An international study on the effect of urban-transport factors on transportation energy consumption according to the development of transportation infrastructure

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In recent years, in each city in the world, people's travel range has expanded due to motorization parallel to economic development, and urban structure is changing with suburbanization. However, there is insufficient quantitative research which clarifies at the international level the causal relationship between the urban-transport factors in the context of individual and urban scale. Especially, research on the relationship between rail infrastructure and transportation energy consumption is lacking.

Under this background, this research built a database of cities concerning transportation energy consumption of private modes reflecting travel behaviors calculated by Person Trip data from 81 cities in 16 countries. In addition, this research analyzes how travel behaviors differ by the development of rail system in cities and how transportation energy consumption is influenced factors at the individual and urban scale according to the development of rail system.

Key Words: *Transportation energy consumption, Railway system, Urban structure, Travel behavior, Person trip data, Multilevel analysis*

1. INTRODUCTION

In recent years, the range of individual travel behavior is expanding with the progress of motorization, and this parallels economic development in cities of the world. The world is shifting toward faster modes that are also more energy intensive[1)]. In order to combat this, new city planning methods and management strategies for technical development that shift popularity from cars to public transit and reduce transportation energy consumption are required. Many planning techniques and research projects since 1970 have focused on developing urban structure based on the concept of sustainable development. Additionally, it is recognized that it is important to develop alternatives that are of sufficiently high quality to attract drivers away from their cars.

Since 1970, many new urban rail systems have been opened worldwide. Most of these were mainly metros and light rail systems. In recent years, particularly in North America and Western Europe, The Tramway has become much more popular, with a total of 89 tram systems opening in these areas since 1980[2)]. Tram systems have emerged as a safe and reliable high-capacity public transit system, as it has shorter station spacing and its operational capacity at street level is compatible with pedestrians. Also, Tram has significantly lower capital cost than heavy rail transit systems, thus it is often regarded as an appealing rail transit system that provides quality transit services[3)]. This may partially explain why Tram systems have gained increasing popularity and there are more Tram systems than heavy rail transit systems in Western Europe and North America[2)].

On the other hands, an international survey study conducted by Mackett and Edwards[4)] reported several reasons for developing urban public transit systems, improving public transport, reducing traffic congestion, serving the city center better, improving the environment, and stimulating development. In addition, reducing transportation energy consumption by getting rid of traffic congestion is widely considered one of the commons reason for building new transit systems. And also, rail system has been well received as a transit mode that promotes transit-oriented development (TOD), which in the United States is often translated into compact, mixed-use, and pedestrian-friendly development around transit stations, as an alternative to sprawl.

In this context, Wiston and Langer[5)] indicated that congestion costs of Private Motorized Modes (PMM) decrease in a city as rail transit mileage expands. Traffic congestion growth rates declined in several US cities after Tram service was established. Baum-Snow and Kahn[6)] found significantly lower average commute travel times in areas near rail transit than in otherwise comparable locations that lack rail, due to rail's higher travel speeds compared with PMM or bus under the same conditions. In addition, Litman[2)] shows that per capita congestion delay is significantly lower in cities with high quality rail transit systems than in otherwise comparable cities with little or no rail service. Rail system expansion generally occurs in large and growing urban areas in response to increasing congestion. As a result, simplistic analysis often shows a positive correlation between rail transit and energy consumption by congestion.

Likewise, the development of rail systems can be on the rise as an alternative for lightening car dependence that can be the main cause of excessive transportation energy consumption. Understanding the factors of individual characteristics that influence daily travel behaviors (mode choice, trip number etc) according to the development of rail systems is important. It has been estimated that travel patterns are different according to the development of infrastructure. However, there is insufficient quantitative research which clarifies the factors that influence transportation energy consumption in the context of individual-urban scale at the international level. Especially, research on the relationship between rail systems and transportation energy consumption is lacking.

Under this background, this research built a database of cities concerning transportation energy consumption of PMM reflecting travel behaviors by Person Trip(PT) data, concerning an individual's travel behavior from 81 cities in 16 countries. This is important for transit planning, demand modeling, and transit oriented development. And also, PT data describes some of the factors associated with demographic information on the individual.

Finally, this research analyzes how the factors in the level of individual-urban according to the development of rail systems affect travel behaviors by private motorized modes and transportation energy consumption.

2. ESTIMATION METHODOLOGY

The idea behind this research is to examine the factors in individual-urban level according to the development of rail transit systems influence travel behaviors by private motorized modes and transportation energy consumption. For this, this research utilizes a *Multilevel analysis model* that is possible to consider the data in hierarchical structure at the same time; two levels in individual-urban scale; by using PT data. Data in two level is composed by individual characteristics related to demographic and travel behaviors by PMM in individual level, and statistical data on urban characteristics is aggregated in urban level for each area in Korea, Japan, the United States, and developing countries, which was originally collected by research institutes around the world (The official names of the institutes are listed in the Notes).

(1) Model structure in this research

Multilevel analysis model is appropriate when there is correlation among clusters of subjects. For example, data obtained from surveys of individuals within individuals across different urban areas may constitute a two level hierarchy- individuals (level 1), urban area (level 2). It is the presence of within-cluster correlation that justifies the use of a multilevel model. Multilevel modeling is commonly used in social contexts and individual behaviors. The hierarchical structure of data is often seen in field of urban and transport planning[14)]. In the case of aggregation analysis on zone cluster, zones include individual travel behaviors then it is possible to consider that zones are macro level (level 2) and individual travel behaviors are micro level (level 1).

Suppose we have collected data on *N* subjects (level 1) nested within J organization (level 2). With two-level structure data, three different equations can be formulated: individual-level model (level 1 model), organization-level model (level 2 model), and combined model. Assuming normally distributed errors, for subject ij we have a level 1 model as

$$Y_{ij} \sim N(\hat{Y}_{ij}, \sigma^2_{ij});\ \ r_{ij} \sim (0, \sigma^2);$$

$$\hat{Y}_{ij} = \hat{\beta}_{0j} + \hat{\beta}_{1j}X_{ij} + \hat{\beta}_{2j}X_{ij} + \hat{\beta}_{3j}X_{ij} \ldots ;$$

$$Y_{ij} = \beta_{0j} + X_{ij}(\beta_{1j} + \beta_{2j} + \ldots + \beta_{qj}) + r_{ij} \quad \text{(level 1 model)} \quad (1)$$

where β_{0j} is the intercept, β_{1j} the regression coefficient associated with the predictor X_{ij}, and r_{ij} is the residual accounting for level 1 random effect.

Although this formulation is similar to a linear regression model, there is an important difference in that both intercept and regression coefficients have subscript j, indicating that the intercept β_{0j} and the slope coefficient β_{1j} are permitted to vary across organizations (level 2). At the organization level, the units are organizations and the regression coefficients in the level 1 model for each organization are conceived as outcome variables depending on organization-level characteristics. Generally, there are three submodels in multilevel models depending on whether or not the intercept β_{0j} and the slope coefficient β_{1j} are assumed to vary across organizations. In this application, the intercept β_{0j} is assumed to vary across organizations as a function of a grand mean, a single explanatory variable, and an error term, but the slope coefficient β_{1j} is assumed not to vary across organizations. Then, the intercept β_{0j} and the slope coefficient β_{1j} are formulated as follows:

$$\beta_{0i}=\gamma_0 + \gamma_1 W_{1i} + \gamma_2 W_{2i} + \dots + \gamma_s W_{si} + u_i \qquad \text{(level 2 model) (2)}$$

In Eqs. (2) note that the gammas (regression coefficients) do not have subscript j because they are not assumed to vary across organizations. This model corresponds with a random-intercept model[7),8)]. Substituting Eqs. (2) into Eq. (1) yields the combined model:

$$Y_{ij}= \gamma_0 + \gamma_1 W_{1j} + \gamma_2 W_{2j} + \dots + \gamma_s W_{sj} + X_{ij} (\beta_{1j} + \beta_{2j} + \dots + \beta_{qj}) + u_j + r_{ij} \qquad \text{(combined model) (3)}$$

where Y_{ij} is the out some variable for the ith subject at level 1 and the jth unit at level 2, γ_0 the intercept, W_j the organization-level characteristic, X_{ij} the individual-level characteristic, γ_0 the regression coefficients associated with organization-level characteristic and individual-level characteristic, respectively, u_j a random effect accounting for the random variation at level 2, where $u_j \sim (0, \sigma^2_u)$ and r_{ij} is the individual-level random effect, where $r_{ij} \sim N(0, \sigma^2)$.

Table 1 shows the variables in hierarchical structure; individual (level 1) and urban (level 2) for this research. Data in level 1 is composed with individual characteristics and trip purpose. Data in level 2 is composed with information on urban density, economic status of urban area and infrastructure.

3. ASSESSING TRANSPORTATION ENERGY CONSUMPTION

(1) Definition of trip in this research

From the viewpoint that reduction of transportation energy consumption can be obtained by controlling individual modes of transportation appropriately, the current research extracted data for trips made by Private Motorized Modes (PMM; passenger car, motorcycle, and taxi). Hence, freight traffic, which is mainly through-traffic making it difficult to determine the supplying and consumption districts for fuel, was excluded from this research. In addition, the trip mode used in trips with the longest trip time in a complete trip was treated as the representative mode for the trip. Furthermore, extracted trips below 4 km/h on the representative mode was excluded from target trip as walking. In this research, trips that obey the above limitations were extracted from the total trip made within the target area and used for estimation of transportation energy consumption.

Table 1 Description of variables used in analysis

Variable	Description and unit
Dependant variable	
·Transportation energy consumption	·Note chapter 3
Urban level characteristics	
·Urban density	·persons/ha
·GRDP	·$/person
·Road length	·m/1000persons
·Metro length	·m/1000persons
·Tram length	·m/1000persons
·Passenger car	·vehicle/1000persons
·Car occupancy	·persons/vehicle
Individual level characteristics	
·Gender	·1 if man, 0 woman
·Passenger car	·1 if owns passenger car, 0 otherwise
·21 to 40	·1 if age is between 21 and 40
·41 to 60	·1 if age is between 41 and 60
·more 60	·1 if age is more 60, 0 otherwise
·Trip number	·Trips/day/person

(2) Estimation method for transportation energy consumption

The most common method to estimate transportation energy consumption is to measure the total consumption of fuel in a city by applying statistical data of the total amount of sold fuel, and then converting the total consumed sold fuel into energy per unit amount of fuel [9),10)]. In addition, it is difficult to determine the supplying and consumption districts for fuel[11)]. Alternatively, in Japan, as an estimation method of transportation energy consumption, integrating energy intensity and trip length is generally used. Although the former is suitable for grasping a discharge of the total amount or total evaluation of the measure against fuel, there are limitations regarding vehicle type and the evaluation of travel behavior in an independent trip[10]. Since the latter may differ in the estimation value of energy intensity with various statistical materials, comparison between cities could be difficult. This research exploits the data on traffic behavior for every individual trip based on PT data and the formula for fuel efficiency of a gasoline vehicle considering travel speed defined from measurement of the “sdsdynamo” experiment conducted by the ministry of the environment in Japan. From this data and estimation formula, transportation energy consumption is calculated using Eq. (4).

$$E_k = (T_i \times 365) / O_k \tag{4}$$

E_k = Annual transportation energy consumption by private motorized modes per capita in city k (MJ per capita)
T_i = Transportation energy consumption by private motorized modes in single trip i (MJ)
(i=1,…, n^k; n^k : the number of trip sample in city k)
o_k = Average occupancy ratio of passenger car in city k
I_i = Expansion coefficient of each trip i
P_k= Urban population in city k

Moreover, in formula (4), Transportation energy consumption by private motorized modes in single trip i can be calculated using Eq. (5).

$$T_i = FC_{(V_i)} \cdot HV \cdot L_i \tag{5}$$

HV = Average calorific value of gasoline (MJ/L),
$FC_{(V_i)}$ = Fuel efficiency of a vehicle on trip i at speed v (cc/km; Motorcycle is assumed to have a half the efficiency of a car and vehicle is assumed to be gasoline vehicle; Refer to notes for the background)
L_i = Trip length of trip i (km)
V_i = Trip speed of trip i by private motorized modes (km/h)

However, in this research, private motorized modes are limited to passenger cars, taxi, and motorcycles. Fuel efficiency of private motorized modes on trip i at speed v is obtained using Eq. (6) [12].

$$FC_{(V_i)} = [829.3/V_i] - 0.8572V_i + 0.007659{V_i}^2 + 64.09 \tag{6}$$

The model parameters in Eq. (6) are inferred from the results of research conducted in at the Japanese research institute. However, the model parameters can be customized to country or vehicle type. The results in Eq. (6) are based on the use of a passenger car. Eventually, the renewal estimation method becomes a function of vehicle speed in an individual trip.

4. DATABASE ON TRANSPORTATION ENERGY CONSUMPTION IN THE CITIES OF THE WORLD

(1) Target metropolitan areas

This research targets 81 metropolitan areas based on previous research [13]. Target cities listed in Table 4 page 6.

The 81 cities in 16 countries each had a population of over 800,000, and differed in economic status. The distribution of the target cities was as follows: 21 cities in Asia (7 cities in Korea and 14 cities in Japan), 46 cities in the United States, 14 cities in developing countries.

(2) Definitions and calculation methods of travel behavior

Table 2 defines the data definition used in the current research and the origin of the data. The definition of the annual transportation energy consumption for private motorized modes is explained in Chapter 3.

The latter half of this chapter describes the procedures used to calculate the average trip length, average vehicle speed, number of daily trips, and modal share of private motorized modes in a city. Since this research employs PT data, various data regarding different properties of travel behavior can be extracted. The definition of calculation methods agrees with the definition of data possessing bounded means. Table 3 shows the calculation method for each aspect of travel behavior. To estimate transportation energy consumption, four main travel characteristics were considered: trip length, trip speed, daily trip number, and modal share of private motorized modes, as mentioned in the previous chapter. These data on travel characteristics were calculated from person trip data released by public institutes around the world. However, the data fields of the person trip data differ by country.

It should be noted that the calculation method of travel behavior in Table 1 differs slightly by country and depends on the how the person trip data was configured.

(3) Urban classification

In this research, we try to determine that what is the major factor generating the diversity of the relationship between transportation energy consumption and the features of urban-transport. Fortunately, we have Person Trip data which offers individual information on demography and travel behavior in detail. In this context, we clarify which factors of urban-transport and demography mainly have an effect on transportation energy consumption and how the impacts of urban-transport factors differ.

Table 2 Definition of data in this research

No	Indicator	Unit	Definition of data	(Num. of data source)
1	Urban City	N/A	Boundaries of a metropolitan area are set based on different factors. Search for the most relevant area to study mobility, that is, an economic area where the bulk of daily home-work journeys occurs, which is sometimes referred to as the "labor catchment area"	Korea:(3), Japan: (3), USA:(3), Developing countries:(3)
2	Population	inhabitants	Total number of residents in the urbanized area	Korea:(2), Japan: (2), USA:(2), Developing countries:(2),
3	Urban Density	Inhabitant /ha	Ratio between the population(Indicator 2) and urban surface area	Korea:(2), Japan: (2), USA:(2), Developing countries:(2),
4	GRDP per capita	$/ person	Ratio between the GRDP of the urbanized area and its population.	Korea:(4), Japan: (4), USA:(5), Developing countries:(2),
5	Passenger cars per thousand inhabit-ants	vehicle/ 1000 inhabitants	Number of passenger cars in urbanized area includes all vehicles with three/four wheels or more used primarily for private transportation of persons, but does not include taxis or public transport vehicles -Population figures used to compute the ratio is defined above (indicator 2)	Korea:(4), Japan: (4), USA:(4), Developing countries:(2),
6	Average trip distance of PMM	km/trip	With reference to trips defined by indicator 8, including automobiles, motorcycles, and taxis, the actual distance is sought, not a straight line distance -In this case, trips extending beyond the urbanized area are considered.	Korea:(3), Japan: (3), USA:(3), Developing countries:(3),
7	Average trip duration of PMM	Min/trip	With reference to trips defined by indicator 8, including automobiles, motorcycles, and taxis, the actual travel time	Korea:(3), Japan: (3), USA:(3), Developing countries:(3),
8	Daily trips per capita	Trip/ day/ person	Characterized as: -Trips made by persons over 5 years of age who reside in the urbanized area -Trips with at least one extreme (origin and/or destination) inside the urbanized area -All reasons for travel and all transport modes, motorized, or otherwise -Trips on foot are included -Trips made using several modes are counted as one trip and assigned to a "primary mode"	Korea:(3), Japan: (3), USA:(3), Developing countries:(3),
9	Annual transportation energy consumption	MJ/ person	Evaluating value of annual transport energy consumption by private motorized vehicles and motorcycles per capita	Korea:(4), Japan: (4), USA:(4), Developing countries:(2),

Table 3 Calculation methods to explain travel behavior data

Data on travel behavior	Applied cities (Num. of sample cities)	Equations	Data resources (Num. of data source)
Trip length (Km)	Korea (7)	$L_k = Avg\_V_k \cdot Avg\_D_k$	Avg_D_k: (3), Avg_V_k:(4)
	Japan (14) USA (46)	$L_k = \frac{\sum_1^n l_i^k}{Num.of\ total\ Trip_k}$	(3)
	Developing countries(14)	$L_k = \frac{\sum_1^n d_i^k \cdot Avg\_V_k}{Num.of\ total\ Trip_k}$	Avg_V_k: (2), (3)
Vehicle speed (Km/h)	Korea (7)	$V_k = Avg\_L_k / Avg\_D_k$	(4)
	Japan (14) USA (46)	$V_k = \frac{\sum_1^n l_i^k / d_i^k}{Num.of\ total\ Trip_k}$	(3)
	Developing countries(14)	Avg_V_k	(2),
Number of daily trips (trips/day/ person)	Korea (7)	$T_k = \frac{\sum trip_k}{Num.of\ total\ population_k}$	(3)
	Japan (14), USA (46)	$T_k = \frac{\sum_1^n trip_i^k}{Num.of\ total\ Trip_k}$	(3)
	Developing countries(14)		(3)
Modal share 1.Private motorized mode(2+3) 2,Private passenger vehicle, 3.Motorcycle	Korea (7)	$M_k^r = \frac{Num.of\ total\ trips\ on\ mode_r^k}{Num.of\ total\ tirps\ in\ every\ modes}$	(3)
	Japan (14), USA (46)	$M_k^r = Avg\_M_k^r$	(2)
	Developing countries(14)	$M_k^r = \frac{Num.of\ total\ trips\ on\ mode_r^k}{Num.of\ total\ tirps\ in\ every\ modes}$	(3)
Average car occupan-cy of passen-ger car	Korea (7)	$O_k = Avg\_O_k$	(3)
	Japan (14), USA (46)	$O_k = \frac{\sum_1^{n^k}(x_i \cdot I_i)}{\sum_1^{n^k} I_i}$	(3)
	Developing countries(14)	$O_k = Avg\_O_k$	(2)

Note: K = Cities (k=1,…,81), i=Individual of sample (i=1,..,n), l_i=Trip length of i, d_i=travel time of i, r=representative trip mode (r=1,..,n), L_k=Average trip length in city k, V_k=Average vehicle speed in city k, D_k=Average travel time in city k, T_k=Average daily trip number in city k, M_k^r=Trip share on mode r in city k

Table 4 The urban classification

No	Nation	City	No	Nation	City
1	Korea	Ulsan	41	Japan	Kyoto
2	Lebanon	Tripoli	42	Japan	Kobe
3	Cambodia	Phnom Penh	43	Japan	Fukuoka
4	China	Chengdu	44	Korea	Seoul
5	Nicaragua	Managua	45	Korea	Pusan
6	Indonesia	Jakarta	46	Korea	Daegu
7	Vietnam	Ho Chi Minh	47	Korea	Kwangju
8	Vietnam	Hanoi	48	Korea	Daejon
9	Kenya	Nairobi	49	Korea	Inchon
10	USA	Austin	50	Syria	Damascus
11	USA	Charlotte	51	Malaysia	Kuala Lumpur
12	USA	Cincinnati	52	Peru	Lima
13	USA	Columbus	53	USA	Atlanta
14	USA	Hartford	54	USA	Boston
15	USA	Houston	55	USA	Chicago,
16	USA	Indianapolis	56	USA	Cleveland
17	USA	Jacksonville	57	USA	Los Angeles-Long Beach-Santa Ana
18	USA	Kansas City	58	USA	Miami-Fort Lauderdale
19	USA	Louisville	59	USA	New York
20	USA	Milwaukee	60	USA	Washington
21	USA	Nashville-Davidson	61	USA	Baltimore
22	USA	Norfolk-VA Beach-Newport News	62	Japan	Hiroshima
23	USA	Oklahoma City	63	USA	Memphis
24	USA	Orlando	64	USA	New Orleans
25	USA	Phoenix	65	USA	Portland
26	USA	Providence	66	USA	Seattle
27	USA	Rochester	67	Japan	Chiba
28	USA	San Antonio	68	Japan	Kawasaki
29	USA	Honolulu	69	Japan	Kitakyushu
30	Japan	Sapporo	70	Philippines	Manila
31	Japan	Tokyo	71	USA	Buffalo-Niagara Falls
32	Japan	Osaka	72	USA	Dallas-Fort Worth Arlington
33	Romania	Bucharest	73	USA	Denver Aurora
34	Egypt	Cairo	74	USA	Detroit
35	USA	Philadelphia,	75	USA	Minneapolis-St. Paul
36	USA	San Francisco-Oakland	76	USA	Pittsburgh
37	Japan	Sendai	77	USA	Sacramento
38	Japan	Saitama	78	USA	St. Louis
39	Japan	Yokohama	79	USA	Salt Lake City
40	Japan	Nagoya	80	USA	San Diego
			81	USA	Tampa-St. Petersburg

Urban type	*Type Ⅰ*	*Type Ⅱ*	*Type Ⅲ*
Description	*(All of the 81 target cities including Type Ⅱ, and Type Ⅲ)*	(*No railway, only Road the 29 cities*)	(*Metro + Tram only the 7 cities*)
Urban number	*No. 1~81*	*No. 1~29*	*No. 30~36*

We are also interested in the energy impact of the presence and absence of railway systems.

For this, first we classify the urban types into three groups (all of target cities, cities having no railway system and cities having Metro + Tram) to grasp the diversity of the relationship between transport energy consumption and urban structure and demographic and transport characteristics in individual and urban level by the urban type.

The result of classification is organized in Table 4 above.

5. ESTIMATION THE FACTORS INFLUENCING OF TRANSPORTATION ENERGY CONSUMPTION BY URBAN TYPE

Using the database and multilevel model here, we examined the impact of factors at the individual-urban level on transportation energy consumption and travel behaviors by private motorized modes. We did this by applying the multilevel analysis model, which can indentify not only the diversity of the relationship between energy use and urban-transport characteristics among the cities, but also can explain that diversity.

In this study, we plan the basic models of three urban types. The first one, (*Type Ⅰ*) is a pooling type that considers all of the 81 target areas for identifying the global relationship between transportation energy consumption and urban-transport characteristics at the urban-individual level. We can find out the general tendency of the factor's effects on transportation energy consumption.

The second one, (*Type Ⅱ*) is an automobile dependence type that considers cities having only roads as transport infrastructure.

The last one, (*Type Ⅲ*) is the type of public transit dependence that considers cities having Metro and Tram.

At first, fully unconditional models are estimated for three types of rail systems. Then, the proportion of the variance in the outcome between the level 2 units is examined by the "Intra-class Correlation Coefficient (*ICC*)". In general, the variance of the outcome in standard multilevel models consists of two components: the variance of u_j (τ_0) and the variance of r_{ij} (σ^2). The σ^2 parameter captures variability within groups and τ_0 captures variability between groups. With these two variances, the intra-class correlation coefficient for standard multilevel models is calculated using the following equation Eq.(8) to measure the proportion of the variance in the outcome between the level 2 units.

$$ICC = \tau_0^2 / (\tau_0^2+\sigma^2) \tag{8}$$

If *ICC* is sufficiently close to zero, then there is effectively no variation in the subjects between the level 2 units, suggesting that standard subject level models are adequate for these data. Table 5 shows the results of estimation on unconditional models. The purpose of unconditional models is to, indentify intra-class correlation (*ICC*) and the difference of impact between 2-level variables, and also the first status of deviance.

For obtaining estimates of between and within group variance, unconditional (*Null*) models are estimated (Table 5).

Table 5 The estimation results of unconditional models

City classification	*Type Ⅰ*	*Type Ⅱ*	*Type Ⅲ*
Dependant variable: Transportation energy consumption			
Fixed effect			
Intercept	48,233.6***	56,277.5***	18,418.6**
Random effect			
Intercept	42,680.0***	44,379.4***	17,487.6***
Sample number,	248,101	86,731	64,124
ICC	0.294	0.236	0.770
Deviance	6,211,745	2,204,361	1,300,870

*Note; *p < 0.10, **p < 0.05, ***p < 0.01*

The intra-class correlation coefficient (*ICC*) is 0.294 for *Type Ⅰ* indicating that 29.4 % of the total variation in *Type Ⅰ* exists between urban areas, and may be explained by urban-level variables.

Inversely, 70.6% (1－0.294) of total variation in *Type Ⅰ* is explained by predictors at the individual level. The *ICC*s for *Type Ⅰ* to *Ⅲ* in Table 6 are 0.294, 0.236 and 0.770 relatively indicating large variance between urban-level variables. And all urban types are statistically significant, suggesting that all coefficients of fixed effect and random effect are statistically appropriate with significance level of 1%.

As a result urban-level predictors are useful for estimating statistical models for these urban types. And it should be noted that roughly more than 70% of the total variation in *Type Ⅲ* is attributable to the variability of urban level, suggesting that *Type Ⅲ* is significantly influenced by characteristics of urban level.

Meanwhile, deviance in the unconditional model can be a reference standard suggesting model fitness. In general, reducing deviance more than 2 against inputting one independent variable into analysis model, and the model can be regarded fitness model. Through Table 5 and Table 6, it is possible to identify that all the deviances are decreased after inputting predictors into the model.

Based on the results of unconditional models, the influences of factors in each urban type are separately estimated.

Table 6 below presents the estimation results of the models on *Type Ⅰ* to *Ⅲ* in which individual and urban features are included as predictors.

First, we examine the results at the individual level. The results at the individual level in Table 6 show that urban density generally has a negative effect on energy consumption of transport. This result has widely demonstrated how important urban structure is in helping to explain the macro patterns of urban transportation, especially the level of automobile dependence and transportation energy consumption[9)].

Table 6 The estimation results considering all variables

City classification	Type Ⅰ	Type Ⅱ	Type Ⅲ
Dependant variable: Transportation energy consumption			
Fixed effect			
▸*Urban-level*			
Intercept	48,823.0***	57,225.7***	18,423.0***
Density	-141.4**	-258.5**	-880.7***
GRDP	0.22	0.11	0.79***
Road	10.10***	11.67***	19.70***
Metro	-311.0		-592.9***
Tram	-33.1		-257.6***
Car occupancy	-6,388.4	-5,308.1	
Car ownership	12.34		
▸*Individual-level*			
Passenger car	2,437.5	4115.9	952.1***
21 to 40	3,876.2***	2677.1**	2,593.2***
41 to 60	4,606.2***	3865.1*	1,934.6***
More 60	2,461.6*	1574.0	2,445.7***
Gender	1,746.3***	1252.5	1,835.8***
Trip number	5,974.1***	3795.5***	4,470.1***
Random effect			
Intercept	25,931.7***	26101.2***	2,915.7***
Deviance	6,208,213	2203923	1,291,061

*Note; *p < 0.10, **p < 0.05, ***p < 0.01*

Table 7 Average population density of each urban type

City classification	Type Ⅰ	Type Ⅱ	Type Ⅲ
Average population density (persons/ha)	35.7	19.7	73.7

Here especially, the prediction coefficient of density in TypeⅢ shows the largest reduction effect on a dependent variable. And it is possible to find out that the effect of road length in TypeⅢ is also the largest and statistically effective of urban types. It could mean that population density in urban areas has an effect on road congestion, namely constructing additional road under highly denser urban structure can induce road congestion, and consequently excessive transportation energy consumption. Actually, we looked at average population density of each urban type and *TypeⅢ* shows the highest population density, more or less two times of *Type Ⅰ* and *Type Ⅱ* (Table 7 above).

Next, the results differ in GRDP which means the outcome obtained from the production activity in a city shows a positive effect on transportation energy consumption regardless of the urban types. It is impossible to determine in this analysis which transport mode (road, buses or railway based) largely acts upon GRDP, however, it is apparent that travel behavior by private motorized modes is one of the roots of GRDP. Especially, statistically the largest impact on GRDP is shown in *TypeⅢ*. This result is proved by the findings in our previous research[15], in which the efficiency of transportation energy consumption is the highest under the urban type having well estimated railway system (the cover ratio of railway in *TypeⅢ* is highest: 3.30 m/ha; Table 7). We clarified in previous research[15] that energy efficiency of transport, defined by the ratio between energy consumption of transport and the combination daily trip number of each mode (private and public) and GRDP, is the most effective in the urban type having Metro + Tram. Therefore, it is possible to conjecture that the travel behaviors under the urban type having Metro + Tram (maybe they are well linked) might demonstrate the most effective production activities.

Meanwhile, the impacts of rail transit at the urban level show diversity related to restraining at the transportation energy use by the urban type. As shown in Table 6, generally, Metro length and Tram length act to restrain energy use of transport. However, the result in *Type Ⅰ* is not statistically sufficient. On the other hand, Metro and Tram length in *TypeⅢ* are statistically significantly acting on reducing transportation energy consumption, and the coefficients in *TypeⅢ* are much larger than the global average of *Type Ⅰ*. In this way, from the findings of urban level above, *TypeⅢ* which has Metro + Tram is the urban type of denser urban structure and the linked railway systems act to control the automobile dependence in an effective way. Therefore, it should be noted that in the urban type which maintains dense urban structure Metro and Tram development statistically have an effect on reducing transportation energy consumption compared to other urban types.

Next, we examine the results at the individual level in Table 6. First, the dummy of passenger car ownership acts positively on transportation energy consumption regardless of the urban types. And the effect of *Type Ⅱ* with no railway system is the largest, even though it is not statistically significant.

The second, according to the results at the individual level of *Type Ⅰ* and *TypeⅢ* in Table 6, age groups are statistically significant on energy consumption of transportation. It is shown that transportation energy consumption is more likely to be generated in the age 41 to 60 group compared to other ages. Especially, the group of more than 60 years old, known as seniors who generally do not work, shows relatively less consumption. Meanwhile, we can find that the prediction coefficients of the age group in *TypeⅢ* are lowest among the urban types and the prediction coefficients in *Type Ⅱ* are not statistically significant.

The third, transportation energy consumption, is more likely to be generated by males (Gender dummy means that 1 is male, 0 is female) who own a private passenger car with significance level of 1%. However, in *Type Ⅱ*, gender is not significant. Namely, the differentiation between male and female is smaller in the use of passenger car in *Type Ⅱ*. In addition, considering the second findings above at the individual level, where there is no significance in the difference of ages, it is possible to conjecture that people in *Type Ⅱ* have more dependence on automobile regardless of gender of ages.

Finally, examination of random effects suggests that there is a significant variation in the probability of transportation energy consumption (all of the coefficients of random effects are significantly different in each urban type). It should be noted that the fixed effects in urban-level for predicting transportation energy consumption of *Type Ⅲ* capture a significant portion of the variation across urban types, as reflected by random effect coefficients showing relatively smaller value (2,915.7). In terms of both *Type Ⅰ* and *Type Ⅱ*, in contrast, the random error terms (u_j) suggests that relatively greater unobserved variation exists regarding factors that influence the probability of transportation energy consumption across urban types (after the fixed effects in urban-level characteristics have been accounted for). This indicates a need to introduce additional urban-related explanatory variables in *Type Ⅰ* and *Type Ⅱ* for explaining transportation energy consumption in future research. These variables might include travel characteristics under individual-level, and urban structure-related factors such as CBD intensity, density of inner-outer areas, etc. In addition to variables employed in this study, it is believed that particular types of rail system outcome probabilities may also be associated with more detailed characteristics of rail transit (Station number, frequencies, fare etc.). Including these variables into the models may improve the accuracy of the prediction models according to rail system.

As shown in Table 6, the results of passenger car ownership present conflicting results that transportation energy consumption is likely to be small under rail system conditions (*Type Ⅲ*), and to be larger under non-rail system (*Type Ⅱ).*

6. CONCLUSION

This research describes the estimation of statistical models of the variables at the individual-urban scale according to the development of rail systems for establishing effects on travel behaviors by private motorized modes and transportation energy consumption. Using Person Trip (PT) data from the institutes in targeted cities, models that predict the probability of travel behaviors and transportation energy consumption were estimated for targeting whole cities, the cities of Non-railway and cities of Metro + Tram. Since the data is hypothesized in a hierarchical structure, multilevel modeling could be employed.

The results of this paper indicate that the effects of individual characteristics and urban factors can be modeled by multilevel analysis. It can be identified that urban density has a negative effect on transportation energy consumption throughout all urban types. Particularly, the urban type, such as *Type Ⅲ*, in which constructed rail systems based on the denser urban structure reveals a striking reduction effect on energy use of transport. In contrast, the urban type having only road and based on lower density, *Type Ⅱ*, shows that people are more dependent on automobiles regardless of gender of age. The ownership of a passenger car also acts as a big part on transportation energy consumption in *Type Ⅱ*.

Here it should be noted that as we can see in Table 5 and Table 6, the urban-transport characteristics at the urban level can explain a large portion of dispersion. Especially *Type Ⅲ* in which constructed rail systems based on the denser urban structure shows that more than 70% of dispersion is explained by the factors in urban level. This interesting fact shows the importance of the initiatives related to urban policy on introducing new transport system from the possibility that urban sustainable development might be controlled by well established infrastructure of public transport based on denser structure.

Notes

(1) KTDB: Korean Transport Database, MLITT: Ministry of Land, Infrastructure, Transport and Tourism, JICA: Japan International Cooperation Agency, FHWA: Federal Highway Administration U.S. Department of Transportation.

(2) Korea: Population and housing census(2005), Developing countries: The reports “The study on master plan for urban transport in the metropolitan area-(Cairo. Tripoli(2001); Phnom Penh, Chengdu, Jakarta, Kuala Lumpur(2000); Damascus. Managua(1998); Manila(1997); Bucharest(1999); Lima. Hanoi(2005); Ho Chi Minh(2003); Nairobi(2004))”.

(3) Korea: Household Travel Survey((2005), Japan: The Nationwide Person Trip Survey(2005), U.S.A: NHTS(National Household Travel Survey(2001), Developing countries: Household Interview Survey of each country-(Cairo, Tripoli(2001); Phnom Penh, Chengdu, Jakarta, Kuala Lumpur(2000); Damascus, Managua(1998); Manila(1997); Bucharest(1999); Lima, Hanoi(2005); Ho Chi Minh(2003); Nairobi(2004)).

(4) Korea: The Statistics Report of each city(2005), Japan: The

Statistics Report of each city(2005), U.S.A: U.S. Department of Transportation, Federal Highway Administration. Highway Statistics 2001.

(5) U.S.A: Regional Economic Accounts Bureau of Economic Analysis U.S. Department of Commerce http://www.bea.gov/regional/

(6) All of vehicle in this research is assumed as gasoline vehicles due to the limitation on the data characteristics (We cannot find out which trip is made by diesel vehicles).

(7) Fuel efficiency of motorcycle is assumed a half of passenger car.

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