of 0.67–0.8, exceeding the permissible threshold of 0.6 (Rencher 2002). According to Equations (2 and 3), $\Delta L$ should have a positive correlation with $\rho_i$ and a negative correlation with $S\prime$. Indeed, the MR model showed that $\Delta L$ and $\rho_i$ were positively correlated across all frequency bands. The improvement in $\rho_i$ decreased gradually when it exceeded a certain level. Of course, this aspect may have been amplified because this relationship was assumed to follow a logarithmic model. However, contrary to expectations, the $\Delta L - S$ relationship was found to vary between negative and positive correlations depending on the frequency band. Besides, the significance level (p-value) of $S\prime$ exceeded 0.05 in the 80, 315, and 630 Hz frequency bands of the MR model. This indicates that $S\prime$ does not have a statistically significant effect on $\Delta L$. For the results that do not fit with the sound transmission theories, additional analysis is provided in Section 5.

In a comparison of the three types of prediction surface based on the smallest $\rho_i$ values (i.e., 40 kg/m$^2$) illustrated in Figures 9–11, Type A shows positive values of $\Delta L$ in the 63–160 Hz frequency range (Figure 9). In contrast, Type B is possible to amplify the heavy impact sound at 63 Hz, as the prediction shows a negative value (Figure 10), and Type C can cause amplification throughout the 63–160 Hz frequency range (Figure 11). In the 200–315 Hz range, $\Delta L$ of Type A is predicted over 10 dB. Type B is expected to show slightly better sound insulation performance than Type C, and Type C will start to show a sound insulation effect without amplification from this frequency range based on the $\rho_i$ of 40 kg/m$^2$. Also, the difference between predicted $\Delta L$ of three types appears to decrease from the observation range over 400 Hz.

### 3.2.3. Derivation of PCR models

To derive a more generally applicable model than previous MR models, another empirical modeling process was performed. Instead of variable extraction, another way to derive an estimation model that minimizes the influence of multicolinearity is to suppress the variable (Li et al. 2015). This involves using PCs obtained through PCA that have orthogonal and uncorrelated relationships as the explanatory variables. PCA is a process of deriving new variables through the variance of data with different units. For unit unification, normalization is required. The PCA results of the log-transformed and normalized variables are presented in Table 3, which also lists the eigenvectors and cumulative variances of the PCs.

On closer examination of the PCA results, PC3 is mainly dominated by $S\prime$, whereas $S\prime$ has a dominant influence on PC4 via the $C_{ratio}$. It is particularly noteworthy that PC4 contains a large volume of information about the ratio of the connection between the top and bottom surfaces. In addition, PC1 and PC2 account for 0.67 of the total dataset variances, with PC3 and PC4 accounting for 0.17 and 0.15, respectively. To construct PCR models, the number of PCs to be used as explanatory variables must be determined. According to the cumulative variance shown in Table 3, as PC1–PC3 account for 84% of the total variance, it is reasonable to construct a model only using these three variables. However, by including PC4 in the PCR modeling, one can account for 99% of the total variance of the dataset. Consequently, it is necessary to compare models that include PC4 with models that do not. The sets of equations derived from the two different PCR processes according to the number of explanatory variables are termed PCR3 and PCR4 models. These two PCR models and their coefficients of determination are compared in Table 4.

Similar to the results of the previously investigated MR model, the signs of the regression coefficient of the PCs that contain large amounts of information regarding $S\prime$ (i.e., PC3 and PC4) vary between positive and negative depending on the frequency range. Comparing the average $R^2$ values of each model, the values decrease in the order of MR (0.71) > PCR4 (0.67) > PCR3 (0.66), but the difference between PCR4 and

#### Table 3. Eigenvectors and cumulative variance of PCs.

| Explanatory variable | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 |
|----------------------|-----|-----|-----|-----|-----|-----|
| $\rho_i$             | 0.32| 0.68| -0.14| 0.03| -0.65| -0.00|
| $h$                 | 0.52| -0.36| -0.23| 0.26| 0.69| 0.00|
| $S_{top}$           | -0.55| 0.26| -0.30| 0.25| 0.08| 0.69|
| $S_{bottom}$        | -0.56| 0.34| -0.20| 0.11| 0.13| -0.71|
| $C_{ratio}$         | 0.13| -0.45| -0.44| 0.70| -0.28| -0.14|
| $s'$                | 0.07| -0.16| -0.78| -0.61| 0.00| -0.00|
| % cumulative variance | 0.41| 0.67| 0.84| 0.99| 1.00| 1.000|

Values in bold indicate the most influence variables for each PC.
PCR3 is not significant. It is not sufficient to discuss the merits of these models based on the analysis presented thus far; therefore, comparison and validation of the estimation performance of the models are assessed using additional experimental data.

4. Model validation

Model validation was conducted focusing on type A expected to improve sound insulation most, considering the estimation result derived from proposed models. To improve their practical applicability, single-layer panels were manufactured for the model validation. The panels were designed to satisfy two requirements. The first requirement was that $\rho_s$ should not cause sound amplification throughout the observed frequency range when the resilient material exhibits the medium level of $s'$ used in the data collection phase. Accordingly, $\rho_s$ was set to be greater than 80 kg/m$^2$ based on the regression equations in Figure 9. The second requirement was that the panel size should consider the manual workability according to the determined value of $\rho_s$. Thus, the size was adjusted to 400 mm $\times$ 400 mm so as not to exceed a weight of 15 kg per panel. Panels of this size are smaller than the panels of the Type A substructure (500 mm $\times$ 500 mm) used in the data collection phase but have larger values of $\rho_s$. The manufactured panels were applied to the Type A shape and employed for collection of the validation data. Because of their size difference, these panels required more pedestals for support, which generated slight differences in the connection state as well as in the rigid body traits. The section drawing and explanatory variables of the validation sample are provided in Figure 12.

The sound pressure level of the installed sample condition ($L_{\text{specimen}}$) was measured using the same procedure and environment described in 3.1.2. The data from the five impact positions were also averaged using Equation (6). Simultaneously, based on the explanatory variables, $L_{\text{specimen}}$ was estimated using the three developed empirical models. As in several other studies, the AER was used for an objective analysis of the estimation results (Ji, Park, and Lee 2012; Kwon et al. 2017, 2019a). Thus, the estimates were expressed as $L_{\text{specimen}}$ using Equation (7) even though the three models estimated $\Delta L$ for a clearer observation of the sound improvement effect. The AER was calculated using Equation (8):

$$\text{AER(\%)} = \frac{L_A - L_E}{L_A} \times 100 \quad (8)$$

where $L_A$ and $L_E$ denote the actual and estimated $L_{\text{specimen}}$. Larger AER values indicate greater estimation errors and reduced accuracy. Table 5 presents the

| Table 4. Comparison of PCR models. |
|-----------------------------------|
| **PCR3 (explanatory variables: PC1–PC3)** | **PCR4 (explanatory variables: PC1–PC4)** |
| Estimation model | $R^2$ | Estimation model | $R^2$ |
| $\Delta L$ | $-8.6 + 3.6PC_1 + 1.2PC_2 + 2.5PC_3$ | 0.33 | $-5.2 + 4.1PC_1 + 1.4PC_2 + 2.2PC_3$ | 0.34 |
| $\Delta L$ | $-9.8 + 8.5PC_1 + 3.2PC_2 + 0.7PC_3$ | 0.64 | $-5.9 + 9.0PC_1 + 2.6PC_2 + 2.0PC_3$ | 0.64 |
| $\Delta L$ | $-8.7 + 9.8PC_1 + 4.2PC_2 + 0.4PC_3$ | 0.73 | $-10.0 + 9.7PC_1 + 4.3PC_2 + 0.8PC_3 + 0.7PC_4$ | 0.73 |
| $\Delta L$ | $2.8 + 7.1PC_2 + 7.9PC_3 - 6.0PC_1$ | 0.69 | $1.4 + 6.5PC_1 + 8.4PC_2 - 4.6PC_3 + 2.8PC_4$ | 0.70 |
| $\Delta L$ | $-3.5 + 8.0PC_1 + 9.9PC_2 - 2.1PC_3$ | 0.71 | $5.7 + 8.0PC_1 + 9.9PC_2 - 1.6PC_3 + 1.2PC_4$ | 0.71 |
| $\Delta L$ | $-8.1 + 7.8PC_1 + 9.9PC_2 + 3.2PC_3$ | 0.72 | $-4.5 + 6.9PC_1 + 9.9PC_2 + 1.4PC_3 + 3.4PC_4$ | 0.73 |
| $\Delta L$ | $-2.1 + 6.8PC_1 + 7.6PC_2 - 0.3PC_3$ | 0.66 | $-6.9 + 6.6PC_1 + 7.8PC_2 - 1.1PC_3 + 2.7PC_4$ | 0.67 |
| $\Delta L$ | 4.5 + 5.2PC_1 + 6.8PC_2 + 2.8PC_3$ | 0.65 | $3.7 + 5.1PC_1 + 6.9PC_2 + 2.5PC_3 + 0.5PC_4$ | 0.65 |
| $\Delta L_{115}$ | 0.4 + 6.2PC_1 + 7.0PC_2 + 3.1PC_3 | 0.63 | $-4.3 + 6.3PC_1 + 6.8PC_2 + 3.5PC_3 + 2.9PC_4$ | 0.64 |
| $\Delta L_{500}$ | $-1.7 + 8.0PC_1 + 8.7PC_2 + 2.1PC_3$ | 0.79 | $-6.9 + 8.1PC_1 + 8.4PC_2 + 2.9PC_3 + 3.4PC_4$ | 0.79 |
| $\Delta L_{500}$ | $-3.1 + 8.1PC_1 + 10.6PC_2 + 2.1PC_3$ | 0.72 | $-6.8 + 8.3PC_1 + 10.3PC_2 + 3.2PC_3 + 2.3PC_4$ | 0.73 |
| $\Delta L_{500}$ | $-1.9 + 7.8PC_1 + 12.6PC_2 - 1.0PC_3$ | 0.63 | $-10.3 + 7.7PC_1 + 12.4PC_2 - 0.9PC_3 - 5.2PC_4$ | 0.65 |

Figure 12. The section drawing and specifications of validation sample.
differences and AERs between the actual and estimated values for each model.

The mean absolute differences and AERs between the measurements and estimates obtained using the three models were 2.73 dB and 7.78% for MR, 3.55 dB and 9.81% for PCR3, and 3.39 dB and 9.54% for PCR4. A comparison of the models shows that the MR model had the smallest estimation errors. The error of the PCR4 estimate was slightly lower than that of the PCR3 estimate, and PCR3 showed the largest estimation errors. Looking closely at the absolute differences and AERs across the observation frequency bands, all models showed differences of over 8.15 dB and AERs of more than 36.3% at the 630-Hz octave band; this represents a limitation of the models in terms of their estimation capabilities. On the other hand, all models demonstrated very good estimation capabilities, with absolute differences and AERs not exceeding 4 dB and 7% in the range of 0–315 Hz, respectively. However, the absolute difference and AER of MR, PCR3, and PCR4 in the 100-Hz range were 5.65 dB (10.17%), 7.54 dB (13.57%), and 7.03 dB (12.66%), respectively; this indicates limited accuracy compared to the other frequency bands. This result is attributed to the stack of cement boards causing excessive resonance during the experiments in the data collection phase.

5. Discussion

5.1. Experimental results from data collection phase

As shown in Figure 7(b), no significant ΔL improvement was obtained in the experiments by varying the resilient layers in the range from 29.2 to 51.6 MN/m² of s’. Consequently, the proposed empirical estimation models are robust against the influence of the dynamic stiffness of the resilient material s’. This characteristic can be used to differentiate heavy impact sound insulation from light impact sound insulation. s’ was selected as an explanatory variable in the experiments according to the results of previous studies, which indicated that ΔL under tapping machine impacts is negatively correlated with s’ (Gudmundsson 1984); however, resilient materials with extremely low values of s’ were excluded from the investigation as such materials can cause discomfort on the sensation of hardness while walking (AURUM 2013, Matsuda and Shimizu 2017). However, previous experimental data regarding the relationship between heavy impact sound insulation performance and s’ (Kim et al. 2009) indicate that s’ does not exhibit a significant effect in the range over 10 MN/m³. Therefore, to derive an empirical model that accurately reflects the influence of s’, more observation data corresponding to very low values of s’ should be included in the empirical modeling.

5.2. Coefficients of determination and validation results of developed models

The mean coefficients of determination of the three proposed models were 0.74 (MR), 0.69 (PCR3), and 0.7 (PCR4), except at 50 Hz. The difference between the R² values of the MR and PCR models can be explained by the fact that not all variables related to sound transmission are included in these models. The explanatory variables in the PCR models can be considered as the results obtained by substituting the qualitative variable in the MR model (i.e., the floating floor type) with other quantitative variables describing the connection state. Accordingly, the variables added to the PCR model may not fully describe the information expressed by the floating floor type. Nevertheless, R² and the estimation accuracy were slightly improved by adding PC4 to the PCR model. Thus, the ε_estao, i.e., the dominant quantity contained in PC4, is useful for explaining the sound insulation characteristics of floating floors and increasing the estimation accuracy. As PCR modeling is relatively free from multicollinearity problems, it is possible to improve the estimation accuracy by adding related explanatory variables.
Thus, including variables in PCR or other empirical modeling processes that are difficult to include in analytical models but that contain relevant information (e.g. variables regarding constituent materials) is expected to improve the estimation accuracy.

In terms of the model validation results, the results showed slight differences of 5 dB below 500 Hz; that is, the difference that is difficult to be easily perceived by people. The errors also seem to be acceptable when compared with the predictions of other studies using empirical approaches (Kwon et al. 2017, 2019b). Further, the validation experiment was planned such that amplification would not occur anywhere in the observed frequency band, and the results confirmed this. However, the proposed models tended to underestimate the sound insulation performance of the floating floors in the higher frequency range, resulting in estimation errors of 8.15–8.92 dB at 630 Hz. The fact that the proposed models themselves were developed to be robust against variations in $s'$ could be one of the causes of this phenomenon. In contrast, approximately 10 dB of estimation errors were observed below 100 Hz in a previous study, which estimated the sound pressure level when a homogenous bare slab was impacted by a rubber ball using an analytical approach (Robinson and Hopkins 2015). This accuracy level does not differ substantially from that of the estimation results obtained for tapping machine impacts using analytical approaches (Hopkins 2014). According to comparisons with analytical models, the three proposed models yielded competitive estimates in the low-frequency range below 100 Hz, where the estimation accuracy of the analytical models is low. In addition, their estimates are relatively inaccurate in the range above 400 Hz, where estimates by the analytical model become more accurate. In other words, empirically and analytically derived models exhibit good estimation accuracy in opposing frequency ranges. Just as analytical models are considered useful despite the error of approximately 10 dB in a specific frequency range, the three proposed models were confirmed to be sufficiently useful and to have good accuracy in the following order: MR > PCR4 > PCR3. According to previous experimental results (Mak and Wang 2015; Ohlrich 2011), the inevitable omission of cross-coupling in analytical estimation modeling could cause the estimates to deviate at low frequencies. Therefore, future research regarding the complementary use of the two approaches is necessary to improve estimation accuracy.

### 5.3. Applicability of developed models

According to the collected data in 3.1.3 and the estimation result based on empirically derived models in 3.2, the difference in sound insulation depending on the form of floating floors appears large in the relatively low-frequency domain where the force of heavy impact source concentrated. Also, under the condition that $\rho_s$ and $s'$ are the same, the expected sound insulation performance is estimated to be in the following order: Type A > B > C. In this respect, the validation of derived models was conducted first for Type A which is expected to show good sound insulation performance, to consider the applicability.

For scientific investigation, sound pressure level measurements provide values that are frequency dependent. However, to evaluate the sound insulation effect more intuitively in practical applications, the acoustic performance is generally expressed by converting the frequency-dependent value into a single numerical quantity (ISO 717-2 2013; KS F 2863-2 2007). By converting the estimates and measurements listed in Table 5 using the standard method, the single numerical quantities $L_{i, F_{\text{max}}, AW}$ of the three models are calculated as 43 dBA (actual), 44 dBA (MR), 45 dBA (PCR3), and 45 dBA (PCR4). Based on this result, the differences between the proposed models are not more than 2 dBA. The $L_{i, F_{\text{max}}, AW}$ calculation is largely dominated by the value in the frequency band in which the sound pressure level is high. Accordingly, the error is reduced when converting to the value used for rating because the impact force of the rubber ball is concentrated at low frequencies, where the proposed models exhibit better estimation accuracy. Therefore, even though the proposed models show low accuracy in some frequency ranges, they can be used to precisely estimate $L_{i, F_{\text{max}}, AW}$ and provide construction managers or designers with useful information regarding the expected acoustic performance of residential buildings during the design stage. Moreover, it is appropriate to use the MR model first due to its higher accuracy.

### 6. Conclusions

Despite the recent increase in demand for quieter residential environments, the available techniques for estimating the sound insulation performance in residential buildings remain limited. This limitation includes estimation of sound insulation performance under the impact of a rubber ball representing barefoot impacts or children jumping. Mathematical determination of the impact force of the rubber ball has obstacles for solving the problem through analytical approaches. Therefore, the objective of this research was to empirically estimate the sound insulation performance of floating floors under rubber ball impacts. To consider the various types of floating floors, three empirical models (MR, PCR3, and PCR4) were derived using information that can be easily obtained during the design stage by referring to previous analytical modeling literature.
The model validation was focused on Type A which is expected to show the most improvement. It revealed that the MR model, which was the most accurate of the proposed models, showed an average estimation deviation of 2.73 dBA at 50–630 Hz. The proposed models showed relatively precise estimation abilities at low frequencies but were slightly inaccurate at 400–630 Hz. This is in contrast to other analytically derived estimation models, which have low accuracy below 100 Hz. Thus, it is expected that these empirical estimation methodologies may help reduce the estimation error caused by the omission of cross-coupling from more widely accepted analytical modeling methods. Moreover, from a practical viewpoint, a single numerical quantity for rating sound insulation performance can be obtained by estimating ΔL with the proposed models using the specifications of floating floors as input variables and adding this estimated attenuation value to the sound pressure level of the base structure. As the proposed models have high accuracy in the low-frequency range, where the impact force of the rubber ball is concentrated, they show better accuracy at estimating this single numerical quantity. Therefore, when considering the acoustic performance of concrete residential buildings, construction managers or architectural designers can use these empirically derived models to compare the single numerical quantity of various sound management methods during the design stage. As such, this research contributes to noise management research by presenting a method for estimating sound insulation performance using an empirical approach.

The observed limitation in the proposed models at high frequencies may be because of the lack of data for resilient layers with low dynamic stiffness. Moreover, different surrounding structures (e.g., modular or CLT housing), junction conditions or the complex constituent materials of floating floors may not have been adequately considered. Thus, the MR model is the most accurate of the proposed models at present; however, if these factors are considered, and relevant data is collected in future research, PCR modeling, which boasts improved accuracy due to the addition of relevant variables, may be more promising than MR, which only uses qualitative variables. Otherwise, other empirical methodologies free from the multicollinearity problem offer a more precise estimation of sound insulation performance under heavy impacts.

Disclosure statement
No potential conflict of interest was reported by the authors.

Funding
This work was supported by the National Research Foundation of Korea [2017R1A2B2007050].

Notes on contributors
Jongwoo Cho is a PhD candidate at the Department of Architecture of Seoul National University. He received a bachelor’s degree from Hanyang University School of Architecture in 2011. In 2015, he graduated master’s course for construction management in 2015 at SNU. His main research area is construction engineering and management including sound insulation methods and built environment.

Hyun-Soo Lee received bachelor’s degree in 1983 and master’s degree in 1985 at the Department of Architecture of Seoul National University. He has studied Construction Engineering & Management at the University of Michigan since 1988 and finished doctor’s degree in 1992. And he worked for the Dept. of Architecture Engineering in Inha University as a professor. Since 1997, he has been working as a professor at the Department of Architecture and Architectural Engineering of Seoul National University. His major research area is Construction Engineering and Management.

Mooneso Park got into Department of Architecture of Seoul National University in 1985, completed the courses for a bachelor’s degree in 1989, and graduated master’s course for City Planning at SNU in 1992. In 1998-2001, he received master’s degree and doctor’s degree for Project Management in MIT. After graduation, he worked for the Dept. of Building in National University of Singapore as an assistant professor. Since 2005 he has been working as a professor at the Department of Architectural Engineering of Seoul National University. Currently, his major research area is systematic approach for construction, knowledge-based construction etc.

Kwonsik Song received his PhD in 2017 in Construction Engineering and Management from Seoul National University, South Korea. He earned his MS degree in Construction Engineering and Management from Seoul National University in 2013 and BA in Architectural Engineering from Sejong University in 2010. His research focuses on smart and connected communities, human-building interaction, and energy-efficient buildings. He is a research associate in the Department of Civil and Environmental Engineering at the University of Michigan and a research professor at Kyungpook National University.

Jaegon Kim received a bachelor’s degree in Architecture from Wonkwang University in 2001. In 2012, he got a master’s degree in construction management from Seoul National University and continues his research at SNU as a Ph.D. student.

Nayyun Kwon got a bachelor’s degree in Architecture from Hanyang University in 2010 and then graduated a master’s course for Construction Management at Seoul National University in 2014. In 2018, he received a doctor’s degree for Construction Engineering and Management at Seoul

Acknowledgments
This work was supported by the National ResearchFoundation of Korea (NRF) grant funded by Korea government (MSIT) [2017R1A2B2007050] and Institute of Construction and Environmental Engineering at Seoul National University. The authors wish to express their gratitude for the support.
National University. After the graduation, he has worked for Hanyang University ERICA campus as a post-doctoral researcher. His main research area is Construction Engineering and Management, including construction environment, risk assessment, and facility management. Recently, he has participated in projects that estimates workers’ productivity and evaluates fatigue and risk of the workers in construction sites.

References
Abdi, H., and L. J. Williams. 2010. “Principal Component Analysis.” Wiley Interdisciplinary Reviews: Computational Statistics 2 (4): 433–459. doi:10.1002/wics.101.
AURUM (Architecture and urban policy information Center). 2013. “AURU Policy Updates.” Architecture and Urban Research Institute 8: 33–52. (in Korean).
Berglund, B., T. Lindvall, and D. H. Schwela. 1999. Guidelines for Community Noise. Geneva: World Health Organization. https://apps.who.int/iris/handle/10665/66217.
Caniento, M., F. Betarello, P. Fausti, A. Federiga, L. Marsich, and C. Schmid. 2017. “Impact Sound of Timber Floors in Sustainable Buildings.” Building and Environment 120: 110–122. doi:10.1016/j.buildenv.2017.05.015.
Cho, T. 2013. “Experimental and Numerical Analysis of Floating Floor Resonance and Its Effect on Impact Sound Transmission.” Journal of Sound and Vibration 332 (25): 6552–6561. doi:10.1016/j.jsv.2013.08.011.
Cremer, L., M. Heckl, and B. A. T. Petersson. 2005. Structure-borne Sound - Structural Vibrations and Sound Radiation at Audio Frequencies. New York: Springer-Verlag, Berlin.
Dickow, K. A., J. Brunskog, and M. Ohlrich. 2013. “Modal Density and Modal Distribution of Bending Wave Vibration Fields in Ribbed Plates.” The Journal of the Acoustical Society of America 134 (4): 2719–2729. doi:10.1121/1.4818889.
e Sousa, A. N., and B. M. Gibbs. 2011. “Low Frequency Impact Sound Transmission in Dwellings through Homogeneous Concrete Floors and Floating Floors.” Applied Acoustics 72 (4): 177–189. doi:10.1016/j.apacoust.2010.11.006.
e Sousa, A. N., and B. M. Gibbs. 2014. “Parameters Influencing Low Frequency Impact Sound Transmission in Dwellings.” Applied Acoustics 78: 77–88. doi:10.1016/j.apacoust.2013.10.013.
Eom, C. S., and J. H. Paek. 2009. “Risk Index Model for Minimizing Environmental Disputes in Construction.” Journal of Construction Engineering and Management 135 (1): 34–41. doi:10.1061/(ASCE)0733-9364(2009)135:1(34).
Flood, L., and R. R. A. Issa. 2009. “Empirical Modeling Methodologies for Construction.” Journal of Construction Engineering and Management 136 (1): 36–48. doi:10.1061/(asce)co.1943-7862.0000138.
Gerretsen, E. 1999. “Predicting the Sound Reduction of Building Elements from Material Data.” The Journal of the Acoustical Society of America 105 (2): 1200. doi:10.1121/1.425651.
Grimwood, C. 1997. “Complaints about Poor Sound Insulation between Dwellings in England and Wales.” Applied Acoustics 52 (3–4): 211–223. doi:10.1016/0003-682X(97)00027-3.
Gudmundsson, S. 1984. “Sound Insulation Improvement of Floating Floors.” Report TVBA-3017. Lund, Sweden: A study of parameters, Lund Institute of Technology.
Haron, Z., K. Yahya, and M. I. Mohamad. 2009. “Probability Approach for Prediction of Construction Site Noise.” Journal of Asian Architecture and Building Engineering 8 (2): 571–577. doi:10.3130/jaabe.8.571.
Ho, S. W., and S.-J. Yoon. 2019. “Experimental Evaluation of Reinforced Concrete Slab Reinforced by Composite Mortar in Terms of Flexural Behavior and Floor Impact Noise Evaluation.” Journal of Asian Architecture and Building Engineering 18 (2): 81–88. doi:10.1080/13467581.2019.1596813.
Hopkins, C. 2014. Sound Insulation. Oxfordshire: Routledge.
Inoue, K., M. Yasuoka, and H. Tachibana. 2000. “New Heavy Impact Source for the Measurement of Floor Impact Sound Insulation of Buildings.” In Proceedings of Inter-Noise, 1493–1496. Nice, France.
ISO 10140-3. 2010. Acoustics - Laboratory Measurement of Sound Insulation of Building Elements - Part 3: Measurement of Impact Sound Insulation.
ISO 10140-5. 2010. Acoustics - Laboratory Measurement of Sound Insulation of Building Elements - Part 5: Requirements for Test Facilities and Equipment.
ISO 16283-2. 2018. Acoustics - Field measurement of sound insulation in buildings and of building elements - Part 2: Impact sound insulation.
ISO 717-2. 2013. Acoustics – Rating of Sound Insulation in Buildings and of Building Elements – Part 2: Impact Sound Insulation.
ISO 9052-1. 1989. Acoustics-Determination of Dynamic Stiffness – Part 1: Materials Used Under Floating Floors in Dwellings.
Ji, S.-H., M. Park, and H.-S. Lee. 2012. “Case Adaptation Method of Case-Based Reasoning for Construction Cost Estimation in Korea.” Journal of Construction Engineering and Management 138 (1): 43–52. doi:10.1061/(ASCE)CO.1943-7862.0000409.
Kim, K.-W., G.-C. Jeong, K.-S. Yang, and J. Sohn. 2009. “Correlation between Dynamic Stiffness of Resilient Materials and Heavyweight Impact Sound Reduction Level.” Building and Environment 44 (8): 1589–1600. doi:10.org/1016/j.buildenv.2008.10.005.
Korea Environment Corporation (K-eco). 2018. Inter-Floor Noise Consultation Center Operation Report, Incheon, Korea.
KS F 2863-2. 2007. Rating of Floor Impact Sound Insulation for Impact Source in Buildings and of Building Elements - Part 2: Floor Impact Sound Insulation Against Standard Heavy Impact Source.
KS F 4760. 2008. “Raised Access Floor.”
Kwan, S. H. 2008. Multivariate Data Analysis and Application. Seoul, Korea: Freedom Academy.
Kwon, N., J. Cho, H.-S. Lee, I. Yoon, and M. Park. 2019a. “Compensation Cost Estimation Model for Construction Noise Claims Using Case-Based Reasoning.” Journal of Construction Engineering and Management 145 (8): 04019047. accepted. doi:10.1061/(ASCE)CO.1943-7862.0001675.
Kwon, N., J. Lee, M. Park, I. Yoon, and Y. Ahn. 2019b. “Performance Evaluation of Distance Measurement Methods for Construction Noise Prediction Using Case-Based Reasoning.” Sustainability 11 (3): 871. doi:10.3390/su11030871.
Kwon, N., M. Park, H.-S. Lee, J. Ahn, and S. Kim. 2017. “Construction Noise Prediction Model Based on Case-based Reasoning in the Preconstruction Phase.” Journal of Construction Engineering and Management 143 (6): 04017008. doi:10.1061/(ASCE)CO.1943-7862.0001291.
Kwon, N., K. Song, H.-S. Lee, J. Kim, and M. Park. 2018. “Construction Noise Risk Assessment Model Focusing on Construction Equipment.” Journal of Construction Engineering and Management 144 (6): 04018034. doi:10.1061/(ASCE)CO.1943-7862.0001480.
