Development and Application of Impact Structure Analysis Model on CO2 Emissions Affected by the Characteristics of Urban Spatial Structure

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Abstract

This study has intended to develop and apply the impact structure analysis model on CO_2 emissions affected by the characteristics of urban spatial structure. To reach the goal, this study defined the concept of urban spatial structure and found the characteristics of urban spatial structure through literature review. Second, this study established a greenhouse gas inventory for 107 municipalities and calculated the amount of CO_2 emissions following IPCC guidelines. Third, this study selected the factors of urban spatial structure characteristics, classified city types using cluster analysis, and verified the differences of the amount of CO_2 emissions between groups. Finally, this study developed the impact structure analysis model and applied it to the 107 municipalities using a structural equation model.

As a result, this study has found the following results. First, among the urban spatial structure characteristics, the number of households using bus, population density, apartment residency ratio, financial self-reliance ratio, employment number, and senior population ratio showed negative relationship CO_2 emissions reduction per capita. In contrast, the number of automobiles, the total length of roads, and the number of houses positive relationship with CO_2 emissions.

Second, as for the causal relationship of high-density development with CO_2 emissions, this study has found that high-density development was positively related to CO_2 emissions reduction per capita.

Third, the characteristics of private house ownership and private automobile centrality directly increased the CO_2 emissions and indirectly increased the CO_2 emissions by suppressing high-density development.

Fourth, CO_2 emissions from oil were most affected by spatial characteristics, followed by physical characteristics, city types, and social characteristics. By contrast, CO_2 emissions from electricity were most affected by physical characteristics, followed by social characteristics, spatial characteristics, and city.

Fifth, city types had direct effects on all spatial, physical, economic, and human-social characteristics and indirect effects on CO_2 emissions from oil and electricity.

Future researches must consider the social cost and predicted changes in CO_2 emissions to suggest most efficient CO_2 emissions reduction policy.

Keyword: Characteristics of Urban Spatial Structure, Carbon Dioxide, Structural Equation

1. Introduction

Carbon dioxide (CO_2) generated from the combustion of fossil fuels is a major cause of climate change due to global warming (IPCC, 2007). Climate change affects socioeconomic factors including human health, living conditions, and industrial activities, as well as the natural ecosystem. It has already been identified that energy generation creates the majority of CO_2 emitted (Korea Energy Management Corporation, 2011; IEA, 2011). With this in mind, research investigating the close relationship between urban spatial structure and energy consumption continues, with an increase in research on finding the most efficient urban spatial structure for reduced energy consumption (Rickaby et al., 1992; Bae and Richardson, 1993; Frank et al., 2000, Norman et al., 2006; Reckien et al., 2007; Stone et al., 2007; Kadian et al., 2007; Dodman, 2009; Dhakal, 2009; Hankey et al., 2010; Glaeser and Kahn, 2010; Sovacool and Brown, 2010; Poumanyvong and Kaneko, 2010; Liu and Sweeney, 2012; Sarzynski, 2012).

Although the accumulated research results indicate that in terms of urban spatial structure, high-density cities reduce energy consumption and air pollution, research on the relationship between density and energy consumption does not show consistent results. This is because previous researches have studied the relationship between energy consumption and urban city structure without considering certain characteristics of it. Prior studies of urban spatial arrangement for CO_2 emissions reduction have tended to be idealistic mathematical theory based on the assumption of purely geometric urban forms (such as a single center) (Mills and Song, 1979; Chae, 1997; Kim and Jeong, 2001; Jeong, 2003) or one that still in the level of effects model research which does not reflect the specific space arrangement only by analyzing the influencing relationship between independent and dependent variables although it is based on the positive data (Muniz and Galindo, 2005; Hwang et al., 2001; Yoo, 2005; Nam et al., 2005; Woudsma et al., 2008 ; Choi et al., 2007; Koo et al., 2009). Domestic research mainly concentrated on transport energy consumption and characteristics of urban spatial structure, with a scant amount of analysis of the actual proof of how urban spatial structure influences CO_2 emissions (Koo et al., 2009; Kim, 1984; Kim, 2003; Kim, 2011; Ahn, 1998; Soan et al., 2008; Cho, 2009; Cha, 2008; Hwang et al., 2001; Kim et al., 2009; Shim, 2000; Lee, 2000; Lee, 2011).

Thus, in order to understand the influence that characteristics of urban spatial structure have on CO_2 emissions, a comprehensive approach based on the concept of "structuralism," considering both the parts and the whole, has to be taken.

Hence, this research can be presented in three detailed objectives as follows : 1) To identify the characteristics of urban spatial structure that affect CO_2 emission, 2) To classify the city type depending on the characteristics of urban spatial structure, and 3) To develop and apply the analysis model of impact structure of how characteristics of urban spatial structure affect CO_2 emissions.

2. Literature Review

2.1 Characteristics of Urban Spatial Structure

Prior to examine the characteristics of urban spatial structure, the components of urban spatial structure need to be examined. Same as the concept of urban spatial structure is defined in several different ways, the components of urban spatial structure are classified into various classes and contents depending on the scholars or analysis objectives. (Lee, Jae-Sub, 2011).

First, Kevin Lynch (1960) classified five components of a city: are path, district, node, edge and land mark. He delineates that when these constituents are arranged in balance, the city can give good impressions (Kim, 1991). Simons (1965) classified artificial and natural elements, and said that natural elements; major elements: geographical factors and natural phenomenon, the direction of natural forces can be altered to a certain degree by the human which is he classified as the minor element. Foley (1964) divides factors by values or society, functional factor, and factors in materialsitic form, and Bourne (1982) classified decision elements into notification form, facilities and interactions between activities, and above elements as an organized mechanism. G. Eckbo (1978) viewed urban spatial structure as an affiliated from of these three elements: open space, structure and nature. Besides, he discerned abstract element into dimension, time, energy then specific elements into light, land, road and utility and landscape elements, saying these components are formed with unity, order, harmony and balance. Catanese and snyder (1979) said urban spatial structure needs to be understood as total transformation that accompanying physical, spatial, social, economical and political changes in the city. Kim Hyung Guk (1981) said when viewing the urban spatial structure as a single system, non-spatial factors such as social, economical and political factors become causes for the change in physical and spatial urban spatial structure. Yun Jung Sub (1982) classified land, population and facility as the three elements and Hwang Yong Ju (1984) divides them into citizens, activities, lands, facilities and others.

We discovered that the components of the urban spatial structure are interdependent and have a complementary relationship with each other. This is because components making up the urban spatial structure interact to adapt to changing conditions in time, thus causing the characteristics of the urban spatial structure to appear. Thus, the characteristics of the urban spatial structure also have an interdependent relationship. Depending on which characteristics are more dominant, urban spatial structures can have a spatial dispersion pattern. The characteristics of the urban spatial structure can be classified by these dispersion patterns. That is, characteristics of the urban spatial structure indicate the interactivity between urban components can be understood through the mechanism yielding the urban spatial structure. Understanding an urban spatial structure according to its characteristics enables indirect emissions structures as well as indirect ones found in CO_2 emission.

Thus, this research intends to provide criteria that can be used to measure urban spatial structures along with concepts or criteria presented so far. Based on previous studies, the concepts of the urban spatial structure are defined in Table 1 and four characteristics of the urban spatial structure are drawn.

Table 1 Defined Concepts of Urban Spatial Structure

Classification	Characteristic	Meaning
Organic structure where the base and components of cities form urban types and are shown in the interaction of urban activities	Physical Characteristics (macroscopic form)	The degree to which components making up the cities developed in the space distribution or macroscopic form
	Spatial Characteristics (internal from)	The degree to which components making up the city formed depending on the degree of organization as regions within the city, such as space distribution or form
	Human and Social Characteristics (Social interaction)	The degree to which the patterns by interaction of cities are shown as social and cultural Characteristics
	Economic Characteristics	The ability to produce, distribute, and consume the goods or labor needed to form the city

In this research, the concept of the urban spatial structure was defined as organic structure where the base and components of cities form urban types and are shown in the interaction of urban activities. According to this, characteristics of the urban spatial structure generally fall into one of four categories. The degree to which components making up the cities developed in the space distribution or macroscopic form are "physical characteristics." The degree to which components making up the city formed depending on the degree of organization as regions within the city, such as space distribution or form, are "spatial characteristics." The degree to which the patterns by interaction of cities are shown as social and cultural characteristics are "human and social characteristics." The ability to produce, distribute, and consume the goods or labor needed to form the city are "economic characteristics."

2.1 Previous Studies

Various studies analyzing the relationship between energy consumption in cities and urban spatial structures have been conducted since the 1990s, which offer two conflicting views (Rickaby et al., 1992; Bae and Richardson, 1993; Frank et al., 2000, Norman et al., 2006; Reckien et al., 2007; Stone et al., 2007; Kadian et al., 2007; Dodman, 2009; Dhakal, 2009; Hankey et al., 2010; Glaeser and Kahn, 2010; Sovacool and Brown, 2010; Poumanyvong and Kaneko, 2010; Liu and Sweeney, 2012; Sarzynski, 2012).

First is the view that a high-density city is more efficient than a low-density city in terms of energy consumption (Jenks and Burgess, 2000; Newman and Kenworthy, 1989; Rickaby, 1992; Banister et al, 1997; Kim, 1984; Ahn, 2000; Kim, 2001; Kim et al, 2003; Nam and Kim, 2008; Cho, 2009; Koo and Lee, 2009). This research promotes the idea of a compact city, where homes and workplaces are in close proximity and with general features, such as high-density buildings, combined land use, high accessibility of public transport and facilities and improved transportation. It is argued that improved accessibility and a high dependence on public transport are environmentally desirable as energy consumption and CO_2 emissions would be reduced. Developing the inner parts of a city reduces indiscriminate urban sprawl and prevents inner-city decline. It can provide social equality by offering a variety of urban lifestyles with the pursuit of complex usage development. By reusing existing structures, a compact city has the advantage of reduced cost in terms of energy supply through optimal installment of facilities . Because of these reasons, a compact city with high density is an efficient option, alleviating the energy consumption problem that can be caused by urban sprawl, and promoting sustainable development. As an example of this research, Newman and Kenworthy (1989) proposed the efficiency of high-density cities by comparing gas consumption per head in 32 major cities around the world. As a result of their analysis, they argued that gas consumption per head in US cities varied by up to 40% depending on land use and transportation plan factors, rather than on the difference in price or income. By analyzing the transportation energy efficiency of 20 cities in England, using the TRANUS integrated model of land use, Rickaby (1992) suggested that a centralized form of town center development showed approximately 9% reduction and a dispersed form of centralized town showed approximately 14% reduction in efficiency of transportation energy. In contrast, there is an argument that a high-density city has an inefficient energy consumption (Owens, 1992; Williams et al., 2000; Zhang, 2000; Chiu, 2002; Gordon and Richardson, 1989; Breheny, 1992; Kim et al., 2003; Lee, 2008; Shim, 2009; Kim et al., 2009). Their suggestion derives from the merits of the compact city. Their common assertion is that travel demand can increase with a reduction in travel cost as travel distance shortens, and that more air pollutants can be emitted in short-distance travel than in long-distance travel. This can result in a degradation of the general environment quality, decline in health, and concerns over individuals' privacy. It is our current position that research on the effect of energy reduction by automobile concentration in high-density cities is still inconclusive, and could even cause inefficiency of energy reduction. Following analysis of data from large cities in the USA, particularly of Los Angeles, Gordon and Richardson (1989) concluded that dispersion does not necessarily trigger traffic congestion or an increase in energy consumption. Breheny (1995) concluded that the dynamic range of energy consumption is very small after analyzing the results of an energy consumption change simulation assuming that cities in England are developed with high density and dispersed with low density. On the other hand, they argued that problems could be an increase in crime, reduced privacy, and an increase in noise, aside from problems in economic and environmental aspects.

Analysis methods for investigating the influence of urban spatial structure and energy consumption can largely be divided into two stages. The first stage involves analyzing the relationship with energy consumption after measuring urban spatial structure, depending on the perspective of the researchers. Research using functional formula of density gradient of C. Clark and entropy index are the researches about measuring method of urban spatial structure (Mills and Song, 1979; Chae, 1997; Kim and Jeong, 2001; Jeong, 2003). In this research, the most general elements used for the measurement of urban spatial structure were population and employment densities because these can be used as an important indicator of urban spatial structure, representing the centrality of activities within various cities. Additionally, data can be obtained easily (Seo et al., 2013). These researches went further and classified cities as either mononucleic-multinucleic or concentrated-dispersed (Guiliano and Small, 1991; Mcmillen, 2003; Song, 2003; Kim et al., 2009; Seo et al., 2013; Kim, 2013). In South Korea, Seo Won Suk and Kim Lee Young (2013) classified urban spatial structure after measuring it based on the level of concentration or dispersion of cities, as representative researches that measured mononucleic and multinucleic cities. However, to understand polycentrality and monocentrality, they measured them using Z-score of employment, which Song Mi Ryung (2003) and Kim Seung Nam., et al (2009) used. Here, buildings, roads, and rivers in a geographical information system (GIS) were selected and used to complement the error of distance between adjacent regions. As a result, 82 cities in the nation were classified: 36 as multinucleic cities and 46 as mononucleic cities. Based on previous research, Kim Byung Suk (2003) judged administrative regions (dongs) with more than 5,000 employees and in the top 30% as high-density cities using the standardized value of employment density, and selected them for central nuclei. As a result, the cities were classified into 28 multinucleic cities and 54 mononucleic cities.

Meanwhile, in a research analyzing the relationship between energy consumption and urban spatial structure, Muniz and Galindo (2005) used regression analysis and set the major independent variables to measure the energy consumption change depending on the urban spatial structure. Allen, Browne, and Cherrett (2012) and Woudsma et al. (2008) studied the relationship between energy consumption and CO_2 emissions depending on the city form using arithmetic calculation and spatial autocorrection regression (SAR).

Meanwhile, based on the evidence of earlier studies, it is recognized that most of the greenhouse gases emitted come from energy production process (Korea Energy Management Corporation, 2011; IEA, 2011). As the debate on urban spatial structure having a close relationship with energy consumption continues, research regarding the urban spatial structure efficiency for energy consumption was examined. Consequently, the pros and cons about whether high-density cities are a viable option for an energy-efficient urban spatial structure are inconclusive, and there is no single agreed view regarding the most efficient urban spatial structure for energy saving.

The cause of this can be said to be the limitation of using the correlation between energy consumption and urban spatial structure as the sole analysis method, or that the previous research only considered the morphological Characteristics of cities, or measurements based on the social and economic indicated aggregate data. This is because the domestic research has been mainly limited to the Characteristics of urban spatial structure and transportation energy consumption. To find the appropriate relationships, it is necessary to know causal relationships through adopting an objective viewpoint and integrated research methods.

3 Analysis Methods

This study was conducted in three stages: Calculation of CO_2 Emissions' Amount, Selection of Factors for Urban Spatial Structure Characteristics and Classification of Types, and Development and Application of the CO_2 Emissions Impact Structure Analysis Model.

First, the concept and characteristics of urban spatial structure were established based on a theoretical study of urban spatial structure, climate change, and the relationship between urban spatial structure and CO_2 emissions.

Moreover, a literature review was conducted and main issues, analytic methods, and analytical indicators of energy-efficient urban spatial structure were examined. Subsequently, to structurally analyze the effect of emissions, the CO_2 emissions per capita for each type of energy source was calculated for 107 cities based on IPCC guidelines. Using analytical indicators derived from previous studies, the results were classified according to the characteristics of urban spatial structure in order to analyze CO_2 emissions factors using scattering plots and coefficients of variation. In addition, we classified cities according to urban spatial characteristics. Lastly, we developed a structural analysis model to identify the effects of urban spatial structure characteristics on CO_2 emissions using the PLS structure equation

Table 2 Research methods according to the study process

	[Step 1]		[Step 2]		[Step3]
[Category]	**Calculation of CO2 Emissions' Amount**	►	**Selection of Factors** · Scatter plot analysis method · Coefficient of variation analysis method **Classification of Cities**	►	**Development and Application of the CO2 Emissions Impact Structure Analysis Model**
[Methods]	· CO2 Emissions' amount calculated for 107 cities based on IPCC guidelines		· Non-hierarchical cluster analysis · Variance analysis · Profile analysis		· PLS-SEM (Partial Least Square- Structural Equation Modeling)

3.1 Calculation Method for CO2 Emissions

Korea's greenhouse gas emissions come under the energy category (85.7%). Also, when considering the emissions level of energy resources, greenhouse gas discharged in the oil and electricity category are: oil 43.1%, electricity 42.3%, and LPG 14.4%. When deciding which carbon emissions data to use, depending on the whole emissions quantity and whether data is available, this study excluded the categories of industrial processing, land use, and waste. Energy, except oil, electricity undetermined in energy part, for that reason consider limiting of building data and efficiency and exclude from calculation list. Standard of building data is 2012 and site is total 107 local governments in the whole country including mega cities. Energy consumption quantity measurement was based on consumption quantity collected from Korea National Oil Corporation (for oil) and Korea Electric Power Corporation (for power). These consumption quantities are annual using data to produce oil and electricity. This total gives the CO_2 emissions.

Energy sector of IPCC Greenhouse gas emissions calculation, industry · home · commerce · public · indirectness (Electricity and water), greenhouse gas emissions are calculated using Tier 1 method. Further, the same method is used in 1994 (the Third) and 2006 (the Forth). When greenhouse gases are calculated using Tier 1 method, required activeness data about consumed fuel amount from each emissions source and greenhouse gas emissions factor in each fuel. Calculation formula is given as formula (1).

Table 3 Greenhouse Gas Emissions Quantity of Stationary Combustion.

$$\text{Emission}_{GHG,fuel} = \text{Fuel Consumption}_{fuel} * \text{EmissionFactor}_{GHG,\ Fuel}$$

$$\text{Total'Emission}_{GHG} = \sum_{fuels} \text{Emissions}_{GHG,fuel} \quad \cdots\cdot \quad \text{Formula (1)}$$

※ $\text{Emission}_{GHG,fuel}$: Depending on calculated Greenhouse gas emissions quantity (kg GHG)

※ [illegible]

※ emissions Factor GHG,fuel : Depending on calculated Greenhouse gas emissions quantity (kg GHG)

※Source : Environmental management corporation (2009)

When total greenhouse gas emissions calculated using the above method for each greenhouse gas or fuel consumption, calculated total greenhouse gas of industry · home · commence emissions field. However, so far as emissions factor, parts of emissions factors in stationary combustion and mobile combustion revised and case of Korea according to energy enforcement regulations in part of fuel developed emissions factor by standard of announced caloric value in 2011 has to apply to "greenhouse gas emissions in 2012~2016," and in part of electricity annually calculated emissions factor. Consumption of oil and electricity are calculated considering oil conversion factor and carbon emissions factor because of different consumption units (ℓ, Mwh).

3.2 Selection of Factors for Urban Spatial Structure Characteristics and Classification of Cities

CO_2 emissions factors drawn from preceding researches were examined to select CO_2 emissions factors for each characteristics of urban spatial structure. Factors are classified into groups with similar characteristics. Later, scatter plot analysis and coefficient of variation analysis were conducted to confirm the correlation with CO_2 emissions calculated through this study.

Urban classification is necessary to investigate the effect of differences in environment of each urban area on CO_2 emissions. These differences started from all environments including physical environment, social environment, and economic environment. Therefore, this study classified the standards of urban classification with characteristics of urban spatial structure because the 4 characteristics of urban spatial structure found in this study include physical, social, economic, humanistic, and spatial elements of urban areas. Non-hierarchial cluster analysis was used to divide into clusters and statistical significance of cluster was obtained through analysis of variance. Characteristics of categories were analyzed through profile analysis.

3.3 Development and Application Method for the Impact Structure Analysis Model

3.3.1 Method to Develop CO2 Emissions Impact Structure Analysis Model

3.3.1.1 Selection of Model and Measuring Indicators

Structural Equation Modeling (SEM), a technique for testing causal relations, was used as a method of analysis. Structural Equation Modeling can be divided into ML-Structural Equation Modeling that estimates covariance of each measurement factor using Maximum Likelihood, and LS-Structural Equation Modeling that minimizes prediction error using least squares. We reviewed both ML-SEM and LS-SEM and choose PLS-SEM (Partial Least Squares) because the variable and the result variable can be formulated as a linear equation and each variable can be classified as a latent variable and an observed variable, a measurement indicators and a measurement error. Consequently the method used in this study is SEM, which considers correlation of latent variable, measurement indicators, and measurement error at the same time and analyzes a causal relationship. Also, PLS-SEM is similar to regression analysis in its characteristic aspects. It can explain a measurement model and a structure model at the same time (Chin, 1998). This study can show empirically the influencing relationship between urban spatial structural characteristics and CO_2 emissions. With PLS-SEM, it is possible to take advantage of the small sample size and carry out exponentiation and modeling without being constrained by the normal distribution method

Measuring indicators of construct can be classified into reflective indicator and formative indicator according to the causal direction (Bollen and Lennox, 1991; Diamantopoulos and Winklhofer, 2001; Chin, 1998; Jarvis et al., 2003; Petter et al., 2007). An indicator that reflects the result of construct is referred to as reflective indicator, and extremely high correlation is shown between indicators. On the contrary, a measuring indicator that forms or becomes the cause of construct is referred to as formative indicator. As formative indicators in general have low correlation, reliability test on measurement items is not a requirement. However, while two indicators constitute latent variables using different methods in selection of measuring indicator, there is no clear standard for selection of measuring indicator. Selection of indicator in a measurement model relies on the judgment of researcher about theoretical relationship between measuring indicator and latent variables (Gotz et al., 2010). All indicators of the measurement model in this study were formative indicators. Formative indicator is the same as a regression equation in which latent variable becomes dependent variable and multiple measuring indicators become independent variables. Unlike reflective indicator that extracts covariation among measuring indicators, latent variable made using formative indicator is a useful method for constructing measurement model when latent variable is established by limited measuring indicator, because all measuring indicators act as a construct of latent variable. In comparison to reflective indicator in which cause explains indicator, formative indicator in which various attributes constitute a single cause was determined as more appropriate for this study.

3.3.1.2 Configuration of Study Model

In urban spatial structure, emissions structure that affects CO_2 emissions can be divided into two contexts.

First is a factor of characteristics created by components of urban spatial structure. Characteristics of urban spatial structure are subdivided into internal characteristics made by components of urban spatial structure and external characteristics classified by city type. Therefore, as structure that affects CO_2 emissions can differ according to the city type, the city type was configured as a dummy variable for examination of each type.

In the arrangement of urban spatial structure characteristics, physical characteristics (macroscopic type), spatial characteristics (internal type) and social characteristics are expected to show direct influence on CO_2 emission. On the contrary, while economic characteristics do not have direct effect on CO_2 emission, they are expected to affect physical characteristics, spatial characteristics, and social characteristics emissions structure can also be classified by energy sources that emit CO_2. Carbon dioxide for each energy source is ultimately emitted by oil, electricity and city gas. In this study, CO_2 emissions of each energy source computed was configured as the structure to show the relationship with urban spatial structure.

Accordingly, hypotheses to examine CO_2 emissions impact structure according to characteristics of urban spatial structure are formulated according to the following criteria. First to examine the relevance between characteristics of urban spatial structure and CO_2 emission, primary hypothesis was set forth as 'Characteristics of urban spatial structure will affect CO_2 emission'. Also, another hypothesis was that economic characteristics expected to have indirect effect and city type as a dummy variable will affect physical, spatial and social characteristics (see Figure 1).

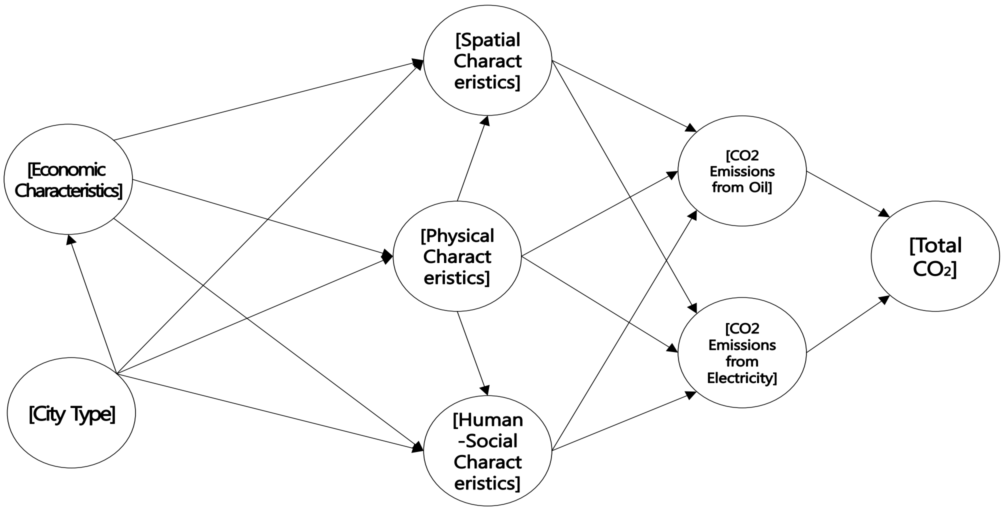

Figure 1 Configuration of Study Model

3.3.2 Method to Apply and Test the Model

3.3.2.1 Method to Apply the Model

Coefficient estimation process can be largely divided into four stages as shown in Figure 2 (Peng and Lai, 2012). First stage is called outer approximation and finds approximation of latent variables using measuring indicators. Second stage is the process to find path coefficient of structure model. It computes the coefficient that maximizes explanatory power of variance (coefficient of determination) for endogenous latent variable which becomes dependent variable of structure model. Third stage recomputes score (inner approximation) of latent variable using the computed path coefficient. Lastly, fourth stage uses inner approximation to compute outer approximation from first stage. The same process is repeated until the difference between the computed outer load (weight) and value used in first stage falls below the prescribed level.

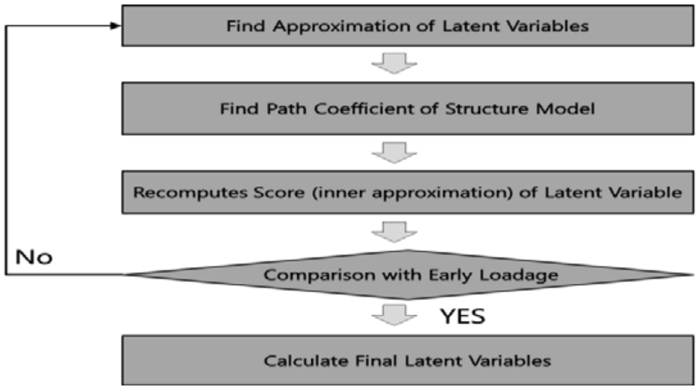

Figure 2 Process of Coefficient Presumption of PLS-SEM

3.3.2.2 Method to Test the Model

Testing of formative indicators used in this study can be seen as different from general testing of reflective indicators because characteristics of the two indicators are different. In formative indicators, measuring indicators are components of latent variable and change in measuring indicators lead to change in latent variable (Chin 2010, Jarvis et al., 2003). Accordingly, formative indicators do not require tests on internal consistency, convergent validity and discriminant validity of measuring indicators performed in reflective relationship. Instead for testing of measuring indicators in formative indicators, multicollinearity test, direction of path coefficient of measuring indicator showing positive (+) and negative (-) relationship, indicator relevance based on comparison of path coefficient between indicators, and statistical significance are important (Gotz et al, 2010).

Since PLS statistics technique is not used for testing of structure model, fitness evaluation on the overall structure model considering influential relation of all paths was not conducted. PLS is not an analysis method to maximize chi-square (χ^2) as fitness of structural equation model but a method to maximize determination coefficient (R^2 or R-square) through minimization of error. It cannot evaluate fitness of the overall model and only calculates explanatory power for endogenous variables (Chin, 2010). In addition, Duarte and Raposo (2010) explain that fitness of a structure model can be evaluated by strength of each path coefficient and explanatory power of exogenous variable, suggesting that the value of R^2 must be 0.1 or higher. Therefore in testing of structure model with PLS, model is evaluated by the R^2, effect of each exogenous variable (f^2), direction and strength of latent variables as for measurement model, and statistical significance level (Gotz et al., 2010). The criteria for assessing model are shown in Table 4.

Table 4 Valuation Basis of PLS-SEM using Formative Indicator Model

Classification	Indicators	Standard value
Formative measuring indicators	Significance of estimated coefficient	Significance test using bootstrapping (over 5,000 samples of bootstrap)
	Ulticollinearity	VIF values for all formative measuring indicators are 10 or less
	Heterogeneity	Tests if the weighted value of indicators among specific groups within sample are different
Structural model	Determination coefficient of endogenous latent variable	Over 0.75: substantial Over 0.5: moderate 0.25 and less: weak
	Significance of path coefficient	Test of significance using bootstrapping, jackknifing, and blindfolding
	Prediction validity of exogenous variable	$Q^2 > 0$ (test of cross-validated redundancy on each latent variables using blindfolding technique)
	Heterogeneity	Test of comparing or moderating effect between groups in case that there is difference of path coefficient between groups

※Source : Hair et al (2011)

4 Development and Application of CO2 Emissions Impact Structure Analysis Model

4.1 Development and Application of the CO2 Emissions Impact Structure Analysis Model

4.1.1 Development of CO2 Emissions Impact Structure Analysis Model

To analyze 107 cities in South Korea, the variables related to the emissions of CO_2 were selected as the energy consumption factors (Table 5) by using the structural model of the CO_2 emissions effect, which was constructed earlier according to the characteristics of urban spatial structure. When selecting the final variables, their correlations with the CO_2 emission, coefficient of variation between regions, and multicollinearity of each characteristic were considered. Meanwhile, since the city type displayed differences in the amount of CO_2 emissions by its characteristics, these city type were selected as dummy variables.

Finally, the typical indicators selected from the physical characteristics were the number of vehicles, total length of roads, number of houses, and number of households using the bus. The indicators selected from the spatial characteristics were the population density and apartment residency ratio. From the economic characteristics, financial self-reliance ratio and employment number were selected, while senior population ratio was selected from the social characteristics.

Table 5 Selected Final Variable

Classification	Measurement Indicators	Unit	Rredictive Sign
Physical Characteristics	Number of Vehicles	per head/vehicles	+
	Total Length of Roads	per head/m	+
	Number of Houses	per head/houses	+
	Number of Households Using Bus	households	-
Spatial Characteristics	Population Density	person/㎢	-
	Apartment Residency Ratio	%	-
Economic Characteristics	Financial Self-Reliance Ratio	%	+
	Employment Number	person	+
Human-Social Characteristics	Senior Population Ratio	%	-
City Type	Dummy Variables		

This study has suggested the following model based on the finally selected variables and research model previously set for development and application of the model (Figure 3).

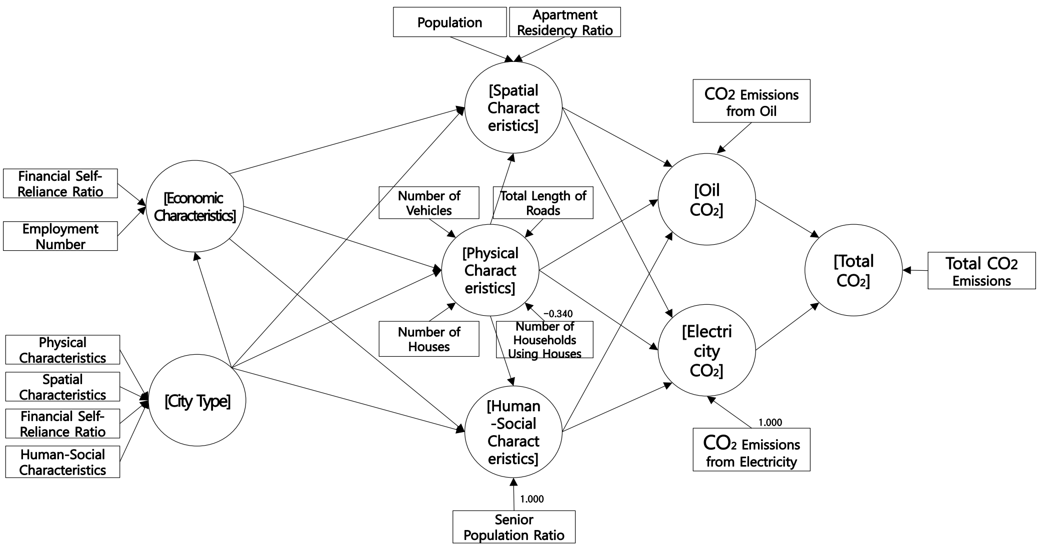

Figure 3 Suggested Model

4.1.2 Application and Verification of the Model

4.1.2.1 Evaluation of Measurement Models

Average variance extracted (AVE) can be used as a reference which can decide whether latent variable represent the measurement indicators well. latent variables can take more than 0.5 (Fornell and Larcker, 1981) for the level of significance. In average variance extracted of latent variables, every latent variable showed 0.56 ～0.78, and these can be seen as variables that latent variables represent measurement indicators because they can decide they at least contain more than 56%～78% of information of measurement indicators belonging to them (see Table 6).

Table 6 Average Variance Extracted of Latent Variables

Classification	Physical Characteristics	Spatial Characteristics	Economic Characteristics	Human-Social Characteristics	City Type
AVE	0.560284	0.788583	0.701376	1.000000	0.719838

The reason that verification of multicollinearity is needed is the value of R^2 can be extremely high as well as occurrence of information overlap in the case that multicollinearity exists between measurement indicators, independent variables since the relation of measurement indicators and latent variable is decided by multiple regression analysis. In general, if the value of VIF is more than 10.0, it is considered there is a problem of multicollinearity. The highest value of VIF among every measurement indicator of this research is 3.191, so it is judged that there is no problem of multicollinearity.

We could analyze the measurement model after checking there is no problem regarding multicollinearity between measurement indicators. Table 7 presents the result of measurement model in this research.

Table 7 Result of Measurement Model

Classification	Measurement Indicators	Original Sample (O)	T Statistics (|O/STERR|)	Result of Testing
Physical Characteristics	Number of Vehicles	0.293	4.774430	Adoption
	Total Length of Roads	0.274	3.780849	Adoption
	Number of Houses	0.428	5.503513	Adoption
	Number of Households Using Bus	-0.340	5.191831	Adoption
Spatial Characteristics	Population Density	0.387	4.920767	Adoption
	Apartment Residency Ratio	0.725	9.013237	Adoption
Economic Characteristics	Financial Self-Reliance Ratio	0.793	17.047386	Adoption
	Employment Number	0.966	5.430126	Adoption
Human-Social Characteristics	Senior Population Ratio	1.000	-	Adoption

From all these results, we can say most of measurement indicators excluding some part properly forms the relevant latent variables. More than two measurement indicators constituting latent variables were shown to be all similar statistically and it turned out that there is no multicollinearity between measurement indicators. Besides, all the average variance extracted was more than 0.5, which means that measurement indicators represent latent variable. Hence, analysis of structural model is possible for measurement indicators properly forms the latent variables overally.

4.1.2.2 Evaluation of Structural Models

The criterion that evaluates the suitability of entire structural model PLS-SEM has not yet established. However, prediction and degree of dispersion explanation of endogenous latent variables are important standards because the purpose of PLS-SEM lies in the prediction of endogenous latent variables. PLS-SEM, because it has a purpose of estimating the path-coefficient and weighted value that can predict the latent variables, which become the final dependent variable, the best, the prediction about the latent variables as well become the valuation basis that determines the suitability of the model. (Gotz, 2010) Thus, goodness of fit test of structural model about PLS structural equation can be evaluated by the value of R^2 and Q^2. First, prediction index Q^2 evaluated the suitability with the redundacy index, cross-validated test statistic of Stone-Geisser. This index is an statistic estimator of structual equation model, and it is evaluated it has quality of structural equation model when it has a positive value (Chin, 1998; Tenenhaus et al., 2005). As a result of analysis of PLS structural equation model, redundancy value of every endogenous variable was ~~were~~ shown to have positive values. Thus, it was demonstrated that structural model of structure equation is suitable.

Meanwhile, the value of R^2 in CO_2 from oil showed very high coefficient of determination, 0.428, and the value of R^2 in the CO_2 from electricity showed coefficient of determination at a medium-level, with the value of 0.241. Q^2 signified more than 0, thus prediction was significant (see Table 8). According to this, the model for analysis of influencing structure of CO_2 emissions in this research has secured overall validity when viewed in the purpose of PLS-SEM, explanation and prediction about dependent variables.

Table 8 R-squared and Q-squared

Classification	Oil	Electricity
R^2 (R-squared)	0.428	0.241
Q^2 (Q-squared)	0.415	0.234

Significance test regarding path-coefficient of PLS structural equation model was conducted. Generally, significance test of path-coefficient uses Bootstrap method. (Tenenhaus et al., 2005; Temme et al., 2006). This research tested the significance extracting 500 specimens through random specimen extraction using Bootstrap technique. As a result of significance test of path-coefficient using PLS Bootstrap method, structural model and path-coefficient representing causal link between latent variables were shown as follows.

Table 9 Results of Path Coefficient Analysis

Classification	Original Sample (O)	T Statistics (|O/STERR|)	Result of Testing
Physical Characteristics→ CO_2 Emissions from Oil	0.444	2.837**	Adoption
Physical Characteristics→ CO_2 Emissions from Electricity	0.630	4.543***	Adoption
Spatial Characteristics→ Emissions from Oil	-0.720	3.892***	Adoption
Spatial Characteristics→ CO_2 Emissions from Electricity	-0.242	1.808*	Adoption
Human and Social Characteristics→ Emissions from Oil	-0.645	4.690***	Adoption
Human and Social Characteristics→ CO_2 Emissions from Electricity	-0.747	6.116***	Adoption
Economic Characteristics→ Physical Characteristics	-0.256	2.134**	Adoption
Economic Characteristics→ Spatial Characteristics	0.196	1.765*	Adoption
Economic Characteristics→ Human and Social Characteristics	-0.251	2.499**	Adoption
Physical Characteristics→ Spatial Characteristics	-0.172	1.972**	Adoption
Physical Characteristics→ Human and Social Characteristics	-0.090	0.855	Rejection
City Type→ Physical Characteristics	0.644	3.152**	Adoption
City Type→ Spatial Characteristics	-0.598	3.131**	Adoption
City Type→ Human and Social Characteristics	0.730	3.122**	Adoption
City Type→ Economic Characteristics	-0.912	3.734***	Adoption

<0.10(t>1.645), **p<0.05(t>1.96), ***p<0.001(t>3.30)

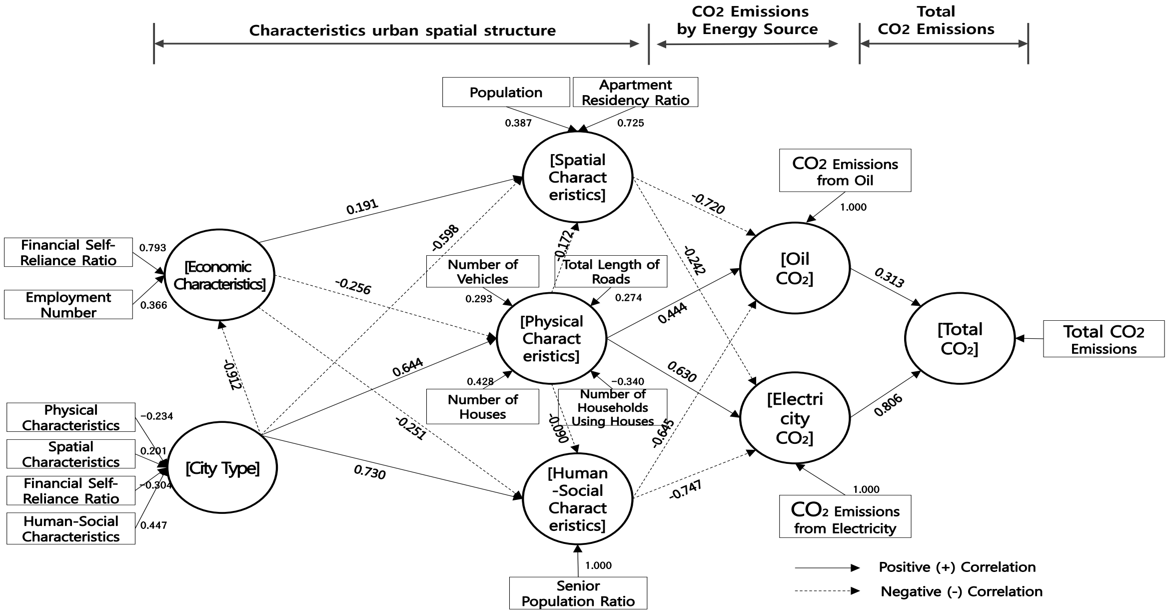

Figure 4 Testing Results of the Impact Structure Analysis Model on CO2 Emissions Affected by the Characteristics of Urban Spatial Structure

4.1.3 Comprehensive Analysis

In order to interpret the effect of energy consumption factors on the amount of energy consumption and energy source, firstly, the meaning of latent variables estimated by the measurement indicators should be interpreted. In particular, the latent variables estimated by more than one measurement indicator have a complex meaning, so the meaning of relevant latent variables should be clarified to be able to interpret the effect of each latent variable on its dependent variables.

The interpretation of the meaning of the latent variables depends on the sign and effect size (weighted value) of each measurement indicator on the latent variable it belongs to. Main results appear in Table 10. Among the measurement indicators of the physical characteristics, the number of vehicles, total length of roads, and number of houses showed positive (+) signs, while the number of households using bus showed negative (-) sign; thus, the physical characteristics are the latent variables that are composed of the measurement indicators with the characteristics opposing each other. Since the score of the physical property latent variable was high in the areas with high number of vehicles per person, high total length of road per person, and high number of houses, and low number of households using bus, the latent variable displays the characteristics of "personal vehicle centric and private house ownership." The measurement variables that indicate the spatial characteristics consist of population density and apartment residency ratio, and they all showed positive signs. High population density and high apartment residency ratio displays the characteristic of "high density development." Since the senior population ratio is the only measurement variable that indicates the human-social characteristics, the characteristic of this latent variable is indicated by the "ratio of senior population." The measurement variables that indicate the economic characteristics consist of financial self-reliance ratio and employment number, and they all showed positive signs. High financial self-reliance ratio and high employment number indicate the characteristic of "economic power of city." Meanwhile, the urban spatial structure characteristics that indicate the city type showed positive signs for the physical and human social characteristics, and negative signs for the spatial and economic characteristics. The latent variable score of city type estimated using these four dummy variables was higher in those regions with high number of private vehicles and houses, high senior population ratio, low population density, and low urban economic activities. Hence, it can be interpreted that the latent variables of the city type show the characteristics of mid-small cities.

Table 10 Calculation Results of Measurement Indicators Weighted Value

Classification	Measurement Indicators	Unit	Weighted Value
Physical Characteristics	Number of Vehicles	per head/vehicles	0.293429
	Total Length of Roads	per head/m	0.274436

	Number of Houses	per head/houses	0.428061
	Number of Households Using Bus	households	-0.339787
Spatial Characteristics	Population Density	person/㎢	0.387021
	Apartment Residency Ratio	%	0.725079
Economic Characteristics	Financial Self-Reliance Ratio	%	0.792635
	Employment Number	person	0.365896
Human-Social Characteristics	Senior Population Ratio	%	1.000000
City Type	Physical Characteristics	-	0.201094
	Spatial Characteristics	-	-0.234309
	Economic Characteristics	-	-0.304029
	Human-Social Characteristics	-	0.446543

The path coefficient observed earlier showed direct effect with the consumption of energy resource and characteristics of urban spatial structures. Physical, spatial, or social characteristics affected the emissions of CO_2, but the city type or the economic characteristics could also influence it. Hence, in order to understand the effects of each factor on the household energy consumption and CO_2 emission, both direct and indirect effects must be considered. Factors that had direct effects on CO_2 emissions from oil and electricity were the physical, spatial, and social characteristics, while the urban and economic characteristics were the factors that showed indirect effects. First, the direct effect of each measurement indicator and latent variables on the CO_2 emissions from oil and electricity can be expressed as follows:

$$CE_i = 0.44(PC_i) - 0.72(SC_i) - 0.64(HC_i) + e_{1i}$$
$$EE_i = 0.44(PC_i) - 0.24(SC_i) - 0.74(HC_i) + e_{1i}$$
$$SC_i = 0.725(Apartment\ Residency\ Ratio_i) + 0.387(Population\ Density_i)$$
$$PC_i = 0.29(Nmber\ of\ Vehicles_i) + 0.27(Total\ Lenght\ of\ Roads_i) + 0.42(Nmber\ of\ Houses_i) - 0.34(Nmber\ of\ Households\ Using\ Bus_i)$$
$$HC_i = 1.00(Senior\ Population\ Ratio_i)$$

where CE and EE represent oil CO_2 and electricity CO_2, respectively; SC, PC, and HC represent spatial characteristics, physical characteristics, and human-social characteristic, respectively; i denotes 107 cities; and ε is the error term.

The CO_2 emissions from oil and electricity are determined by spatial characteristics (SC), physical characteristics (PC), and human-social characteristics (HC). From the sign of the coefficients, it was observed that the CO_2 emissions increased as the physical characteristics increased, and the emissions decreased as the spatial and human-social characteristics increased. Physical characteristics (PC) increased as the number of vehicles and total length of roads increased, and it decreased as the number of households using bus increased. Because the increase in the number of vehicles, total length of roads, and number of houses increase the physical characteristics, they increase the CO_2 emission, while the number of households using bus has an opposite effect. Cars, roads, and buses are related to the traffic and consumption of oil energy, while the number of houses is related to the consumption of electricity energy. Because the number of households using bus could be perceived as the public transport service, the traffic-energy consumption can be reduced by economy of scale effect (direct effect) of many people travelling in a single vehicle and the reduction of private vehicle ownership and usage. Moreover, because an increase in the number of houses is related to the increase in households, it can be regarded as a factor that increases the CO_2 emission. The spatial characteristics (SC) increased as the population density and apartment residency ratio increased, and the CO_2 emissions decreased as the spatial characteristics increased, so it could be perceived as a factor that decreases the CO_2 emissions from oil. Within dense urban regions, the travelling and driving distances are short, so the consumption of oil is reduced, and consequently the energy consumption of oil is decreased. House heating systems depend more on gas rather than oil, and in the case of apartment households, they have a higher heating efficiency than regular households do, so the oil consumption decreases comparatively. Human-social characteristics (HC) increased as the senior population ratio increased, and because CO_2 emissions decreased as human-social characteristics increased, the senior population ratio could be perceived as a factor that decreases the CO_2 emission. Since the increase in the senior population ratio was measured by each city, it needs to be approached at the macroscopic level instead of interpreting the household characteristics in accordance with the increase in senior population.

In contrast, the factors that indirectly affect the CO_2 emissions can be expressed as follows:

$$SC_i = 0.19(EC_i) - 0.25(UT_i) - 0.17(PC_i) + e_{1i}$$

$$PC_i = -0.25(EC_i) + 0.64(UT_i)$$
$$HC_i = -0.25(EC_i) + 0.73(UT_i) - 0.08(PC_i) + e_{1i}$$
$$EC_i = -0.91(UT_i)$$

where SC, PC, HC, and EC represent spatial characteristics, physical characteristics, human-social characteristics, and economic characteristics, respectively; UT is the city type ; i denotes 107 cities; and e is the error term.

The spatial characteristics increased as the economic characteristic increased, and decreased as the city type and physical characteristics increased. This indicates that the mid-small cities have negative relationship with the dense cities, while the financial self-reliance ratio and employment number have positive relationship with the spatial characteristics. The physical characteristics decreased as the economic characteristics increased, more so in mid-small cities. This was because the number of vehicle per person, total length of roads, and the number of houses are the characteristics of mid-small cities. Consequently, the city type increased physical characteristics and an increase in physical characteristics increased the CO_2 emission; hence, city type could be perceived as a factor that affects CO_2 emission. On the other hand, the financial self-reliance and the employment number have negative effects on the physical characteristics of mid-small cities, and this could be perceived as a factor that decreases CO_2 emission. Human-social characteristics were affected by the physical characteristics, economic characteristics, and the city type. An increase in economic characteristics such as financial self-reliance and employment number decreases the senior population and increases CO_2 emission.

Based on this, the total effect (direct effect + indirect effect) of the urban spatial structure characteristics that affects CO_2 emissions from oil and electricity is shown in Table 11. Note that the total effect of the urban spatial structure characteristics includes the indirect effect, so the effect size largely varies depending on the energy source. In other words, the effect on the oil and electricity could become greater or smaller. In Table 11, the total values of effect depending on the physical, spatial, and human-social characteristics and the city type are all significant, while the economic characteristics have a negative sign for the CO_2 emissions from oil and electricity. This was actually not because the economic characteristics do not have a large impact on the amount of energy consumption, but because it has both increasing and decreasing effects. The economic characteristics showed positive sign for the spatial characteristics that directly affect energy consumption, while it showed negative sign for physical and human-social characteristics. Besides, each of these characteristics directly affects both energy consumption of oil and electricity.

Thus, to understand the effect of urban spatial structure characteristics on CO_2 emission, research would be needed to subdivide energy by its purpose and source. In particular, to understand the change in CO_2 emissions due to the energy consumption, more research would be necessary to understand the change in consumption by energy source.

Table 11 Influence Comparison of Direct Effect and Indirect Effect by Urban Spatial Structure

Classification		Physical Characteristics	Spatial Characteristics	Human-Social Characteristics	Economic Characteristics	City Type
Oil	Direct Effect	0.444***	-0.720***	-0.645***	-	-
	Indirect Effect	0.178***	-	-	-0.136	0.485***
	Total Effect	0.623***	-0.720***	-0.645***	-0.136	0.485***
Electricity	Direct Effect	0.630***	-0.242***	-0.747***	-	-
	Indirect Effect	0.109***	-	-	-0.048	0.118***
	Total Effect	0.739***	-0.242***	-0.747***	-0.048	0.118***

Energy consumption factors, through the direct and indirect effects on consumption by each energy source observed earlier, ultimately affected the households' CO_2 emission. However, because the estimated path coefficient was the same as the regression coefficient of multiple regression analysis, only the effect size between the coefficients that affect the same latent variables can be compared, while the effect size on other latent variables cannot be directly compared with the estimated coefficient. Therefore, in PLS-SEM, an effect size was used to compare the effect size of each latent variable on the endogenous latent variables.

The comparison of the effect size of each latent factor on CO_2 emissions is shown below in Table 12.

Table 12 The Effect Size for CO2 Emissions by Urban Spatial Structure Characteristics

Classification	Physical Characteristics	Spatial Characteristics	Human-Social Characteristics	Economic Characteristics	City Type
Oil	0.078671	0.132867	0.006993	-0.00874	0.022727

Electricity	0.14361	0.01581	0.059289	-0.00659	0.007905

Firstly, the factors that highly affected the CO_2 emissions from oil in descending order were spatial characteristics, physical characteristics, city type, and social characteristics. It can be seen that the oil energy consumption leads to differences in CO_2 emissions according to the spatial characteristics; the physical characteristics also had a huge effect. Hence, to reduce CO_2 emissions from oil, suppression of the low-density development in suburbs and promotion of the high-density development would be needed by regulating connected developments and land development plans. In addition, this suggested that the public transport priority policy should be promoted, but it should be done while maintaining the balance of traffic system.

On the other hand, the factors with the biggest effect on CO_2 emissions from electricity were physical characteristics, social characteristics, and spatial characteristics in descending order. Unlike the CO_2 emissions from oil, physical environment was the biggest factor with electricity, and this indicated that human-social effect was bigger than the effect of high-density development and low-density development characteristics. However, the smaller R-squared value of CO_2 emissions from electricity than the R-squared value of CO_2 emissions from oil implied that the factors affecting the electricity CO_2 emissions are more difficult to estimate than the factors affecting the oil CO_2 emissions because of the complexity of various activities. Hence, to reduce the electricity CO_2 emission, subdivided consumption factors should be understood and appropriate regulations on the energy-guzzling groups should be prepared to promote the stabilization of power demands.

Further, the path coefficient of PLS-SEM has the same meaning as the standardized coefficients of linear regression equation, so the effects of energy consumption factors on the change in actual CO_2 emissions cannot be intuitively understood from the estimated coefficients. Therefore, it is necessary to calculate the change by using standard coefficients. To measure the effect of increase/decrease of CO_2 emissions by each energy source, the measurement indicator, the weighted value between latent variables, and the path coefficients between latent variables are used. A formula calculating is given in Formula (4).

$$1\ \textit{increase of}\ X' = Y'\ \textit{increases by}\ \beta 1' \times 1 = Y\ \textit{increases by}\ \beta 1' \times 1 \times s_y$$
$$X\text{의}\ s_x\ \textit{increase of}\ X = X'\ \textit{increases by}\ 1$$
$$\therefore s_x\ \textit{increase of}\ X = Y\ \textit{increases by}\ \beta 1' \times 1 \times s_y$$

Formula (4)

※ Source: Noh S, C, (2013)

For instance, the decreasing effect of oil CO_2 emissions according to increase in the total length of roads per person can be computed as follows:

Increase in total length of road per person (standard deviation 2.47) → CO_2 emissions due to oil consumption

= (weighted value x path coefficient) x standard deviation of CO_2 emissions from oil consumption

= (0.27 x 0.623) x 1648 = 277.21 (kgCO_2)

In other words, the CO_2 emissions from oil per person increases 277.21 (kgCO_2) annually when the total length of roads per person increases by 2.47 m. The following Table 13 shows the increase/decrease forecast of CO_2 emissions calculated according to each measurement indicator change by using the same method.

Table 13 Increase/Decrease Forecast of CO2 Emissions Calculated According to Each Measurement Indicator Change

Classification	**Measurement Indicators**	**Explained Variation (standard deviation)**	**CO_2 Emissions Increase and Decrease Variation (per head/KgCO_2)**		**Total**
			Oil	**Electricity**	
Physical Characteristics	Number of Vehicles	0.053743	301.2647	905.7575	1207.022
	Total Length of Roads	2.472748	281.7645	847.1299	1128.894
	Number of Houses	0.025366	439.4919	1321.34	1760.832
	Number of Households Using Bus	43485.64	-348.861	-1048.86	-1397.72
Spatial Characteristics	Population Density	2497.87	-459.224	-391.214	-850.438
	Apartment Residency Ratio	24.91434	-860.35	-732.935	-1593.28
Economic Characteristics	Financial Self-Reliance Ratio	15.18823	-177.652	-158.92	-336.572
	Employment Number	118065.2	-82.0075	-73.3607	-155.368

Human-Social Characteristics	Senior Population Ratio	7.064717	-1062.96	-3120.22	-4183.18
City Type	Physical Characteristics	0.4861	160.7304	99.11642	259.8468
	Spatial Characteristics	0.4060	-187.278	-115.488	-302.766
	Economic Characteristics	0.3458	-243.004	-149.852	-392.856
	Human-Social Characteristics	0.4019	356.9129	220.0948	577.0077

The calculated results indicated that when all measurement indicators increased by their own standard deviation, the number of vehicles, total length of roads, and number of houses increased the CO_2 emissions and the indicators, such as number of households using bus, population density, apartment residency ratio, financial self-reliance ratio, employment number, and the senior population ratio decreased the emission.

Therefore, the direction and size of each indicator's effect on the CO_2 emissions differed. However, since the social cost for the characteristics of each spatial structure and the change in each indicator differs, this should be considered for the most effective CO_2 reduction policy. For instance, in human-social characteristics, the senior population ratio was measured as an indicator that decreases CO_2 emission, but a policy to increase the senior population ratio cannot actually be implemented. Hence, when considering the most effective policy, social cost must be included.

The urban spatial structure directly and indirectly affects the CO_2 emissions effect. Moreover, the effect on CO_2 emissions differs by the city spatial structure and, therefore, especially for the spatial structure of complex cities, energy consumption factors should be derived. Finally, to understand the effect of each factor on energy consumption and CO_2 emission, it would be necessary to conduct further study to determine the urban spatial structure and energy consumption in cities by usage and energy source.

5 Conclusions

This research can be presented in three detailed objectives as follows 1) to identify the characteristics of urban spatial structure that affect CO_2 emission, 2) to classify the city type depending on the characteristics of urban spatial structure, and 3) to develop and apply the analysis model of impact structure of how characteristics of urban spatial structure affect CO_2 emission.

As a result, this study has found the following results. First, among the urban spatial structure characteristics, the number of households using bus, population density, apartment residency ratio, financial self-reliance ratio, employment number, and senior population ratio showed negative relationship CO_2 emissions reduction per capita. In contrast, the number of automobiles, the total length of roads, and the number of houses positive relationship with CO_2 emissions. Second, as for the causal relationship of high-density development with CO_2 emissions, this study has found that high-density development was positively related to CO_2 emissions reduction per capita. Third, the characteristics of private house ownership and private automobile centrality directly increased the CO_2 emissions and indirectly increased the CO_2 emissions by suppressing high-density development. Fourth, CO_2 emissions from oil were most affected by spatial characteristics, followed by physical characteristics, city types, and social characteristics. By contrast, CO_2 emissions from electricity were most affected by physical characteristics, followed by social characteristics, spatial characteristics, and city. Fifth, city types had direct effects on all spatial, physical, economic, and human-social characteristics and indirect effects on CO_2 emissions from oil and electricity.

Future researches must consider the social cost and predicted changes in CO_2 emissions to suggest most efficient policies to reduce CO_2 emissions.

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