Artificial Neural Network-Based Residential Energy Consumption Prediction Models Considering Residential Building Information and User Features in South Korea

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Abstract: When researching the energy consumption of residential buildings, it is becoming increasingly important to consider how residents use energy. With the advancement of computing power and data analysis techniques, it is now possible to analyze user information using big data techniques. Here, we endeavored to integrate user information with the physical characteristics of residential buildings to analyze how these elements impact energy consumption. Regression analysis was conducted to accurately identify the impact of each element on energy consumption. It was found that six elements were influential in all seasons: the number of exterior walls, housing direction, housing area, number of years occupied, number of household members, and the occupation of the household head. The elements that had an impact in each period were then derived. Based on the results of the regression analysis, input variables for the training of an artificial neural network (ANN) model were selected for each period, and residential energy consumption prediction models were implemented based on actual consumption. The elements identified as those affecting energy consumption, through regression analysis, can be used for implementing prediction models with advanced forms. This study is significant in that we derived influential elements from an integrative perspective.

Keywords: artificial neural network; residential energy; user feature; residential building information

1. Introduction

In 2019, the World Green Building Council reported that the energy used by buildings accounted for 30% of the world’s total energy consumption, with residential buildings representing the highest proportion (22%) [1]. The figures are similar for South Korea; the residential sector represents 17.1% of total energy consumption, with electric energy being responsible for 38.8%. This demonstrates the necessity of preparing energy-saving measures for residential buildings [2].

To reduce energy consumption in buildings, various systems for managing energy have been introduced (e.g., the building energy management system (BEMS)), and energy-saving measures have been prepared (e.g., improving physical performances related to building energy). In South Korea, such energy-saving measures and their application scope have been gradually expanded to residential buildings. In residential buildings, energy consumption is significantly affected by the attributes or sociology of the inhabitants, as well as the performance of the building. Therefore, the importance of researching energy saving using user information is increasing [3]. Moreover, it is
necessary to effectively conduct sustainable energy utilization by preparing an energy reduction plan that considers user features.

Thus far, research on how the physical environment affects energy consumption has been intensively conducted; however, it is difficult to collect a large amount of user information owing to its personal nature. It is also difficult to quantitatively reduce and analyze the information on individuals. Nevertheless, the analysis of qualitative data has become possible through national surveys and new methodologies that are capable of nonlinear analysis, such as artificial neural networks (ANNs). In this study, the energy consumption in residential buildings in South Korea was investigated, by integrating the physical characteristics of residential buildings with information on occupant behavior and characteristics, to identify elements that affect residential energy consumption. The elements that were found to be influential were subsequently used to construct energy consumption prediction models.

2. Literature Review

Most studies on the energy consumption of residential buildings have focused on physical characteristics, and those that considered user behavior only considered one or two user elements. However, user information cannot be defined with such few elements; therefore, studies that reflect user information from various perspectives are required. In this study, elements that affect energy consumption were derived considering both the physical characteristics of buildings and user information.

2.1. Effects of Physical Building Characteristics on Energy Consumption

Kim [4] reported that annual power consumption varied depending on the housing type, construction year, number of floors, building structure, and building location. It was found that detached houses with relatively less energy-related facilities consumed more energy than apartments, as did old buildings and those with fewer floors. Kim et al. [5] discovered that the residential area, heating method, number of floors, and building direction all affected heating energy consumption for 181 apartment complexes in Seoul. Similarly, Eum et al. [6] reported that the construction year, household area, building direction, and heating method affected energy consumption in 21 apartment complexes in Daegu, which is located in central South Korea. In another region in central South Korea—Gyeongbuk—Lee and Chae [7] proposed that the main elements affecting energy consumption were the heating method and exterior walls and windows.

2.2. Effects of User Sociology on Energy Consumption

Van den Brom et al. [8] analyzed the actual energy consumption data of 14,000 households to examine how user features affect energy consumption. Schipper et al. [9] and Noh [10] mentioned that the relationship between energy consumption and users varies because the method and pattern of using energy are different depending on a user’s sociology [9,11].

Kim and An [12] considered the types of Korean users and reported that energy consumption was higher as income increased, because users with higher income were more sensitive to changes in their surroundings. Conversely, the energy consumption of users with relatively lower income was more affected by the physical attributes of their buildings, such as building age, than by changes in their surroundings [9].

In residential spaces, energy consumption varies depending on the residence time and lifestyle of household members. Kim et al. [5] proposed that the occupation, type of household members, and number of household members were influential elements [8]. In the case of occupation, office workers consumed more energy than the self-employed. In addition, members with longer residence times consumed more power [13].

Seo et al. [14] reported that power consumption tendency differed depending on the occupants’ income level and the type of residents. Single-person households and families without children consumed less energy, because they were socially and economically more active and thus spent less
time in their houses. However, energy consumption increased upon childbirth, when their residence time and economic activity patterns changed [15].

3. Materials and Methods

Figure 1 shows the research process of this study. First, data from the Household Energy Standing Survey were integrated with the annual regional temperature data of the Korea Meteorological Administration. Second, multiple regression analysis was conducted using the integrated data to obtain the elements affecting energy consumption in each season. Elements found to be influential were then used as input data to construct an ANN model and implement energy consumption prediction models. To accurately derive the elements and construct the prediction model, regression analysis and prediction model construction were conducted for five periods: spring, summer, fall, and winter, as well as annually.

3.1. Household Energy Standing Survey Data

The user data used in this study were collected from the 2016 and 2017 Household Energy Standing Survey, which is conducted annually by the Korea Energy Economics Institute. The survey respondents were from 2520 households in 16 cities and provinces and 3 metropolitan cities, with data on 19 physical housing elements, 14 heating, cooling, and cooking elements, and 14 household and household member elements. The survey also provided the monthly consumption data from 18 energy sources, including general electricity, midnight electricity, and total electricity. It was found that the earlier data were not suitable for integrating and analyzing multi-year data because of limitations in way the composition of items and code disclosure scope were recorded. Therefore, 5040 items of data from 2016 and 2017 were used in this study.

3.2. Seasonal Characteristics in South Korea and their Effects on Energy Consumption

South Korea has four distinct seasons; consequently, different home appliances and energy sources are used in each season. The seasons also affect the length of time residents spend indoors.

Figure 1. Research process.
In spring and fall, residential energy consumption is low, because there are many clear and dry days under the influence of migratory anticyclones. In summer, cooling-related energy consumption increases because the weather is hot and humid under the influence of the North Pacific anticyclone. In winter, heating-related energy consumption increases because the weather is generally cold and dry under the influence of the continental anticyclone [16].

Figure 2 shows the monthly average temperature data of 16 regions in South Korea in 2016 and 2017. In Seoul and Kyunggi-do, the cities with the highest population densities in South Korea, the average annual temperatures were approximately 30.8 and 29.5 °C in 2016, and 31.2 and 30.5 °C in 2017, respectively. The lowest temperature was observed in Kyunggi-do in January 2016, and the highest in Gwangju in July 2017.

Figure 3 shows the seasonal energy consumption data of 4943 households, excluding outliers. It was found that energy consumption was highest in winter. Moreover, energy consumption was high in spring and winter when relatively lower temperatures were observed compared to other seasons. This indicates that heating-related energy consumption significantly affects the total energy consumption of buildings.
Analysis was conducted for each of the four seasons to reflect the influence of energy sources and energy-using devices in each season. Annual energy consumption was examined to identify overall influential elements.

3.3. Derivation of Significant Elements through Multiple Regression Analysis

Machine learning techniques, such as ANNs, can estimate prediction results when trained to predict nonlinear elements. However, it is difficult for them to determine the influence of these elements [17]. In this study, regression analysis was conducted to examine the influence of individual elements and to derive influential elements. The elements found to affect energy consumption were then used as input data to implement the prediction model.

The multiple regression analysis was conducted using SPSS18.0 statistical software. The coefficient \( b_i \) of each variable and the constant term \( a_0 \) of the model were estimated by applying the seasonal energy consumption to the dependent variable \( Y_k \) and substituting the physical characteristics of the building, household characteristics, and seasonal local temperature into independent variables \( x_i \), as shown in Equation (1):

\[
Y_k = a_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n.
\]

(1)

3.4. Prediction of Energy Consumption Using ANNs

According to Neto and Fiorelli [13], simulations and ANNs are both efficient for predicting energy consumption; however, each has its own benefits and drawbacks. In the case of simulation, it is possible to input the operating hours of home appliances by the user, however there are limitations in inputting other detailed information. In the case of ANNs, energy consumption can be predicted by quantifying nonlinear user information [13]. In this study, the ANN method was considered more appropriate to use because a large amount of user information could be integrated and considered.

ANNs are machine-learning algorithms proposed by McCulloch and Pitts [18]. When they were first proposed, implementing the learning models was complicated and there was lack of clear connection between the input and output data. Nevertheless, these issues were solved with the development of deep neural networks (DNNs) that combined the backpropagation algorithm with multi-layers with multiple nodes [19]. Owing to the proposal of new functions and algorithms, as well as improved computer hardware, it is now possible to implement DNN models with one or more hidden layers. DNN models can analyze vast amounts of elements that were previously overlooked for analysis, and it is now possible to implement prediction models to derive outputs through the weight of each node [20].
Figure 4 shows the basic structure of the ANN model described by Equation (2). $R$ is the number of input variables and $S$ is the number of hidden neurons. $p$ represents each input variable, $b$ each hidden layer, and $w$ its weight. The weight of each calculated element is used as the input of the activation function. The output is derived through the sum of the weighted values [15]. The activation function utilized the most commonly used sigmoid function:

$$n^h_k = \sum_{j=1}^{R} w^h_{kj} p_j + b^h_k, k = 1 to S. \quad (2)$$

When an ANN prediction model is created, hidden nodes and layers must be constructed, as shown in Figure 5. As there is no clear standard or methodology for this, it is necessary to find the optimal model with the lowest mean squared error (MSE) value after making as many attempts as possible. For successful learning, the minimum numbers of hidden nodes and layers must be larger than the number of input variables $n$, and the maximum number must not exceed $2n + 1$ [21]. In this study, the ANN model was examined while the number of layers was increased from 1 to 9. In addition, for each number of layers, five cases were created with the minimum number of hidden nodes, the maximum number of hidden nodes, and three intermediate numbers. The model with the lowest MSE, i.e., the highest model performance, was examined.

To verify the performance of the model, three methods were used to construct the household member information input data, and the performance of the three cases were compared. As previously mentioned, influential elements were found through regression analysis. The performance of models using the influential elements as input data were compared to a model that used all the original variables as input data, as well as to a model that used the four household member data derived by a number of previous studies as input data.

The ANN prediction model for residential buildings in South Korea by Whaid and Kim [22] was implemented using 14,260-hour data of 20 apartment complexes in Seoul. Their model used the physical elements of the buildings that had optimal MSE values as input data. Research on a prediction model that integrates user information with the model based on such physical attributes is required.
Lee et al. [15] derived the energy consumption from the same buildings according to the behavioral patterns of the users, and implemented a DNN model for predicting energy consumption through six elements, i.e., gender, age, occupation, income, education level, and length of residency. Their prediction model exhibited 64% accuracy, indicating that the six elements had an impact on energy consumption. As the energy consumption was derived through simulation rather than records of actual energy consumption, the influence of the six elements must be verified through a comparison with the actual energy consumption. In addition, as the research was conducted based on annual energy consumption, it is difficult to determine detailed seasonal consumption and influential elements. It is also necessary to conduct research on different types of residential buildings, such as apartments and detached houses, as the research was based only on multi-family houses.

It is difficult to accurately measure data such as energy consumption in residential buildings owing to its spatiotemporal variability [23]. Data-based models are widely used because they can calculate results through repeated learning, even for cases with limited input variables. ANN techniques are actively used in various areas, as it is easy to identify relationships between different variables, and nonlinear correlations can be analyzed without analyzing the physical phenomena [24].

4. Results and Discussion

4.1. Derivation of Influential Elements

4.1.1. Analysis Process (Multi-Collinearity, Outliers, and Dependent and Independent Variables)

Prior to the analysis, among the 2520 households in 2016 and 2520 households in 2017, the following were removed as outliers: 92 households with unidentifiable data in each item, 2 households located on the 100th or higher floors, and 3 households where there were 4 or more household members aged 65 or older.

The data from all 16 regions comprised 12 physical building elements and 12 user information elements, as shown in Table 1. Regional variables were applied to the analysis to use them as proxy variables that represent the geographic characteristics, social atmosphere, economic characteristics, and annual weather of each region. Among the user information data, the gender, age, education
level, and occupation were analyzed using the information about the household head due to the nature of the data.

Table 1. Data construction, descriptive statistics, and variance inflation factor (VIF) analysis results.

| Code | Variable                  | Category | Mean    | Standard Deviation | N  | Common Difference | VIF |
|------|---------------------------|----------|---------|--------------------|----|-------------------|-----|
| 11   | City                      | Seoul *  |         |                    |    |                   |     |
| 21   | Pusan                     | 0.00647  | 0.24609 | 4943               | 0.703 | 1.423             |
| 22   | Daegu                      | 0.00475  | 0.21282 | 4943               | 0.778 | 1.285             |
| 23   | Incheon                    | 0.00477  | 0.21325 | 4943               | 0.774 | 1.292             |
| 24   | Gwangju                    | 0.00473  | 0.21239 | 4943               | 0.756 | 1.322             |
| 25   | Daejeon                    | 0.00471  | 0.21195 | 4943               | 0.791 | 1.264             |
| 26   | Ulsan                      | 0.00324  | 0.17700 | 4943               | 0.818 | 1.222             |
| 31   | Kyunggi                    | 0.1107   | 0.31374 | 4943               | 0.628 | 1.593             |
| 32   | Kangwon                    | 0.00475  | 0.21282 | 4943               | 0.733 | 1.364             |
| 33   | Chungbuk                   | 0.00453  | 0.20802 | 4943               | 0.744 | 1.345             |
| 34   | Chungnam                   | 0.00637  | 0.24249 | 4943               | 0.667 | 1.500             |
| 35   | Jeonbuk                    | 0.00473  | 0.21239 | 4943               | 0.714 | 1.402             |
| 36   | Jeonnam                    | 0.00627  | 0.24247 | 4943               | 0.676 | 1.479             |
| 37   | Kyungbuk                   | 0.00803  | 0.27181 | 4943               | 0.636 | 1.573             |
| 38   | Kyungnam                   | 0.00807  | 0.27243 | 4943               | 0.626 | 1.598             |
| 39   | Jeju                       | 0.00152  | 0.12225 | 4943               | 0.879 | 1.137             |
| B_a1 | Housing type              |          |         |                    |    |                   |     |
| 1    | Detached                  | 0.3662   | 0.48693 | 4943               | 0.400 | 2.500             |
| 2    | Apartment                 | 0.4574   | 0.49823 | 4943               | 0.226 | 4.433             |
| 3    | Others *                  |          |         |                    |    |                   |     |
| B_a2 | Number of floors          | Numeric  | 8.22    | 7.805              | 4943 | 0.182 | 5.485 |
| B_a3 | Floor number              | Numeric  | 4.34    | 4.943              | 4943 | 0.443 | 2.258 |
| B_a4 | Number of exterior walls  | Numeric  | 4.33    | 1.278              | 4943 | 0.582 | 1.718 |
| B_a5 | Housing direction         |          |         |                    |    |                   |     |
| 1    | East                      | 0.1194   | 0.32425 | 4943               | 0.303 | 3.305             |
| 2    | West                      | 0.00641  | 0.24501 | 4943               | 0.426 | 2.346             |
| 3    | South                     | 0.4200   | 0.49361 | 4943               | 0.162 | 6.189             |
| 4    | North *                   |          |         |                    |    |                   |     |
| 5    | Southeast                 | 0.1993   | 0.39949 | 4943               | 0.224 | 4.473             |
| 6    | Southwest                 | 0.1034   | 0.30448 | 4943               | 0.327 | 30.055            |
| 7    | Northeast                 | 0.03299  | 0.17044 | 4943               | 0.610 | 1.640             |
| 8    | Northwest                 | 0.00190  | 0.13660 | 4943               | 0.694 | 1.440             |
| B_a6 | Construction year         | Numeric  | 3.82    | 1.298              | 4943 | 0.597 | 1.674 |
| B_a7 | Housing area              | Numeric  | 3.17    | 0.867              | 4943 | 0.411 | 2.432 |
| B_a8 | Number of bedrooms (rooms)| Numeric  | 2.72    | 0.728              | 4943 | 0.488 | 20.050 |
| B_a9 | Number of exterior wall windows | Numeric | 8.11 | 3.961 | 4943 | 0.737 | 1.357 |
| B_a10 | Main heating method       |          |         |                    |    |                   |     |
| 1    | Individual                | 0.9092   | 0.28740 | 4943               | 0.785 | 1.274             |
| 2    | Central heating *         |          |         |                    |    |                   |     |
| B_a11 | Cooling method            |          |         |                    |    |                   |     |
| 1    | Air conditioner           | 0.3045   | 0.46023 | 4943               | 0.180 | 5.558             |
| 2    | No air conditioner *      |          |         |                    |    |                   |     |
| B_a12 | Air conditioner set temperature | Numeric | 3.13 | 20.049 | 4943 | 0.160 | 6.239 |
| H_a1 | Number of years occupied  | Numeric  | 10.91   | 8.722              | 4943 | 0.154 | 6.513 |
| H_a2 | Housing ownership         |          |         |                    |    |                   |     |
| 1    | Owned                     | 0.7589   | 0.42782 | 4943               | 0.827 | 1.209             |
| 2    | Not owned *               |          |         |                    |    |                   |     |
| H_a3 | Number of household members | Numeric   | 2.97 | 1.242 | 4943 | 0.487 | 20.054 |
| H_a4 | Number of economically    | Numeric  | 1.45    | 0.767              | 4943 | 0.622 | 1.608 |
Nominal variables were determined by regression analysis through dummy coding. The reference variables of each dummy variable are as follows. The regional variables were based on Seoul, which exhibited the largest temperature changes in 2016 and 2017. In South Korea, as energy efficiency is lowest when a building faces north, coding was performed based on northward facing buildings. Other variables were analyzed based on items for which it was difficult to derive meaningful conclusions when analysis and interpretation were conducted. Variables that were relatively few in number were not applied.

Prior to the analysis, multi-collinearity verification was performed, which could potentially reveal independent variables with high correlations. If multi-collinearity occurs, correlations among independent variables may affect the analysis and lead to wrong results. Consequently, independent variables that have a significant impact on the dependent variable may appear meaningless, or the sign of the regression coefficient may change [25]. The multi-collinearity verification showed that there was no collinearity between the variables, because the variance inflation factor (VIF) value was less than 10 for all items.

Table 2 shows that the regression analysis models for residential energy consumption in the annual period, spring, summer, fall, and winter were appropriate. The Durbin–Watson results were between 1.661 and 1.749; Durbin–Watson numbers close to 2 indicate that there is no autocorrelation. The explanatory power for residential energy consumption, which was the dependent variable of each independent variable, was found to be 12% (annual), 12.5% (spring), 14.2% (summer), 11% (fall), and 12.3% (winter). These values are low compared to previous studies on energy consumption in buildings. This appears to be because user attributes, which are sociological and humanistic elements, were included in the analysis in large quantities.

| H_a5 | Number of household members aged 65 or older | Numeric | 0.47 | 0.743 | 4943 | 0.557 | 1.795 |
| H_a6 | Composition of household members | 1 Children | 0.0500 | 0.21790 | 4943 | 0.756 | 1.322 |
| | 2 No children * | - | - | - | - | - | - |
| H_a7 | Gender of household head | 1 Male | 0.7499 | 0.43309 | 4943 | 0.742 | 1.348 |
| | 2 Female * | - | - | - | - | - | - |
| H_a8 | Age of household head | Numeric | 3.74 | 10.052 | 4943 | 0.486 | 20.056 |
| H_a9 | Education level of household head | 1 High school graduate or below | 0.5855 | 0.49269 | 4943 | 0.624 | 1.602 |
| | 2 University graduate or above * | - | - | - | - | - | - |
| H_a10 | Occupation of household head | 1 Regular employee | 0.4965 | 0.50004 | 4943 | 0.360 | 2.775 |
| | 2 Temporary employee | 0.0558 | 0.22963 | 4943 | 0.770 | 1.298 |
| | 3 Owner operator | 0.2320 | 0.42218 | 4943 | 0.459 | 2.179 |
| | 4 Etc. | - | - | - | - | - | - |
| H_a11 | Unusual features of household | 1 Unusual features | 0.0981 | 0.29750 | 4943 | 0.633 | 1.579 |
| | 2 General * | - | - | - | - | - | - |
| H_a12 | Annual gross income | Numeric | 3.67 | 1.862 | 4943 | 0.426 | 2.347 |

Table 2. Model explanatory power and suitability analysis results.
4.1.2. Elements Affecting Energy Consumption

Table 3 shows the physical elements and user attributes identified through the regression analysis as affecting residential energy consumption annually, as well as in the spring, summer, fall, and winter periods. The detailed results are given in the Appendix Table A1, Table A2 and Table A3 the dummy-coded variables were analyzed through a comparison with the reference group. It was determined that energy consumption increased by the value of the non-standardized coefficient (B) when each of the continuous variables increased by 1.

| Section                   | Code | Variable                      | Spring | Summer | Fall | Winter | Annual |
|---------------------------|------|-------------------------------|--------|--------|------|--------|--------|
| Building factors (12)     | B_a1 | Housing type                  | O      | O      | O    | O      | O      |
|                           | B_a2 | Number of floors              | O      | O      | O    | O      | O      |
|                           | B_a3 | Floor number                  |        |        |      |        |        |
|                           | B_a4 | Number of exterior walls      | O      | O      | O    | O      | O      |
|                           | B_a5 | Housing direction             | O      | O      | O    | O      | O      |
|                           | B_a6 | Construction year             |        |        |      |        |        |
|                           | B_a7 | Housing area                  | O      | O      | O    | O      | O      |
|                           | B_a8 | Number of bedrooms (rooms)    |        |        |      |        |        |
|                           | B_a9 | Number of exterior wall windows|      |        |      |        |        |
|                           | B_a10| Main heating method           | O      | O      | O    | O      | O      |
|                           | B_a11| Cooling method                | O      | O      | O    | O      | O      |
|                           |     | Air conditioner set temperature| O      | O      | O    | O      | O      |
| User features (12)        | H_a1 | Number of years occupied      | O      | O      | O    | O      | O      |
|                           | H_a2 | Housing ownership             | O      | O      | O    | O      | O      |
|                           | H_a3 | Number of household members   | O      | O      | O    | O      | O      |
|                           | H_a4 | Number of economically active household members | O      | O      | O    | O      | O      |
|                           | H_a5 | Number of household members aged 65 or older | O      | O      | O    | O      | O      |
|                           | H_a6 | Composition of household members | O      | O      | O    | O      | O      |
|                           | H_a7 | Gender                        | O      | O      | O    | O      | O      |
|                           | H_a8 | Age of household head         | O      | O      | O    | O      | O      |
|                           | H_a9 | Education level of household head | O      | O      | O    | O      | O      |
|                           | H_a10| Occupation of household head  | O      | O      | O    | O      | O      |
|                           | H_a11| Unusual features of household | O      | O      | O    | O      | O      |
|                           | H_a12| Annual gross income           | O      | O      | O    | O      | O      |

In addition to the regional variables, it was found that among the physical elements of the building, the number of exterior walls, housing direction, and housing area were influential in all seasons. Among the user attributes, the number of years occupied, number of household members, and occupation of household head were found to be influential in all seasons. Figures 6–11 show the annual and seasonal energy consumption distribution charts for these six elements.

Figure 6 shows the seasonal energy consumption distribution charts for the number of exterior walls. Exterior walls refer to walls that directly face the outside air. The number of exterior walls is a continuous variable, from 0 (for the basement) to 6. As shown in the figure, energy consumption showed a tendency to increase as the number of exterior walls increased, because exterior walls are vulnerable to insulation and release heat to the surroundings [19].
The housing direction is the direction that the front of the building faces. In South Korea, it is usually determined based on the position of the living room [26]. This is because Korean users spend a considerable amount of time in the living room. In South Korea, north-facing walls have the lowest daily average solar radiation, resulting in low energy efficiency. Hence, houses are usually designed to avoid the north. The reference variable therefore considered buildings in a north facing direction. The analysis results in Figure 7 show that energy consumption was highest in the northwest direction and lowest in the south direction. This indicates that the northwest direction is more vulnerable to residential energy consumption than the north direction, which is the reference variable, in South Korea.
In South Korea, the “pyeong” unit is usually used in calculating the area of a building. 1 pyeong corresponds to 3.3 m². Five groups were prepared with intervals of 33 m² (10 pyeong) to analyze the effect of housing area. As the area relates to the volume of the building and therefore the volume of internal air, buildings with larger areas are more vulnerable to energy consumption [27]. Figure 8 shows that energy consumption generally increased as the building area increased.
Figure 8. Seasonal energy consumption according to building area: (a) annual; (b) spring; (c) summer; (d) fall; (e) winter.

Time-related variables, such as construction year and number of years occupied, may form a curved distribution. In such cases, general regression analysis for analyzing linear samples may not produce significant results. Nevertheless, regression analysis can be used if the data is converted to a linear distribution by squaring the value of each point. In the case of the construction year, significant results were not obtained. However, for the number of years occupied, a point of inflection
appeared between 4 and 6 years, as shown in Figure 9, indicating that the variable had a curve-type distribution. This suggests that energy consumption increases with an increase in number of years occupied up to 4–6 years, but decreases afterward.
Energy consumption increases as the number of household members increases, because there are more users that directly consume energy. As shown in Figure 10, energy consumption showed a tendency to increase as the number of household members increased in the annual period and all seasons. Moreover, the number of household members appear to be more influential in winter and spring, when energy related to heating and hot water are consumed more frequently, than in summer, when cooling-related energy is consumed.
Figure 10. Seasonal energy consumption according to the number of household members: (a) annual; (b) spring; (c) summer; (d) fall; (e) winter.

For ordinary households in South Korea, the household head is responsible for all household members. The occupation of the household head was applied as occupational data in this study; the occupation was classified as regular employees, temporary employees, business owners, and others. The analysis results showed that business owners had an influence on energy consumption in most periods as shown in Figure 11. This is because many business owners in South Korea use homes for business and residence, and thus their residence time is longer than that of other occupations.
Figure 11. Seasonal energy consumption according to the occupation of household head: (a) annual; (b) spring; (c) summer; (d) fall; (e) winter.

In addition to the six common influential elements, the elements that had an influence in each season are as follows. The temperature was found to be more influential in spring and fall when considered in a comprehensive manner. Detached houses were found to be more vulnerable to higher energy consumption in all periods other than spring. Energy consumption showed a tendency to increase for all seasons as buildings became older, but the influence of building age was lower than that of other elements on an annual basis. The number of exterior walls was only influential in winter and annual periods, while the main heating method was influential in the spring, summer, and fall. The cooling method was influential in summer, fall, and the annual period, and energy consumption was affected by the air conditioner set temperature in fall and winter. Occupant gender had an influence on energy consumption in fall, winter, and the annual period, and the unusual features of household were influential in summer and winter. The annual gross income was influential in all periods except fall. Several elements exhibited an influence in specific seasons. In summer, energy consumption varied depending on the number of bedrooms and the number of household members aged 65 or older. In fall, it varied depending on the composition of household members. In winter, the number of floors, the age of household head, and the education level of the household head were found to be influential.

4.2. Energy Consumption Prediction Model
4.2.1. Input/Output Data

The ANN model was constructed for five periods (annual, spring, summer, fall, and winter). Elements that were found to be influential in each season were selected as input variables for the analysis. In the case of nominal variables, the ANN model was constructed by including the reference group as input variables after performing dummy coding. When the input variables of each model were examined based on the significant elements, it was found that the number of input variables were as follows: 42 for the annual model, 38 for the spring model, 46 for the summer model, 47 for the fall model, and 48 for the winter model.

As shown in Table 4, 4943 data were used for the analysis, excluding outliers. Among them, 3461 data were used for training, 741 for validation, and 741 for testing.

| No. of Samples | Training | Validation | Testing |
|----------------|----------|------------|---------|
| 4943           | 70%      | 15%        | 15%     |
| 3461           | 741      | 741        |         |

4.2.2. Hidden Layer and Node

Table 5 shows six cases with the highest model performances for each seasonal prediction model according to the number of layers. Gradient vanishing, in which prediction models cannot be used when the number of layers exceeds the number presented in the table, occurred.

| Period | Min | Max | Layer | Neuron | R Value of Training | R Value of Validation | R Value of Test | MSE | Terminated Epoch |
|--------|-----|-----|-------|--------|---------------------|-----------------------|-----------------|-----|------------------|
| Annual | 42  | 85  | 1     | 70     | 0.257               | 0.303                 | 0.278           | $10^7 \times 2.5250$ | 12th |
|        | 2   | 35  | 2     | 47     | 0.351               | 0.279                 | 0.306           | $10^7 \times 2.7545$ | 5th  |
|        | 3   | 21  | 3     | 21     | 0.419               | 0.299                 | 0.312           | $10^7 \times 3.4674$ | 5th  |
|        | 4   | 11  | 4     | 11     | 0.361               | 0.288                 | 0.262           | $10^7 \times 2.6649$ | 4th  |
|        | 5   | 13  | 5     | 13     | 0.427               | 0.270                 | 0.272           | $10^7 \times 2.8077$ | 7th  |
|        | 6   | 14  | 6     | 14     | 0.535               | 0.348                 | 0.256           | $10^7 \times 3.1436$ | 12th |
|        | 1   | 47  | 7     | 47     | 0.363               | 0.296                 | 0.235           | $10^6 \times 2.6339$ | 14th |
|        | 2   | 24  | 8     | 24     | 0.391               | 0.284                 | 0.279           | $10^6 \times 2.5981$ | 5th  |
|        | 5   | 8   | 9     | 8      | 0.477               | 0.312                 | 0.246           | $10^6 \times 2.7300$ | 7th  |
|        | 6   | 12  | 10    | 12     | 0.457               | 0.256                 | 0.331           | $10^6 \times 2.7304$ | 4th  |
|        | 7   | 6   | 11    | 6      | 0.376               | 0.283                 | 0.324           | $10^6 \times 2.7068$ | 8th  |
|        | 8   | 7   | 12    | 7      | 0.404               | 0.278                 | 0.317           | $10^6 \times 2.6193$ | 9th  |
| Spring  | 38  | 77  | 1     | 58     | 0.322               | 0.315                 | 0.283           | $10^7 \times 5.3157$ | 12th |
|        | 2   | 23  | 2     | 54     | 0.543               | 0.264                 | 0.243           | $10^7 \times 7.9380$ | 5th  |
|        | 3   | 16  | 3     | 16     | 0.382               | 0.318                 | 0.270           | $10^7 \times 5.1060$ | 7th  |
|        | 4   | 17  | 4     | 17     | 0.382               | 0.247                 | 0.213           | $10^7 \times 6.1292$ | 2nd  |
| Summer  | 46  | 93  | 5     | 58     | 0.322               | 0.315                 | 0.283           | $10^7 \times 5.3157$ | 12th |
|        | 2   | 23  | 6     | 23     | 0.543               | 0.264                 | 0.243           | $10^7 \times 7.9380$ | 5th  |
|        | 3   | 16  | 7     | 16     | 0.382               | 0.318                 | 0.270           | $10^7 \times 5.1060$ | 7th  |
|        | 4   | 17  | 8     | 17     | 0.382               | 0.247                 | 0.213           | $10^7 \times 6.1292$ | 2nd  |
4.2.3. ANN Simulation Result

Figure 12 shows the R-values of the training, validation, and test data of the highest performing annual energy consumption prediction model. The R-value was found to be 0.25745 for the training data, 0.30359 for the validation data, and 0.27886 for the test data. The MSE value was $10^7 \times 2.5250$. This model had one layer and 70 nodes. It was found that the neural network (NN) model exhibited the highest performance.

![Figure 12](image)

Figure 12. Annual energy consumption prediction model (layer: 1, node: 70); (a) Training data regression result; (b) Validation data regression result; (c) Test data regression result.

Figure 13 shows the R-values of the training, validation, and test data of the highest performing spring energy consumption prediction model. The R-value was found to be 0.39154 for the training data, 0.28441 for the validation data, and 0.27986 for the test data. The MSE value was $10^6 \times 2.5981$.

![Figure 13](image)
and the model had two layers and 24 nodes. It was found that the DNN model with two layers exhibited the highest performance.

![Figure 13](image13.png)

**Figure 13.** Spring energy consumption prediction model (layer: 2, node: 24); (a) Training data regression result; (b) Validation data regression result; (c) Test data regression result.

Figure 14 shows the R-values of the training, validation, and test data of the highest performing summer energy consumption prediction model. The R-value was 0.38204 for the training data, 0.31832 for the validation data, and 0.27092 for the test data. The MSE value was $10^5 \times 5.1060$, and the model had three layers and 16 nodes. It was found that the DNN model with three layers exhibited the highest performance.

![Figure 14](image14.png)

**Figure 14.** Summer energy consumption prediction model (layer: 3, node: 16); (a) Training data regression result; (b) Validation data regression result; (c) Test data regression result.

Figure 15 shows the R-values of the training, validation, and test data of the highest performing fall energy consumption prediction model. The R-value was 0.33652 for the training data, 0.2783 for the validation data, and 0.21787 for the test data. The MSE value was $10^6 \times 1.4318$, and the model had one layer and 47 nodes. It was found that the NN model with one layer exhibited the highest performance.

![Figure 15](image15.png)

**Figure 15.** Fall energy consumption prediction model (layer: 1, node: 47); (a) Training data regression result; (b) Validation data regression result; (c) Test data regression result.
Figure 15. Fall energy consumption prediction model (layer: 1, node: 47); (a) Training data regression result; (b) Validation data regression result; (c) Test data regression result.

Figure 16 shows the R-values of the training, validation, and test data of the highest performing winter energy consumption prediction model. The R-value was 0.28741 for the training data, 0.23453 for the validation data, and 0.21289 for the test data. The MSE value was $10^6 \times 5.7602$. This model had two layers and 24 nodes. It was found that the DNN model with two layers exhibited the highest performance.

Figure 16. Winter energy consumption prediction model (layer: 2, node: 24); (a) Training data regression result; (b) Validation data regression result; (c) Test data regression result.

For the annual and fall periods, the performances of the NN models with one layer were found to be excellent. However, the DNN models with two or more layers did not have significantly different MSE values. This indicates that if a sufficient amount of data from the Household Energy Standing Survey were used, the model performance would be improved and the application of DNN models will be possible.

Table 6 compares models with three input data types. The type A prediction models were constructed by conducting regression analysis on the household information elements of the original data, with the influential elements from each season set as input data. The type B prediction models were constructed using all 12 sets of household data as input data for all seasons. The type C prediction models were constructed by applying elements commonly derived as influential elements in previous studies as input data, i.e., the income, number of household members, occupation, composition of household members, etc.

Table 6. Performances of seasonal energy consumption prediction models according to the input data type.
To compare standards for household information, influential elements for each season were applied to models A, B, and C in the same manner as the physical elements of buildings. The same numbers of layers and neurons were also applied to types A, B, and C to control the influence of other factors except the input data of the model. The analysis results showed that type A, which used significant household information as input data in all seasons through regression analysis, exhibited the highest model accuracy. For type B, which used the original data, gradient vanishing occurred in the spring and summer models. Type C had higher prediction accuracy than type A, except in the annual period; however, there was a significant difference in prediction accuracy between the training and test models, resulting in an overfitting problem.

Based on the comparison and analysis results of each model, it was found that identifying the most significant variables through regression analysis could improve model performance, especially when variables that are difficult to quantify, such as household information, are included as input data.

5. Conclusions

An increasing number of studies have been conducted on the energy consumption of residential buildings. This study is different from previous studies in three aspects. First, this study was conducted based on the actual energy consumption of residential buildings in South Korea. Furthermore, the elements were derived by integrating the physical information of buildings with user information and reflecting mutual influence. Finally, energy consumption prediction models were implemented by dividing energy consumption into four seasons and deriving influential elements for each season.

This study found that user information has as much influence on energy consumption as the physical elements of buildings. In each season, the influence of the physical characteristics of buildings and household characteristics as well as the importance of each element was identified. The three representative elements that exhibited the highest influence in each season are as follows.

1. In spring, the building direction was found to be the most influential element, followed by the occupation and cooling method. Buildings facing northwest—the direction with the lowest annual average solar radiation—exhibited the highest energy consumption. Buildings inhabited by business owners, who typically have longer residence times than other occupations, also consumed more energy. Households that used air conditioners for cooling consumed more energy.

2. In summer, the heating method was the most influential, followed by the cooling method and housing area. For residential buildings in South Korea, individual heating and central heating are the two representative heating methods. Households with individual heating were found to consume more energy. Heating energy was mostly concentrated on the use of hot water in
...summer, indicating that individual heating was more vulnerable to the use of energy related to hot water. As in spring, households that used air conditioners consumed more energy, as did households with larger areas.

3. In fall, the housing area was the most influential factor, followed by the housing type and occupation. Households with larger areas consumed more energy, as did detached houses that managed energy individually. As in spring, buildings inhabited by to business owners exhibited the highest energy consumption.

4. In winter, the building direction was the most influential, followed by the housing area and occupation. As in spring, the northwest direction with the lowest solar radiation exhibited the highest energy consumption. As the housing area increased, energy consumption increased. As for the occupation, to business owners with the longest residence time exhibited the highest energy consumption, as in spring and fall.

As seen above, different elements affected energy consumption in each season. The various elements had different influences depending on the season. This must be reflected when preparing systematic energy saving and management measures in the future. Providing data on seasonal energy usage will be possible when people with households displaying specific features will live in the target residential area. If enough information is obtained via matching these users with residential buildings, more sophisticated policies can be implemented, and greater awareness of energy use can be aroused individually. Such measures could be further developed by adding impact-reflecting factors and expanding the scope of the analysis in order to continuously reduce energy.

The suitability of the energy consumption prediction models implemented in this study was compared through a comparison of three types. For type A, a prediction model was constructed using the influential variables of each season derived through regression analysis as input data. For type B, a prediction model was constructed using the four representative user information elements derived in previous studies, i.e., the income, occupation, composition of household members, and number of household members. For type C, a prediction model was constructed using all the household information included in the original data. When the models were compared, it was found that type A exhibited the highest suitability. This indicates that prediction models with a higher performance can be implemented by verifying the influence of individual elements through regression analysis. It can then be applied to future prediction models that measure how atypical data affects energy consumption, such as the household member information. Predictive models of type B can identify influential factors and provide information that can be utilized when drafting a plan for continuous energy reduction from simple usage forecasting. Based on the influence of these individual factors, it is possible to formulate countermeasures in related fields when developing sustainable energy saving measure.

Currently, in South Korea, when evaluating the energy impact of users and buildings, the post-occupancy evaluation (POE) method is used to evaluate the energy impact of users and buildings. If the energy impact of the building and the user can be predicted using the model such as the one proposed in this study, a novel form of energy impact assessment can be conducted. Such assessments can reduce the unreasonable energy consumption of post-occupancy assessments and, furthermore, provide a way to create customized energy-saving residential spaces provided by both, the state or by individuals to create their own living environments.

In the model of this study, although the prediction rate increased by using only influential factors through regression analysis, the performance of the predictive model was limited because only two years’ worth of data were used. However, the dataset used in this study, the Household Energy Standing Survey, is conducted annually; hence, the current limitations owing to this lack of data will be eventually overcome.

The seasonal influential elements derived in this study are expected to be utilized as basic elements that can be used for further research on more accurate energy prediction if they are integrated with the information on detailed climate and building information, such as microclimate information, and information on the ownership and usage of home appliances. Such attempts will be useful as basic research to derive and predict common elements that have an influence on energy
consumption on a national level, beyond residential energy research in the scope of single buildings and survey-based investigations in small areas.

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### Appendix A

**Table A1.** Results of deriving elements that affect energy consumption in the annual period and spring.

|                  | Unstandardized Coefficient | Standardized Coefficient | t     | p     | Unstandardized Coefficient | Standardized Coefficient | t     | p     |
|------------------|-----------------------------|--------------------------|-------|-------|-----------------------------|--------------------------|-------|-------|
|                  | B (Standard Error)          |                         |       |       | B (Standard Error)          |                         |       |       |
| item             | 0.357 (20.728 0.000)        | 0.017 (0.986)            | 430.039 (14.879 0.051) | 2.893 *** (0.000 0.004) |
| cityD2           | -1814.663 (364.398)         | -4.980 *** (0.000)       | -907.482 (113.356) | -0.128 *** (0.000) |
| cityD3           | -1016.515 (400.446)         | -2.538 ** (0.011)        | -391.367 (126.351) | -0.048 *** (0.002) |
| cityD4           | 814.586 (400.820)           | 20.032 ** (0.042)        | 308.361 (127.427) | 0.038 ** (0.016) |
| cityD5           | -11310.071 (4070.010)       | -2.779 *** (0.005)       | -741.729 (126.291) | -0.090 *** (0.000) |
| cityD6           | -7080.094 (398.812)         | -1.776 (0.076)           | -300.561 (124.220) | -0.036 ** (0.016) |
| cityD7           | 433.798 (469.603)           | 0.924 (0.356)            | -83.532 (145.999) | -0.008 0.567 |
| cityD8           | 291.769 (302.461)           | 0.965 (0.335)            | -830.080 (94.586) | -0.015 0.380 |
| cityD9           | 2138.199 (412.616)          | 5.182 (0.000)            | 219.506 (129.448) | 0.027 1.696 *0.090 |
| cityD10          | -1339.813 (419.101)         | -3.197 (0.001)           | -508.758 (130.348) | -0.061 3.903 *** |
| cityD11          | -40.925 (376.899)           | -0.109 (0.914)           | -509.335 (124.624) | -0.071 40.087 *** |
| cityD12          | 271.929 (410.089)           | 0.649 (0.516)            | -376.520 (138.285) | -0.046 2.723 *** |
| cityD13          | -9540.095 (3770.056)        | -2.530 (0.011)           | -805.814 (119.814) | -0.112 6.726 *** |
| cityD14          | -260.189 (346.897)          | -0.750 (0.453)           | -297.113 (109.483) | -0.046 2.714 *** |
| cityD15          | -1647.383 (348.892)         | -4.722 (0.000)           | -751.381 (109.655) | -0.117 6.852 *** |
| cityD16          | -30600.076 (655.856)        | -4.666 (0.000)           | -1345.139 (202.957) | -0.094 6.628 *** |
| B_a1D1           | 732.460 (244.133)           | 0.064 (0.000)            | 76.721 (75.923) | 0.021 10.011 0.312 |
| B_a1D2           | -734.310 (317.726)          | -2.311 (0.021)           | 117.963 (98.802) | 0.034 1.194 0.233 |
| B_a2             | 33.173 (22.561)             | 1.470 (0.142)            | 2.494 (70.016) | 0.011 0.356 0.722 |
| B_a3             | -12.186 (22.855)            | -0.533 (0.594)           | -3.610 (7.105) | -0.010 5.08 0.611 |
| B_a4             | 269.490 (77.128)            | 3.494 (0.000)            | 81.979 (240.000) | 0.060 3.416 *** |
| B_a5D1           | -308.573 (421.521)          | -0.018 (0.464)           | -156.118 (1310.077) | -0.029 -1.191 0.234 |
| B_a5D2           | 173.711 (4700.051)          | 0.008 (0.370)            | 51.469 (146.164) | 0.007 0.352 0.725 |
### Table A2. Results of deriving elements that affect energy consumption in summer and fall.

| Item        | Summer          | Fall            | Summer          | Fall            |
|-------------|-----------------|-----------------|-----------------|-----------------|
|             | Unstandardized  | Standardized    | Unstandardized  | Standardized    |
|             | B               | Error           | B               | Error           |
|             | t               | p               | t               | p               |
| cityD2      | -30.604         | 35.397          | -0.009          | -0.074          |
| cityD3      | -9.140          | 58.628          | -0.020          | -0.156          |
| cityD4      | 2360.065        | 58.826          | 0.061           | 0.041           |
| cityD5      | 340.312         | 59.359          | 0.087           | 0.533           |
| cityD6      | 47.889          | 58.428          | 0.012           | 0.820           |
| cityD7      | 391.711         | 68.883          | 0.083           | 0.568           |
| cityD8      | 103.617         | 44.592          | 0.039           | 0.232           |
| cityD9      | 185.195         | 60.793          | 0.047           | 0.533           |
| cityD10     | 35.501          | 56.874          | 0.001           | 0.063           |
| cityD11     | 240.007         | 61.551          | 0.042           | 0.266           |
| cityD12     | 162.858         | 55.292          | 0.047           | 0.294           |
| cityD13     | -46.584         | 50.822          | -0.015          | -0.917          |

Note. * 90% Confidence interval (p-value < 0.10), ** 95% Confidence interval (p-value < 0.05), *** 99% Confidence interval (p-value < 0.01).
Table A3. Results of deriving elements that affect energy consumption in winter.

| Winter | Unstandardized Coefficient | Standard Error | Standardized Coefficient | t   | p    |
|--------|-----------------------------|----------------|--------------------------|-----|------|
| item   | -0.723                      |                |                          | -0.001 | -0.043 | 0.966 |
| city2D | -0.290.038                  | 197.362        | -0.072                   | -40.018*** | 0.000 |
| city3D | -363.774                    | 199.398        | -0.028                   | -1.824 * | 0.068 |
| city4D | 158.162                     | 202.879        | 0.012                    | 0.708 | 0.436 |
| city5D | -114.696                    | 223.802        | -0.089                   | -5.106 *** | 0.000 |
| city6D | -371.881                    | 197.825        | -0.029                   | -1.880 * | 0.060 |
| city7D | -113.413                    | 243.285        | -0.007                   | -0.466 | 0.641 |
| city8D | 179.269                     | 1510.027       | 0.021                    | 1.187 | 0.235 |
| city9D | 738.232                     | 214.639        | 0.058                    | 3.439 *** | 0.001 |
| city10D| -581.945                    | 213.632        | -0.045                   | -2.724 ** | 0.006 |
| city11D| 263.793                     | 192.844        | 0.024                    | 1.368 | 0.171 |
| city12D| 118.786                     | 218.915        | 0.009                    | 0.543 | 0.587 |
| city13D| -546.911                    | 195.663        | -0.049                   | -2.795 ** | 0.005 |
| city14D| -72.352                     | 188.881        | -0.07                    | -0.383 | 0.702 |
| city15D| -758.888                    | 184.372        | -0.076                   | -4.116 *** | 0.000 |
| city16D| -1399.103                   | 341.562        | -0.061                   | -5.979 *** | 0.000 |
| B_a1D  | 432.979                     | 118.122        | 0.078                    | 3.666 *** | 0.000 |
| B_a2   | -761.329                    | 153.708        | -1.40                    | -4.953 ** | 0.000 |
| B_a2   | 22.486                      | 10.915         | 0.065                    | 2.060 ** | 0.039 |

Note. * 90% Confidence interval (p-value < 0.10). ** 95% Confidence interval (p-value < 0.05). *** 99% Confidence interval (p-value < 0.01).
\( B_{a3} \) -11.662 110.057 -0.021 -10.0550.292
\( B_{a4} \) 105.273 37.345 0.050 2.819 ** 0.005
\( B_{a5D1} \) -24.133 203.936 -0.003 -0.118 0.906
\( B_{a5D2} \) 179.642 227.420 0.016 0.790 0.430
\( B_{a5D3} \) -255.944 183.316 -0.046 -1.396 0.163
\( B_{a5D4} \) -203.349 192.537 -0.030 -1.056 0.291
\( B_{a5D5} \) -143.873 208.770 -0.016 -0.689 0.491
\( B_{a5D6} \) -2.363 273.268 0.000 -0.027 0.979
\( B_{a5D7} \) 1141.306 319.547 0.057 3.572 *** 0.000
\( B_{a6} \) -86.223 36.265 -0.041 -2.286 ** 0.017
\( B_{a7} \) 256.882 65.425 0.082 3.926 *** 0.000
\( B_{a8} \) 18.179 71.536 0.005 0.254 0.799
\( B_{a9} \) 340.052 10.677 0.020 1.384 0.166
\( H_{a2D1} \) 129.345 93.428 0.040 2.819 *** 0.005
\( H_{a3} \) 185.219 41.961 0.085 4.414 *** 0.000
\( H_{a4} \) -54.963 60.132 -0.016 -0.914 0.361
\( H_{a5} \) 560.098 65.579 0.015 8.855 0.392
\( H_{a6D1} \) 6.379 191.959 0.001 0.033 0.973
\( H_{a7D1} \) 175.735 97.560 0.028 1.801 * 0.072
\( H_{a8} \) 103.519 49.491 0.040 2.092 ** 0.037
\( H_{a9D1} \) -172.529 93.428 -0.031 -1.847 * 0.065
\( H_{a10D1} \) 64.811 121.169 0.012 0.532 0.598
\( H_{a10D2} \) 151.951 180.518 0.013 0.842 0.400
\( H_{a10D3} \) 371.304 127.200 0.058 2.919 *** 0.004
\( H_{a11D1} \) -94.230 153.444 -0.010 -0.614 0.539
\( H_{a12} \) 77.452 29.931 0.053 2.588 ** 0.010

Note. * 90% Confidence interval (p-value < 0.10). ** 95% Confidence interval (p-value < 0.05). *** 99% Confidence interval (p-value < 0.01).

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