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Exploring Psychological Factors Influencing the Adoption of Sustainable Public Transit Considering Preference Heterogeneity

Gyeongjae Lee [1], Sujae Kim [2], Jahun Koo [1] and Sangho Choo [2,*]

[1] Department of Urban Planning, Hongik University, Seoul 04066, Republic of Korea; dl874500@gmail.com (G.L.); rwg322@daum.net (J.K.)
[2] Department of Urban Design & Planning, Hongik University, Seoul 04066, Republic of Korea; rtw1119@hongik.ac.kr
* Correspondence: shchoo@hongik.ac.kr

Abstract: Carbon emission reduction strategies are being implemented in the transportation sector by encouraging the adoption of eco-friendly vehicles and introducing demand management policies such as Mobility as a Service (MaaS). Nevertheless, the efficacy of MaaS in reducing carbon emissions remains uncertain. This study introduces Sustainable Public Transit (SPT) as a public transit alternative consisting of only green modes to promote sustainability. We explore the preferences of SPT in a commuting context, incorporating individual preference heterogeneity in a discrete choice model. We systematically identify the relationship between choice behaviors and individual heterogeneity in alternative attributes and psychological factors stemming from socio-demographic characteristics. The integrated choice and latent variable (ICLV) model with a mixed logit form is adopted, and the key findings can be summarized as follows: Preference heterogeneity is observed in the travel cost variable, which can be explained by characteristics such as the presence of a preschooler, household size, and income. CO_2 emissions do not have a statistically significant impact on choices. Furthermore, psychological factors are also explained through socio-demographic characteristics, and it is found that low-carbon knowledge positively influences low-carbon habits. Psychological factors significantly affect choices. Respondents who dislike transfers and prioritize punctuality are less likely to choose SPT, while those who have positive low-carbon attitudes are more likely to do so. Finally, scenario analysis is conducted to forecast mode share based on improvements in SPT alternative attributes and variations in attribute levels. Policy implications are then provided to enhance the acceptability of SPT.

Keywords: sustainable public transit; commuting mode choice; integrated choice and latent variable model; mixed logit; low-carbon attitude

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Citation: Lee, G.; Kim, S.; Koo, J.; Choo, S. Exploring Psychological Factors Influencing the Adoption of Sustainable Public Transit Considering Preference Heterogeneity. *Sustainability* **2024**, *16*, 7924. https://doi.org/10.3390/su16187924

Academic Editors: Béatrice Cahour and Sonia Adelé

Received: 9 July 2024
Revised: 28 August 2024
Accepted: 7 September 2024
Published: 11 September 2024

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1. Introduction

In 2022, the transportation sector accounted for approximately 23% of global carbon emissions, reaching 7.98 Gt CO_2. Although emissions from the transportation sector decreased in 2020 due to the COVID-19 outbreak, they have been steadily increasing since then [1]. To tackle this issue, policies focusing on demand management, such as enhancing public transportation, as well as the promotion of eco-friendly vehicles, are being implemented. Mobility as a Service (MaaS) has recently gained attention as a demand management policy due to its ability to integrate various mobility services on an integrated platform using ICT (Information and Communication Technology) [2,3]. MaaS indirectly promotes low-carbon travel by enabling seamless first mile/last mile connections for public transit and thereby increasing the convenience of using public transit, which could encourage car users to shift their transportation mode. Despite its potential benefits, many studies have shown that people who primarily use private cars tend to prefer MaaS less, raising concerns that the actual carbon emission reduction from introducing MaaS may not

be significant [4,5]. Electric Mobility as a Service (eMaaS) projects have recently emerged, offering mobility solutions solely based on electric-powered vehicles [6]. Such projects take a proactive approach to reduce CO_2 emissions from transportation, which is a direction that should be pursued. Nevertheless, most road transportation is still dominated by internal combustion engine vehicles, which includes public buses. Sustainable transportation options are currently witnessing limited market penetration and ongoing technological development. Consequently, they are often less competitive in terms of time and cost compared to conventional options. Therefore, it is important to provide transportation options within an acceptable range of time and cost for travelers in order to promote sustainable transportation.

Meanwhile, with rapidly emerging transportation technologies and services like autonomous vehicles, electric vehicles, and MaaS, the concept of an evolving landscape in which consumer preferences are becoming increasingly diverse is introduced. This segmentation implies a need for a tailored approach to promoting sustainable transportation, as acceptance and preferences will vary among different user groups.

In this study, we introduce Sustainable Public Transit (SPT), an alternative composed of low-carbon transportation modes, such as electric scooters and electric buses. This study aims to understand travelers' choice behavior according to SPT attributes through a Stated Preference (SP) survey, as a foundational step for establishing an optimal travel alternative provision strategy.

As previously mentioned, capturing various aspects of preference heterogeneity is important. Previous studies have addressed this by introducing latent variables related to individual preferences to explain choice behavior through inherent attitudes or by estimating the distribution of alternative attribute coefficients rather than point estimates to reflect heterogeneity. However, there are still relatively few cases where these two methods have been integrated into a single model. In our study, we build on the ICLV (integrated choice and latent variable) model, which incorporates latent variables into the choice model, and extend the choice model from a multinomial logit model to a mixed logit model to capture preference heterogeneity from various aspects. We expect to identify the differences in the impact of alternative attributes on commuters' utility and the variance in respondents' perceptions through socio-demographic characteristics.

The remaining parts of the paper are organized as follows: Section 2 briefly describes attempts to enhance preference heterogeneity in mode choice models and reviews efforts to incorporate individual psychological factors into these models. Based on this review, the research gap is identified, and the distinctiveness of this study is presented. Section 3 outlines the methodology, including the SP (Stated Preference) survey design strategy and the conceptual framework with mathematical formulas. Section 4 reports the results of the SP survey and interprets the findings from the model analysis based on the obtained data. Section 5 discusses the policy implications derived from the analysis results, the research's limitations, and directions for future research.

2. Related Works

2.1. Mode Choice Model Considering Preference Heterogeneity

Mode choice is a complex decision-making process that is influenced by many factors, including mode characteristics, socio-demographic characteristics, psychological factors, and spatial factors. This decision-making process is based on the principle of utility maximization, which is derived from the random utility theory [7]. Utility is assumed to be influenced by probabilistic factors instead of being deterministic. So, the utility function is split into an observable component and an unobservable component (error terms). The error terms in the most commonly used multinomial logit model (MNL) stem from the IID assumption that they are independent and identically distributed across alternatives, making it difficult to reflect the behavioral diversity of travelers and the interdependence between alternatives. This means that the model cannot perfectly explain travelers' choice behavior, leading to an inability to segment the population and capture

the preferences or taste variations among travelers. In other words, since parameters are estimated as a single value for the entire population (or sample), it is difficult to identify the differences among travelers. This difference is referred to as preference heterogeneity; if preference heterogeneity is not adequately explained, valuable information stemming from the diversity of choice behavior may be lost, and it could result in inconsistent and biased estimates [8,9].

Individual preference heterogeneity is a widely discussed topic. To account for individual preference heterogeneity, empirical analyses using the mixed logit model, which assumes model coefficients as random variables (random parameters), have been actively conducted since the late 1990s [10].

The early mixed logit model simply assumes that the coefficients of mode attributes follow a specific distribution, and the parameters of this distribution are estimated. Therefore, when using the mixed logit model to account for preference heterogeneity, two key aspects must be considered. First, it must be decided which alternative attributes to consider as random parameters, typically determined through the statistical significance of the derived coefficients' mean and standard deviation. In general mode choice situations, travel time [11–14] and travel cost [12,15,16] have been considered as random parameters. In the choice situations for new modes of transportation such as electric vehicles and autonomous vehicles, the purchase cost of the vehicle [17–19], driving range [20], vehicle manufacturer [19] are considered, and in the choice situations for departure time, factors such as congestion and punctuality [21] are considered as random parameters. Secondly, within the mixed logit model, preference heterogeneity is captured through the continuity of parameters that vary according to a predefined probability distribution. Therefore, selecting an appropriate probability distribution must be done with care. The normal distribution, for instance, does not allow for sign constraints, potentially leading to illogical outcomes when applied to empirical attributes with clear signs (such as travel costs and travel time). In such cases, a log-normal or triangular distribution, which allows for sign constraints, is commonly adopted [11].

Furthermore, efforts to improve the model continue, such as decomposing the error components to capture unobserved variations that the standard mixed logit model cannot detect [22]. The extension of the mixed logit model allows for the decomposition and comparison of the heterogeneity in the means of coefficients estimated as random parameters, based on the effects of various socio-demographic characteristics [23–25]. As a result, it not only allows for a more systematic explanation of preference heterogeneity but also enhances the explanatory power of the model [25].

Additionally, the Latent Class Model (LCM) serves as an alternative method for capturing preference heterogeneity. This approach segments respondents into distinct classes based on homogeneity and estimates coefficients for each class independently. The LCM delineates heterogeneity by creating a finite number of unique classes, each characterized by its parameters. A key advantage of this model is its ability to identify the origins of heterogeneity through probabilistic classification of classes based on respondents' characteristics. However, the assumption that preferences within the same class are homogeneous has been criticized for being overly restrictive [26].

2.2. Psychological Factors

An alternative approach to account for individual heterogeneity is to include psychological constructs like attitudes, preferences, and perceptions in the model. A broad range of latent variables from various groups have been utilized to explain the behavior of mode choice, and these can be classified into three main types: (1) related to individual attitudes not tied to any specific mode, including social norms and perception of certain conditions [27,28]; (2) associated with individuals' perceptions of alternatives, such as how comfortable they feel using a specific travel mode [29,30]; (3) related to the actual behavior of individuals [27]. The three categories can vary depending on the subjects being

measured. Previous studies have incorporated aspects such as comfort, safety, reliability, flexibility, convenience, accessibility, and habits into mode choice models.

Recently, due to the growing sense of crisis regarding climate change, several efforts have been made to encourage eco-friendly behaviors, such as promoting electric vehicle ridership and recommending walkable routes. To develop strategies in this regard, various latent variables related to the environment, including individuals' eco-friendly attitudes and concerns about the environment, have been extensively incorporated into models in multiple ways [31–39].

The first approach integrates pro-environmental attitudes as latent variables within mode choice models, such as the ICLV model. Consistent with expectations, findings indicate that individuals with more pronounced environmental consciousness are more likely to opt for public transit solutions, including buses and subways, as well as active modes of transportation, like walking and cycling [31,33,38,39]. Furthermore, the influence of pro-environmental attitudes is analyzed through respondents' socio-demographic characteristics. It is commonly observed that higher levels of education and the presence of children are associated with stronger manifestations of these attitudes. The impact of income and gender, however, appears to vary across studies.

The second approach seeks to identify the moderating effect of various pro-environmental attitudes on explaining green travel behavior through latent variables—including attitudes, subjective norms, perceived behavioral control, internal, and external situational factors—derived from traditional behavior theories, such as the Theory of Planned Behavior (TPB) and the Attitude-Context-Behavior Model (ABC) [34,36]. The interaction between low-carbon awareness, low-carbon knowledge, and latent variables from the TPB is analyzed in the context of purchasing behavior for new energy vehicles [34]. It is revealed that the moderating effect of low-carbon awareness is negligible, whereas low-carbon knowledge significantly enhances the positive influence of attitudes towards new energy vehicles on purchase intention. Conversely, in another study, the emphasis is on the moderating effects of individual internal factors and social context in the formation of green travel behavior intention, as influenced by green travel consciousness [36]. Among individual internal factors, comfort preference and convenience preference have a negative moderating effect on the impact of an individual's environmental responsibility on green travel behavior. On the other hand, in terms of social context, the more negative the social perception towards green travel, the more it reduces the impact of environmental responsibility, similar to the aforementioned internal factors. This implies that even individuals with a high sense of responsibility towards environmental issues may not choose green travel options.

Nevertheless, while these studies consider the interaction between pro-environmental attitudes, other personal internal attitudes, and the social context, a limitation is noted in the insufficient consideration of the interactions among pro-environmental attitudes. Lastly, the process of eco-friendly behavior is sequentially modeled through the relationship between perceptions related to pro-environmental concerns [32]. Specifically, it is demonstrated that environmental cognition shapes a low-carbon consumption preference, which, through interaction with social consumption culture, leads to a tendency towards low-carbon behavior, ultimately manifesting in actual actions.

In studies utilizing latent variables within choice models, the focus is primarily on the impact of latent variables on the utility of alternatives. As a result, unlike research using structural equation modeling, there is a lack of exploration regarding the relationships between latent variables.

2.3. Research Gap

A review of prior studies indicates that incorporating preference heterogeneity in various ways can lead to more systematic interpretations [23,24,27–31,33,38,39]. The use of the mixed logit model not only relaxes the strict assumptions of the MNL model but also, in some studies, allows the coefficients estimated as random parameters to be explained

through individuals' socioeconomic characteristics [23,24]. Furthermore, there are ongoing efforts to better understand mode choice situations by introducing various unobserved individual attitude latent variables [27–31,33,38,39]. However, it has been observed that existing studies rarely attempt to simultaneously consider mixed logit models and latent variables to reflect such individual heterogeneity. Therefore, this study employs the ICVL model in the form of a mixed logit model as the choice model to provide tailored alternatives that enhance the acceptance of new sustainable mobility services according to user characteristics. In this approach, not only are the alternative attribute variables constituting the utility function estimated as random parameters, but they are also decomposed and explained through individuals' socioeconomic characteristics.

To the best of our knowledge, while there have been quite a few studies that incorporated eco-friendly attitudes into discrete choice models for a single new travel mode, study on choice models for mode combinations that consider eco-friendly attitudes, perceptions about travel, and other relevant factors has been limited. Addressing these research gaps, the contribution of this study can be summarized as follows:

- The ICLV model incorporates the mixed logit model as a discrete choice model to account for various sources of heterogeneity among respondents. Through this approach, this study systematically explores the relationship between socio-demographic characteristics and SPT choice behavior, dividing it into two aspects: variance of alternative attributes and respondent travel and low-carbon attitudes.
- By analyzing changes in choice behavior resulting from improvements in alternative attributes and respondent group attributes, this study suggests policy implications for enhancing the acceptability of SPT alternatives.

3. Methodology

3.1. Study Site and Sample

Our empirical study is conducted in the Seoul metropolitan area, South Korea, to understand the choice behavior in alternative SPT, which includes low-carbon travel modes with public transit. Seoul produces the highest amount of CO_2 emissions in the world, with 276.1 $\pm$ 51.8 Mt [40]. While the metropolitan area has experienced rapid sprawl, with residential areas expanding to the periphery, various infrastructures remain concentrated in Seoul, resulting in high travel intensity from the periphery. This sprawl increases the distance between homes and workplaces, which, in turn, raises vehicle-use intensity (causing more frequent and longer trips), leading to higher CO_2 emissions [41–43]. Therefore, commuting trips from the peripheral areas to Seoul are considered a significant target for CO_2 emission reduction, and they are expected to have a substantial effect on reducing CO_2 emissions when converted to low-carbon travel modes. In this study, an SP survey is designed to repeatedly measure the preferred commuting mode for long-distance travel from the periphery to the center. The target population for the survey is individuals aged 20–60 years residing in the Seoul metropolitan area who regularly commute within the region. Stratified random sampling is conducted based on the dimensions of residential area, gender, and age to ensure that the sample represents the target population. The sample proportions for each stratum are determined using commuting sample statistics from the 2020 census data.

3.2. Questionnaire Design

We constructed the survey with a systematic arrangement of three main sections to identify a respondent's preference regarding SPT.

- Include five-point Likert scale questions about respondents' psychological factors, such as travel attitudes and low-carbon attitudes.
- Experiment with respondents' stated choices among alternatives—car (CAR), public transit (PT), and Sustainable Public Transportation (SPT) —in a given situation.
- Collect respondents' socio-demographic characteristics, including gender, age, household members, income, etc.

In the following, we describe in more detail the questionnaire design for Section 1 (psychological measurement instrument) and Section 2 (stated choice experiment).

3.2.1. Psychological Measurement Instruments

To incorporate psychological factors into the choice model, instruments measuring these factors are designed, and in this study, four psychological factors are constructed based on previous research [35,44]. All instruments are measured using a five-point Likert scale ranging from "strongly disagree (=1)" to "strongly agree (=5)".

The SPT we propose in our study fundamentally assumes a combination of public transportation and other eco-friendly modes. In this context, we aim to consider respondents' attitudes toward multimodal combinations and eco-friendly modes.

Kim et al. [44] analyzed MaaS preferences based on individual attitudes, utilizing four latent variables, two of which are related to multimodal combinations. The first is the "preference for transfer", which measures an individual's resistance to transfers, and the second is the "importance of punctuality." Both latent variables significantly influenced MaaS preferences, and therefore, our study adopts these latent variables and the indicators used to measure them, as proposed by Kim et al. [44].

Secondly, since SPT, unlike general multimodal alternatives, combines only eco-friendly modes, we intend to introduce individuals' pro-environmental attitudes as a latent variable. Jia et al. [35] applied low-carbon-related factors in their analysis of commuting mode choices. They considered low-carbon awareness, low-carbon knowledge, and low-carbon habits; however, the low-carbon awareness variable was not statistically significant. Consequently, our study incorporates the latent variables of low-carbon knowledge and low-carbon habits, along with the measurement items for these variables. The indicators for each latent variable can be found in Figure 1.

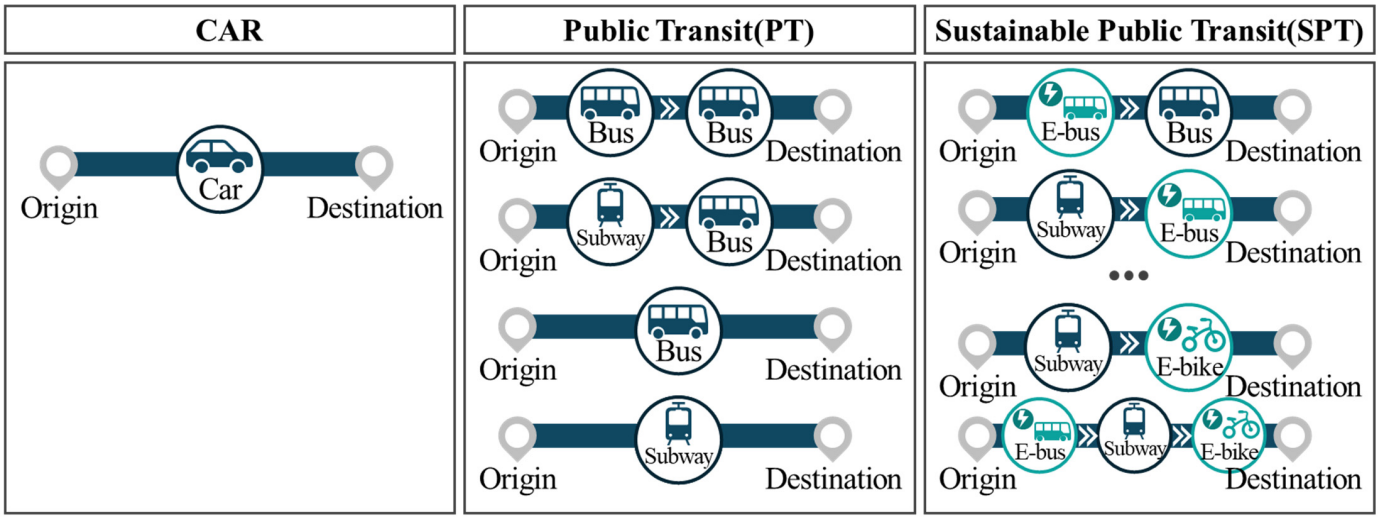


Figure 1. Examples of mode combinations for each alternative.

3.2.2. Stated Choice Experiment Design

Three commuting modes are presented as alternatives in the choice task: two conventional alternatives (CAR and PT) and a new one (SPT). Information on travel time, travel cost, and carbon emissions is presented for each alternative. The first alternative "CAR" is used exclusively without integration with other travel modes. Since the proportion of environmentally friendly cars in the Seoul capital area is only 7%, this study is constrained to focus only on internal combustion engine vehicles. The second alternative, "PT", represents the option of commuting using buses driven by internal combustion engines and subways. It includes situations where either the bus or subway is used individually or when they are used together with transfers. Lastly, the new alternative, "SPT", is defined

as public transit that includes low-carbon travel modes. Low-carbon travel modes refer to eco-friendly vehicles powered by carbon-free energy sources, such as shared electric scooters, shared electric bicycles, and electric buses. To enhance respondents' understanding of the proposed alternatives, we present the mode combinations corresponding to each alternative, as shown in Figure 1.

We consider three attributes for each alternative: travel time, travel cost, and CO_2 emissions. The baseline values for each attribute adequately represent the commuting context in the Seoul metropolitan area. We derive the average distance and time of commuting from the periphery to the center of the Seoul metropolitan area using smart card data for public transit, and they are approximately 25 km and 68 min, respectively.

Since there are no separately measured data for car travel time, we apply the travel time ratio between cars and public transportation for different distance ranges in the Seoul metropolitan area as suggested by KOTSA [45]. For the 10 km distance range, a ratio of 0.72 is suggested, and for the 20–30 km range, a ratio of 0.83 is suggested. In this study, we apply the ratio of 0.83, defining 48 min as the default CAR travel time.

For car travel costs, we apply the car operating costs (including operating costs, fuel costs, and maintenance fees) based on speed as presented by MOLIT [46]. The speed used is 31.25 km/h (25 km ÷ 0.8 hour), calculated based on the travel distance and time obtained earlier. However, since MOLIT [46] presents the data in 10 km/h intervals, we use a 3rd order polynomial curve fitting to derive a cost of KRW 296.4 per km. Accordingly, the default CAR travel cost is set at KRW 7410 (25 km × KRW 296.4). The travel cost for public transportation (PT) is based on the standard fare for public transportation in the Seoul metropolitan area.

We use the mode-specific CO_2 emission factors provided by Ko [47] to calculate the CO_2 emissions for CAR and PT, which are as follows: CAR—147.5 g/passenger·km; PT—41.9 g/passenger·km (an average of bus—50.6 g/passenger·km and subway—33.3 g/passenger·km). In Ko [47], the CO_2 emission factors for cars and buses are calculated by applying the traffic speed and the ratio of registered vehicle types by fuel, ensuring that the characteristics of the Seoul metropolitan area's traffic are reflected. In the case of subways, the CO_2 emissions for the subway sector in the Seoul metropolitan area are calculated by considering the number of passengers and the individual travel distance, resulting in the unit CO_2 emission per passenger per kilometer traveled. When converted into a choice situation, the estimated CO_2 emissions are 3700 g (28 km × 147.5 g/passenger·km) for CAR and 1050 g (28 km × 41.9 g/passenger·km) for PT. Each attribute is classified into three levels: 90%, 100%, and 110% of the baseline value.

However, for the SPT alternative, which includes public transit, the travel time attribute is set the same as PT. Moreover, we controlled the scenarios to exclude any cases where the travel time for SPT is shorter than that for PT in the SP questions. In contrast, for the travel cost and CO_2 emissions attributes, the lowest and highest situations are assumed, leading to the determination of level 1 and level 3, while the median values of level 1 and level 3 are used as the values for level 2. To estimate the maximum values for travel cost and CO_2 emissions for SPT, we additionally analyze smart card data to examine first/last mile travel using town shuttle buses. The analysis results in an average first/last mile travel distance of 2.7 km. Assuming that the most expensive mode for this distance would be a shared electric scooter, we define the maximum travel cost as KRW 3250 by adding the rental cost of the shared electric scooter to the standard public transportation fare. On the other hand, for CO_2 emissions, we assume that the first/last mile is traveled using a carbon-free mode, while the rest of the journey uses public transit as usual, applying a rate of 934 g.

The attribute levels for each alternative that respondents encounter in the choice experiments are summarized in Table 1. Respondents are required to complete a total of four sets of choice experiments.

Choice experiments are designed using a fractional factorial design for survey efficiency. D-efficiency is employed as a design evaluation metric, and it is generally considered

reasonable design when its D-efficiency value is 80% or higher, indicating balanced and preserved orthogonality among attributes. Additionally, in our survey, there may be experiments where certain alternative conditions are evidently favorable compared to other alternatives in some situations. Therefore, it is necessary to control such experiments considering the alternative attributes. Consequently, experiments where the conditions for SPT are clearly more beneficial than those of PT are excluded.

Table 1. Attributes and levels in the choice experiment.

Attributes	Alternatives		
	Car	PT	SPT
Travel time (minutes)	43/48/53	61/68/75	61/68/75
Travel cost (KRW)	6669/7410/8151	1450/1550/1650	1450/2350/3250
CO_2 emissions(g)	3330/3700/4070	945/1050/1155	0/467/934

3.3. Modelling Approach

This study adopts the ICLV model, which theoretically allows for benefits from both the economic and behavioral foundations of the two approaches. By incorporating econometric theory, psychological theory, and economic theory, ICLV models promise to integrate these multiple dimensions into an integrative model [48].

The conceptual framework of the analytical model presented in this study is illustrated in Figure 2.

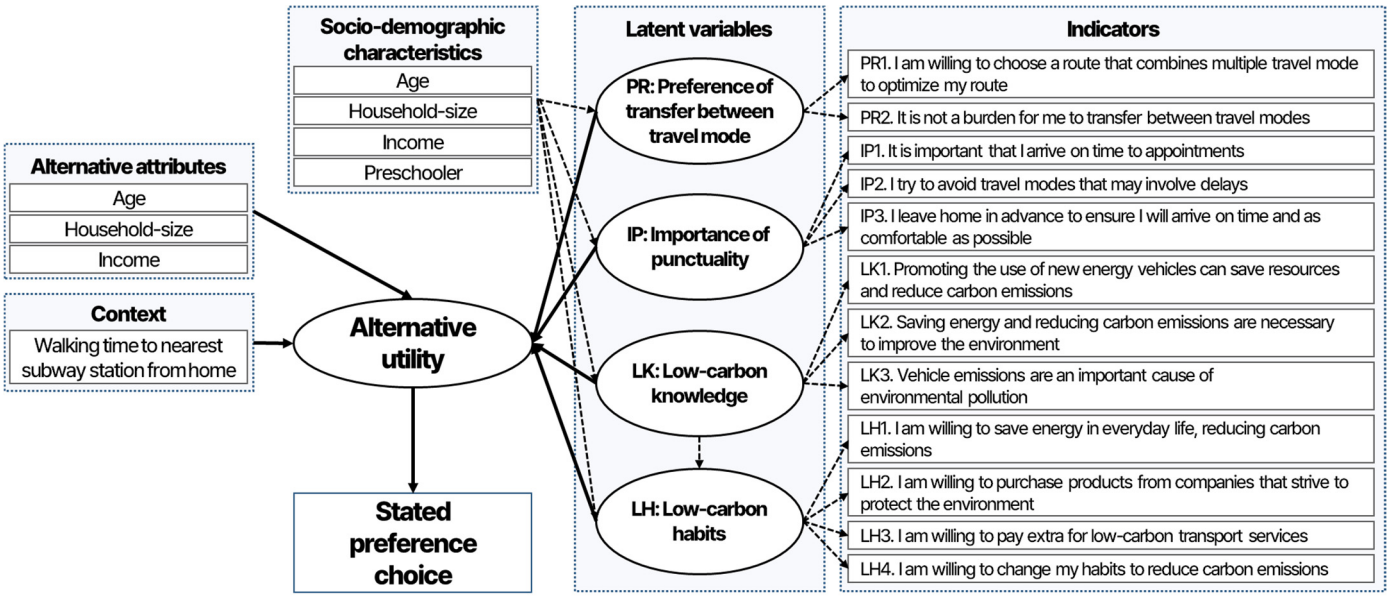


Figure 2. Conceptual modelling framework of ICLV model.

The ICLV model consists of two components: the latent variable model and the discrete choice model. And there are two approaches to estimate the ICLV model: the sequential approach [49–51] and the simultaneous approach [28,38,44,52]. The sequential approach has the disadvantage that it does not adequately address measurement error because it first estimates the latent variable model of the model and then includes the factor score of the latent variable as an explanatory variable in the choice model, which can lead to inconsistent estimates [53]. In contrast, the simultaneous approach that estimates latent variable models and discrete choice models jointly not only produces consistent and efficient estimates, but by estimating the full information, behavioral theories can be identified to include more complex relationships between latent variables and choice behavior [54–57]. This study estimates the parameters of the ICLV model using the simultaneous approach.

3.3.1. Latent Variable Model

The structural relationship between the latent variable and the socio-demographic characteristics is established in the latent variable model. The structural equation for the latent variables can be written as follows:

$$Z_n^L = \Gamma^L X_n^L + w_n^L, \quad w_n^L \sim N(0, I) \tag{1}$$

where L and Z denote the number of latent variables and the socio-demographic variables, respectively. $Z_n^L \in \mathbb{R}^{L\times 1}$ is the unobserved latent variable, $\Gamma^L \in \mathbb{R}^{L\times Z}$ is the parameter to be estimated that represents the effect of the socio-demographic characteristics explaining the latent variable, and $X_n^L \in \mathbb{R}^{Z\times 1}$ is the observed socio-demographic characteristics of respondent n. $w_n^L \in \mathbb{R}^{L\times 1}$ is the structural error term and is assumed to be normally distributed with mean zero and an identity covariance matrix.

Identification of each latent variable depends on indicator instruments measured on multiple ordinal scales. This study employs varying numbers of indicator instruments for each latent variable. As the indicators are measured on a five-point Likert scale, the measurement model is constructed using an ordered logit model. The measurement equation can be written as follows:

$$I_n^{LQ*} = \Lambda^{LQ} Z_n^L + v_n^L, \quad v_n^L \sim Gumbel(0, I) \tag{2}$$

where Q is the number of indicator instruments, $I_n^{LQ} \in \mathbb{R}^{Q\times 1}$ is the indicator of the latent variable, and $\Lambda^{LQ} \in \mathbb{R}^{Q\times L}$ is an unobserved parameter that represents the effect of the latent variable on the indicator. The measurement error term $v_n^{LQ} \in \mathbb{R}^{Q\times 1}$ is assumed to have a mean of 0 and follows a Gumbel distribution of the identity covariance matrix. When the number of scales is given as K, the latent perception of the indicator by respondents and the relationship between observed responses can be written as follows:

$$I_n^{Lq} = \begin{cases} 1, & if\ \tau_1^L < I_n^{Lq*} \le \tau_1^{Lq} \\ 2, & if\ \tau_1^{Lq} < I_n^{Lq*} \le \tau_2^{Lq} \\ \vdots & \\ k, & if\ \tau_{k-1}^{Lq} < I_n^{Lq*} \le \tau_k^{Lq} \end{cases} \tag{3}$$

where I_n^{Lq*} represents the response of respondent n to the q indicator question, while the latent perception I_n^{Lq*} is laid within the range denoted by the threshold value τ_k^{Lq}.

3.3.2. Discrete Choice Model

The multinomial logit (MNL) model is estimated based on the unrealistic assumption that all respondents share the same preferences for alternatives. On the other hand, the mixed multinomial logit model accounts for variation in respondents' preferences by assuming probability distributions for the coefficients of alternative attributes while taking into consideration individual characteristics and stochastic factors. This approach not only reflects the diversity in preferences among respondents but also provides a highly flexible model that can be applied to various types of random utility models [58]. The mixed multinomial logit model has been adopted as the discrete choice model for this study.

The utility function U_{isn} and the choice y_{isn}, where respondent $n \in \{1, \cdots, N\}$ chooses alternative $i \in \{1, \cdots, I\}$ in choice task $s \in \{1, \cdots, S\}$, can be defined as follows:

$$U_{isn} = \beta_{0i} + \beta_n^R X_{is}^R + \beta_i^F X_{isn}^F + \beta_i^L Z_n^L + \zeta_{isn}, \quad \zeta_{isn} \sim Gumbel(0, I) \tag{4}$$

$$y_{isn} = \begin{cases} 1, & if\ U_{isn} = \max\limits_j (U_{jsn}),\ \forall j \in \{1, \cdots, I\} \\ 0, & otherwise. \end{cases} \tag{5}$$

where $X_{is}^{R} \in \mathbb{R}^{R\times 1}$ represents the observed variables of the alternative that explain the utility through random parameters, while $X_{isn}^{F} \in \mathbb{R}^{F\times 1}$ represents the variables of the alternative and respondents that explain with fixed parameters. $\beta_{0i} \in \mathbb{R}^{1\times 1}, \beta_{n}^{R} \in \mathbb{R}^{1\times R}, \beta_{i}^{F} \in \mathbb{R}^{1\times F}$, and $\beta_{i}^{L} \in \mathbb{R}^{1\times L}$ correspond to the parameters that should be estimated for each variable, and ζ_{isn} represents the random disturbance term. β_{n}^{R} is assumed to be a random parameter, following a normal distribution with a mean of μ_{β} and a covariance matrix Σ_{β}.

This study is based on an SP survey, which may result in the phenomenon known as a pseudo-panel effect. This has been observed to cause correlated preferences among respondents in repeated choice tasks [59]. To address this correlation within the same individual's choices, a random parameter denoted as η_{in} is incorporated into the utility function. This parameter varies among individuals but remains constant for each individual's different choice tasks [59–62]. The distribution of η_{in} follows a normal distribution with a mean of zero and a standard deviation of σ_{η_n}. Additionally, the random disturbance term ε_{isn} in the utility function follows a Gumbel distribution.

$$\zeta_{isn} = \eta_{in} + \varepsilon_{isn}, \quad \eta_{in} \sim N\left(0, \sigma_{\eta_i}^{2}\right), \quad \varepsilon_{isn} \sim Gumbel(0, I) \tag{6}$$

The probability that respondent $n \in \{1, \cdots, N\}$ chooses alternative $i \in \{1, \cdots, I\}$ in choice task $s \in \{1, \cdots, S\}$ can be defined by combining the model components as follows:

$$P_{isn}\left(X_{is}^{R},\ X_{isn}^{F}, Z_{n}^{L}; \beta_{n}^{R}, \beta_{i}^{F}, \beta_{i}^{L}, \eta_{in}\right) = \frac{exp\left(\beta_{0i} + \beta_{n}^{R} X_{is}^{R} + \beta_{i}^{F} X_{isn}^{F} + \beta_{i}^{L} Z_{n}^{L} + \eta_{in}\right)}{\sum_{j\in J} exp\left(\beta_{0j} + \beta_{n}^{R} X_{js}^{R} + \beta_{j}^{F} X_{jsn}^{F} + \beta_{j}^{L} Z_{n}^{L} + \eta_{jn}\right)} \tag{7}$$

Assuming mutual independence among the random disturbance terms, we derive the unconditional joint likelihood by integrating the product of the likelihoods over the distribution of latent variables.

$$L_{n} = \int L_{c}\left(y_{n} \middle| X^{R}, X_{n}^{F},\ Z_{n}^{L},\ \eta_{i}; \sigma_{\eta}, \mu_{\beta}, \Sigma_{\beta}\right) \cdot L_{m}\left(I_{n}^{LQ} \middle| Z_{n}^{L}; \Lambda^{LQ}, \tau^{LQ}\right) \cdot L_{s}\left(Z_{n}^{L} \middle| X_{n}^{L}; \Gamma^{L}\right) dZ_{n}^{L} \tag{8}$$

The likelihood function for each component of the model can be written as follows:

$$L_{c}(\cdot) = \int_{\beta_{n}^{R}} \int_{\eta_{n}} \left[\begin{array}{c} \left(\prod_{s=1}^{S} \prod_{i=1}^{I} \delta(y_{isn} = 1) P_{isn}\left(X_{is}^{R}, X_{isn}^{F}, Z_{n}^{L}, \eta_{in}; \beta_{n}^{R}, \beta_{i}^{F}, \beta_{i}^{L}, \sigma_{\eta_i}, \mu_{\beta}, \Sigma_{\beta}\right) \right. \\ \left. \psi\left(\eta_{in} \middle| \sigma_{\eta_i}\right) \varphi\left(\beta_{n}^{R} \middle|, \mu_{\beta}, \Sigma_{\beta}\right) \right) \end{array} \right] d\eta_{n} d\beta_{n}^{R} \tag{9}$$

$$L_{m}(\cdot) = \prod_{q=1}^{Q} \sum_{k=1}^{4} \delta\left(I_{n}^{Lq} = k\right) \left[\frac{exp\left(\tau_{k}^{Lq} - \Lambda^{Lq} Z_{n}^{L}\right)}{1 + exp\left(\tau_{k}^{Lq} - \Lambda^{Lq} Z_{n}^{L}\right)} - \frac{exp\left(\tau_{k-1}^{Lq} - \Lambda^{Lq} Z_{n}^{L}\right)}{1 + exp\left(\tau_{k-1}^{Lq} - \Lambda^{Lq} Z_{n}^{L}\right)} \right] \tag{10}$$

$$L_{s}(\cdot) = \prod_{l=1}^{L} \Phi\left(Z_{n}^{l} - \Gamma^{l} X_{n}^{L}\right) \tag{11}$$

where L_n represents the likelihood function for the choice model, while $\delta(y_{isn} = 1)$ is an indicator for alternative i being chosen by respondent n in choice task s, assigned 1 if selected and 0 otherwise. $\psi(\cdot)$ is the probability density function of η_{in}, which is employed to control for serial correlation, and $\varphi(\cdot)$ is the probability density function of random parameter β_{n}^{R}. L_m represents the likelihood function of the measurement component in the latent variable model, while $\delta\left(I_{n}^{Lq} = k\right)$ represents the indicator for respondent n's choice of the k-th scale in indicator q, assigned 1 if chosen and 0 otherwise. L_s is the likelihood function of the structural component in the latent variable model, and $\Phi(\cdot)$ is the standard normal probability density function.

4. Results

4.1. Data and Prelimanary Analysis

4.1.1. Respondents Profile

The survey was conducted online over a 6-day period from June 14th to 19th, 2023, and we collected responses from a total of 134 participants. After excluding the responses from 17 participants who did not provide consistent answers, we analyzed the data from 119 respondents. The socio-demographic characteristics of the participants are presented in Table 2. The proportions of respondents by gender and age were collected to ensure these matched the stratum proportions in the population. Regarding education level, 94 participants (79.0%) reported completing university education, accounting for 79.0% of the total. In contrast, 14 respondents (11.7%) indicated completing high school or lower in their education. Out of all the respondents, 42.9% reported having a monthly average income between KRW 3 and 6 million. Additionally, 27 respondents (22.7%) earned KRW 6 million or more, which accounts for 22.7%. The survey data show that 35.2% of the respondents lived in households with 1 to 2 members, while 64.8% lived in larger households. This distribution closely matched the national statistics for the metropolitan area (34.7% and 65.3%, respectively), indicating that the sample suitably represented the population. Finally, it is confirmed that 34 respondents, accounting for 28.6%, lived with preschool-aged children.

Table 2. Survey Respondent Profile.

Characteristics		Frequency	Percentage
Gender	Male	66	55.5%
	Female	53	44.5%
Age	20–29	28	23.5%
	30–39	27	22.7%
	40–49	34	28.6%
	Above 50	30	25.2%
Education	Middle school or below	1	0.8%
	High school or below	13	10.9%
	Undergraduate	11	9.2%
	Graduate	94	79.0%
Monthly Income	Less than KRW 1 million	3	2.5%
	KRW 1~3 million	38	31.9%
	KRW 3~6 million	51	42.9%
	KRW 6~10 million	23	19.3%
	More than KRW 10 million	4	3.4%
Household-size	1	21	17.6%
	2	21	17.6%
	3	35	29.4%
	4	37	31.1%
	More than 5	5	4.2%
Preschooler in household	Yes	34	28.6%
	No	85	71.4%

Notes: KRW 1000 ≈ USD 0.79.

4.1.2. Latent Variable Perception

This study constructs four latent variables, which are expected to influence the choice of SPT: preference of transfer between travel modes (PR), importance of punctuality (IP), low-carbon knowledge (LK), and low-carbon habits (LH). Table 3 displays the descriptive statistics of the indicators measuring each latent variable. The indicators for importance of punctuality exhibit higher scores than the other items, revealing that punctuality is generally considered significant. Conversely, the indicators for low-carbon habits show

slightly lower scores, indicating that there is currently not a strong intention to actively reduce CO_2 emissions.

Table 3. Descriptive statistics of indicators of latent variables.

Characteristics	Indicators	Mean	S.D.
Preference of transfer between travel mode (PR)	PR1. I am willing to choose a route that combines multiple travel modes to optimize my route	3.73	1.01
	PR2. It is not a burden for me to transfer between travel modes	3.35	1.16
Importance of punctuality (IP)	IP1. It is important that I arrive on time to appointments	4.41	0.74
	IP2. I try to avoid travel modes that may involve delays	4.30	0.78
	IP3. I leave home in advance to ensure I will arrive on time and as comfortable as possible	4.23	0.76
Low-carbon knowledge (LK)	LK1. Promoting the use of new energy vehicles can save resources and reduce carbon emissions	3.79	0.78
	LK2. Saving energy and reducing carbon emissions are necessary to improve the environment	4.03	0.74
	LK3. Vehicle emissions are an important cause of environmental pollution	4.01	0.83
Low-carbon habits (LH)	LH1. I am willing to save energy in everyday life, reducing carbon emissions	3.66	0.86
	LH2. I am willing to purchase products from companies that strive to protect the environment	3.38	0.84
	LH3. I am willing to pay extra for low-carbon transport services	3.15	1.01
	LH4. I am willing to change my habits to reduce carbon emissions	3.71	0.82

We use confirmatory factor analysis prior to performing the ICLV model analysis to ensure that the indicators appropriately represent each latent variable. Factor analysis with varimax rotation is employed for factor extraction, and indicators with loadings below the critical value of 0.4 are removed. Table 4 shows the results of the factor analysis. The Kaiser–Meyer–Olkin value is 0.784, indicating the sample's suitability for analysis [63]. The intercorrelations among latent variables are significant according to Bartlett's test of sphericity analysis, which confirms the presence of common factors. The internal consistency of each of the four latent variables is measured using Cronbach's α values. The results demonstrate that all of the latent variables attained values exceeding 0.7, indicating an acceptable level of internal reliability for the latent variables.

Table 4. Factor analysis result of latent variables.

Latent Variables	Indicators	Standardized Factor Loading	Cronbach's α
PT	PT 1	0.622	0.752
	PT 2	0.938	
IP	IP 1	0.753	0.818
	IP 2	0.753	
	IP 3	0.751	
LK	LK 1	0.746	0.800
	LK 2	0.735	
	LK 3	0.666	
LH	LH 1	0.518	0.787
	LH 2	0.773	
	LH 3	0.721	
	LH 4	0.579	
KMO measure of sampling adequacy		0.784	

4.2. Model Results

4.2.1. Estimated Results of the ICLV Model

This section presents the estimated results of the ICLV model that explain the behavior of commuting mode choices in the Seoul metropolitan area. First, we describe the estimated results of the latent variable component, followed by the discrete choice component.

The results of the measurement equations and structural equations in the latent variable model are summarized in Table 5.

Table 5. Results of ICLV model (latent variable model component).

Latent Variables			Estimate		*t*-Value
TR	Structural	Aged 40 and over	−0.976	*	−1.835
		Preschooler	−0.978		−0.809
		Household size	0.937	**	2.638
		Income KRW 3 million and over	−0.602		−1.070
		σ_{TR}	2.370	**	2.189
	Measurement	TR 1	1.000		-
		TR 2	0.807	**	5.294
IP	Structural	Aged 40 and over	−0.015		−0.055
		Preschooler	−0.797	*	−1.895
		Household size	0.544	**	3.454
		Income KRW 3 million and over	0.872	*	1.751
		σ_{IP}	0.532		0.541
	Measurement	IP 1	1.000		-
		IP 2	0.775	**	5.725
		IP 3	0.819	**	5.744
LK	Structural	Aged 40 and over	−0.172	*	−1.924
		Preschooler	−0.473		−0.799
		Household size	0.468	**	3.320
		Income KRW 3 million and over	0.687	**	1.850
		σ_{LK}	0.093		0.564
	Measurement	LK 1	1.000		-
		LK 2	0.928	**	6.013
		LK 3	1.000	**	5.897
LH	Structural	Aged 40 and over	−0.456	**	−2.158
		Preschooler	−0.565		−0.643
		Household size	0.704	**	2.990
		Income KRW 3 million and over	0.815	**	2.090
		LK	0.351	**	3.103
		σ_{LH}	0.717	**	3.164
	Measurement	LH 1	1.000		-
		LH 2	1.224	**	4.379
		LH 3	1.171	**	4.362
		LH 4	1.247	**	4.566

Notes: * denotes $p < 0.1$; ** denotes $p < 0.05$.

Beginning with the results of the structural model, the study focuses on evaluating four latent variables' structures based on the respondents' socio-demographic characteristics. The first latent variable (PR) represents the transfer preference among travel modes, and a higher value indicates lower resistance to transfers. This latent variable depends on two socio-demographic variables that have a statistical significance. Respondents aged 40 or older present a lower preference for transfers, whereas the respondents from larger households exhibit a greater preference for transfers. Transfers between modes, especially between subways and buses, require much vertical movement via stairs, so the absence of preference among respondents aged 40 or older is consistent with other studies [64]. The second latent variable indicates the extent to which respondents prioritize punctuality of travel modes. Respondents with a preschooler perceive punctuality as less impor-

tant, whereas respondents with a monthly income of KRW 3 million or more and larger households perceive it as more important. The age variable is not statistically significant.

The third and fourth latent variables related to low-carbon awareness display similar features. The respondents with a higher income exhibit greater levels of low-carbon knowledge and low-carbon habits. This pattern has also been consistently observed in similar studies [65–67]. Household size also has a positive impact on low-carbon attitudes, similar to income, as confirmed in a previous study [68]. It is worth mentioning that low-carbon knowledge positively affects low-carbon habits. This is consistent with earlier studies, suggesting that enhancing low-carbon knowledge through education may potentially result in an increased intention to adopt low-carbon habits [69–72].

The measurement models demonstrate a significant association between all indicators and their respective latent attitudes. Positive estimates suggest that a higher magnitude of a latent attitude increases the probability of respondents "strongly agreeing" with the underlying indicator questions. It can be observed that the results display the expected signs. Moreover, the standard deviation coefficients (σ) of TR and LH indicate that the random error terms significantly influence the latent variables. This implies that despite incorporating the presented observable factors, unobservable noise still remains within the latent equations.

This study aims to incorporate travel time, travel cost, and CO_2 emissions as random parameters. However, as the standard deviation estimate of travel cost is the only statistically significant value, so travel time and CO_2 emissions variables are treated as fixed parameters. It is assumed that travel cost follows a log-normal distribution. Such a distribution is widely employed when the expected sign of the impact of the variable is evident, as log-normal values are positive within any interval. In addition, we perform 1500 random Modified Latin Hypercube Sampling (MLHS) draws, as suggested by [73], when estimating the random parameter to ensure the precision of the model results.

The discrete choice model estimation results are summarized in Table 6. CAR is the baseline alternative in the model. Statistically significant constants are found for both PT and SPT. Travel time and travel cost are found to be statistically significant in reducing the utility of all alternatives, as generally expected. Furthermore, the estimated standard deviation of the random parameter, travel cost, is statistically significant, indicating heterogeneity among respondents to the cost in alternative choice experiments. We attempt to explain this heterogeneity using socio-demographic characteristics. The results show that this heterogeneity can be explained by decomposing it into living with a preschooler, household size, and monthly income. The marginal utility for travel cost is $-\exp[-6.620 - 1.582 \times (preschooler) + 0.243 \times (household - size) - 0.618 \times (income\ KRW\ 3\ million\ and\ over) + 1.190 \times N_d]$, where N_d is a standard normal distribution. Household size has a positive effect on sensitivity to travel cost. However, respondents who live with preschoolers and have a monthly income of KRW 3 million or over have a lower sensitivity towards travel cost.

However, the information presented about the CO_2 emissions of the alternatives in the choice experiments does not demonstrate any statistically significant influence on the respondents' choices. Although travel time and cost are familiar information for respondents, and their perceptions are formed individually (i.e., according to the value of time), CO_2 emissions are relatively unfamiliar information. The limited understanding of the value and significance of CO_2 emission information in influencing their choices could be the reason for the non-significant effect observed in this study.

Furthermore, the influence of latent variables on the choice of commuting mode is investigated. First, all latent variables are found to be statistically significant and have consistent effects in both PT and SPT. The preference for transfers has a positive influence on both alternatives, and the extent of the effect is approximately 1.6 times greater in SPT compared to PT. SPT is more exposed to transfer situations in terms of alternative characteristics than PT. As a result, respondents with less resistance to transfers are more likely to choose SPT. In contrast, respondents who prioritize punctuality tend to have lower

utilities for both PT and SPT, with SPT showing a larger decrease compared to PT. In the Seoul metropolitan area, the adoption rate of electric buses is still relatively low at around 30%. Hence, in the SPT, which includes electric buses as a travel mode, the available public transit options are fewer compared to PT. Thus, the more respondents perceive punctuality to be important, the lower their utility for SPT. Lastly, the impact of low-carbon knowledge and low-carbon habits is examined. In general, the higher the value of these two latent variables, the greater the intention to choose a low-carbon travel mode is expected, and the results are consistent with this. These two pro-environmental attitudes increase the utility of both PT and SPT, but the effect is stronger for SPT, especially for low-carbon knowledge, which is about 2.6 times larger for SPT than for PT, and for low-carbon habits, which is almost twice as large.

Table 6. Results of ICLV model (discrete choice model component).

Latent Variables		Public Transit			Sustainable Public Transit		
		Estimate		t-Value	Estimate		t-Value
Constant (ASC)		−1.224	*	−1.827	−0.976	*	−1.835
Alternative specific variables	Travel time	−0.139	**	−4.288	−0.139	**	−4.288
	Travel cost^{RN} mean	−6.620	**	−16.889	−6.620	**	−16.889
	Travel cost^{RN} std. dev.	1.190	**	4.367	1.190	**	4.367
	CO_2 emissions	-2×10^{-4}		−0.379	-2×10^{-4}		−0.379
Context variables	Walking time to nearest subway station from home	−0.041	**	−2.470	−0.024	**	−2.131
Latent variables	PR	0.224	*	1.931	0.353	**	2.272
	IP	−0.776	**	−2.303	−1.342	**	−1.997
	LK	0.084	*	1.784	0.222	**	2.047
	LH	0.240	*	1.708	0.470	*	1.969
Error component (η)		−1.118	**	−6.609	−1.118	**	−6.609
Random parameter heterogeneity	Aged 40 and over	0.086		0.870	0.086		0.870
	Preschooler	−1.582	**	−2.040	−1.582	**	−2.040
	Household size	0.243	*	1.735	0.243	*	1.735
	Income KRW 3 million and over	−0.618	*	−1.687	−0.618	*	−1.687
LL(Initial)		−3584.799					
LL(Final)		−1593.135					
ρ^2		0.556					
$\bar{\rho}^2$		0.535					

Notes: * denotes $p < 0.1$; ** denotes $p < 0.05$; RN denotes that this variable is treated as random parameter.

The relationships between latent variables, travel cost, and choice behavior are mediated by socio-demographic characteristics. Therefore, we analyze the total effects of these characteristics on the utility of alternatives (Table 7). Non-significant characteristics are excluded from the analysis. Examining the indirect effects of latent variables, it can be observed that living with preschoolers and having a larger household size positively influence the utility of both PT and SPT, with a stronger effect observed for SPT. But, for respondents aged 40 or older and those with a monthly income of KRW 3 million or more, the utility of both PT and SPT decreases. A noteworthy finding is that in the income category, a higher income leads to increased utility due to low-carbon knowledge and low-carbon habits. However, the perceived importance of punctuality simultaneously reduces this utility, leading to an overall reduction.

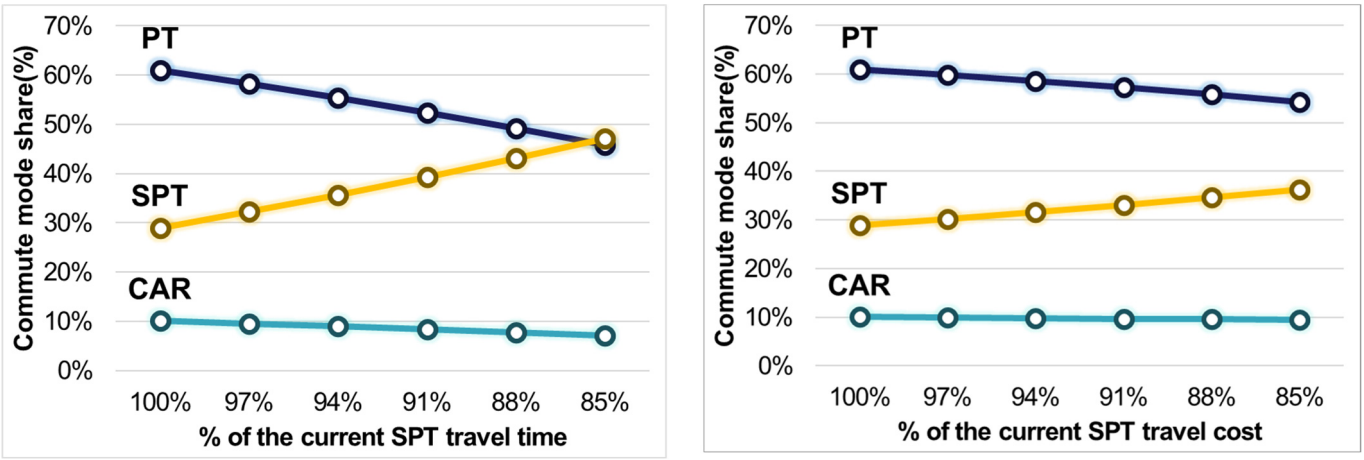
Table 7. Effect of socio-demographic characteristics from ICLV model results.

Variables		PR	IP	LK	LH	Latent Variables	Travel Cost	Total
Aged 40 and over	PT	−0.219	-	−0.014	−0.124	−0.357	-	−0.357
	SPT	−0.344	-	−0.038	−0.243	−0.625	-	−0.625
Preschooler	PT	-	0.618	-	-	0.618	−0.206	0.413
	SPT	-	1.070	-	-	1.070	−0.206	0.865
Household size	PT	0.210	−0.422	0.039	0.208	0.036	−1.275	−1.240
	SPT	0.330	−0.730	0.104	0.408	0.112	−1.275	−1.163
Income KRW 3 million and over	PT	-	−0.676	0.058	0.254	−0.365	−0.539	−0.904
	SPT	-	−1.170	0.152	0.496	−0.522	−0.539	−1.061

4.2.2. Scenario Analysis

- Improvements in SPT attributes

The changes in commuting mode share are examined according to the level of improvement in SPT attributes through the constructed model (Figure 3). It can be assumed that there are improvements in travel time and travel cost. Since SPT comprises electric-powered public transport, the extensive adoption of electric buses could result in better travel time, as mentioned previously. At present, intermodal transfer discounts do not apply to the travel cost of SPT. If such an arrangement between shared mobility and public transit is introduced as a future policy, it could potentially reduce the consumers' expenses.



(**a**) (**b**)

Figure 3. Mode share changes under SPT attribute improvements; (**a**) improvement in travel time; (**b**) improvement in travel cost.

The projection assumes each level starts at the current state of 100% and goes up to the 85% level. Forecasting for mode share is made at 3% intervals, while keeping other variables unchanged. For travel time, mode shares for CAR, PT, and SPT are estimated to be 10.1%, 61.0%, and 29.0%, respectively, at the 100% level. If the travel time for SPT improves up to 85% of the current level, the mode share for SPT increases by 47.1%, and CAR decreases to 7.1%. The improved travel time clearly indicates a significant shift in mode choice towards SPT from PT. It is apparent that the change in magnitude resulting from the improvement in travel cost is relatively smaller than that resulting from the improvement in travel time. If the travel cost of SPT improves up to 85% of its current level, the mode share for SPT would increase to 36.2%, an approximately 7% increase compared to the current status.

- Changes in attitudes

Finally, using approaches from Hess et al. [74] and Kim and Lee [38], changes in the share of commute modes are examined to determine variations in pro-environmental attitudes, as shown in Figure 4.

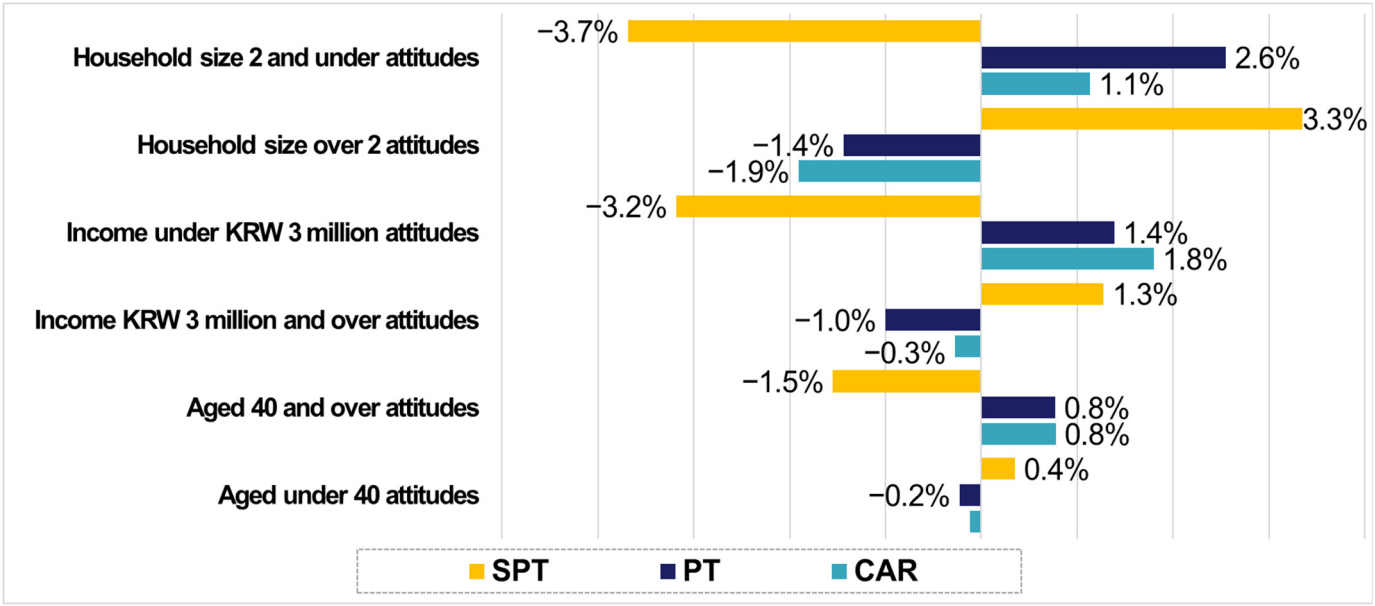


Figure 4. Mode share change when one group of the sample adopts the attributes of another group.

The changes in commute mode share are forecasted by assuming that one group of the sample adopts the attitudes of another group. For instance, this study analyzes the hypothetical change in the commute mode share, supposing that respondents aged 40 years or over adopt the attitudes of those under 40 years. In the previous analysis, it was found that respondents aged 40 years or over have less low-carbon knowledge and less low-carbon habit attitudes compared to respondents under 40 years. If the respondents aged 40 years or over adopt the attitudes of those under 40 years, it can be predicted that the mode share of SPT will increase. Following the finding of statistically significant socio-demographic characteristics in the previous analysis, we categorize the respondents into (1) Age (divided into two groups: under 40 and 40 and over), (2) Income (divided into two groups: under KRW 3 million and KRW 3 million and over), and (3) Household size (divided into two groups: under three and three and over).

If respondents under the age of 40 adopt the attitudes of those aged 40 and over, the mode share of SPT is projected to increase by 0.4%. In contrast, if those aged 40 and over adopt the attitudes of respondents under 40, the mode share for SPT is projected to decrease by 1.5%. Secondly, if relatively low-income respondents adopt the attitudes of high-income respondents, the mode share of SPT would increase by 1.5% in comparison to the current state. In contrast, adopting the attitudes of low-income respondents by high-income ones decreases the mode share for SPT by 3.2% while increasing CAR by 1.8%. Finally, household size shows more pronounced changes compared to other characteristics. Assuming respondents with larger households adopt the attitudes of those with smaller households, the mode share for SPT is expected to increase by 3.3%. This effect is comparable to the previously analyzed scenario where the travel cost of SPT was reduced by 10%.

5. Discussion and Implications

Previous studies have often employed mixed logit models or introduced latent variables to account for individual heterogeneity in choice behavior. However, relatively few attempts have been made to integrate these approaches within a unified framework. This

study addresses this gap by employing the Integrated Choice and Latent Variable (ICLV) model to investigate the influence of latent variables on choice behavior. By incorporating a mixed logit model as the choice model within this framework, this research reveals how sensitivity to alternative attributes varies based on individuals' socio-economic characteristics.

By integrating the ICLV model with mixed logit, this research offers a robust framework for capturing both observed and unobserved heterogeneity in choice modeling. This methodological approach provides a more comprehensive representation of the decision-making process, effectively accounting for the complex interactions between individual characteristics and latent factors. This strength is particularly valuable for advancing the development of choice models that more accurately reflect real-world decision-making.

The study's findings suggest that policies targeting behavioral change should consider the intricate interplay between socio-economic factors, latent variables, and individual sensitivities to alternatives. This nuanced understanding can lead to more targeted and effective interventions, recognizing that individuals' responses to policy measures are mediated by deeper, contextually driven latent constructs.

Based on these methodological strengths, the analysis results of the ICLV model with a mixed logit form suggest two important findings:

- Heterogeneity in Alternative Attributes: This study identifies significant heterogeneity among respondents in sensitivity to travel costs, with larger households showing greater sensitivity. In contrast, travel time and CO_2 emissions were estimated as fixed parameters, with CO_2 emissions not showing statistical significance.
- Influence of Latent Variables: The findings reveal that older age groups tend to resist transfers and exhibit lower levels of low-carbon knowledge and habits. Respondents with larger household sizes or monthly incomes of KRW 3 million or above demonstrate a lower importance on punctuality and higher levels of low-carbon-related attributes. Participants living with preschool-aged children and residing in larger households are more likely to choose SPT.

The practical implications of this study can be distilled into three key points:

- CO_2 Emissions Perception: This study finds no statistically significant link between commuters' preferred travel mode and varying levels of CO_2 emissions, suggesting that respondents may have difficulty perceiving CO_2 emissions compared to travel time and cost. For instance, the study does not clarify the monetary value of reducing 100 g of CO_2 emissions or its influence on transportation mode choice. This underscores the need to provide SPT users with comprehensive information to help them evaluate the value of CO_2 emission reductions. Therefore, it is crucial to demonstrate how SPT can reduce CO_2 emissions compared to existing car or public transit options and highlight the economic benefits to encourage a shift in travel mode.
- Expanding Eco-friendly Public Transport: Expanding eco-friendly public transport options, such as electric buses, and implementing a transfer discount system across various modes of transport may help reduce travel times and increase the mode share for SPT. Reducing SPT travel time by up to 85% could increase the mode share by approximately 18%, as shorter service intervals would make these options more attractive. Additionally, reducing travel costs to 85% of the current level could increase the mode share for SPT by 7.3%. Establishing governance between private sectors, such as shared mobility operators, and public transit authorities is recommended, along with a deliberative process regarding policy instruments like the intermodal transfer discount system. Government subsidies may also be necessary for implementation.
- Educational Programs on Low-carbon Knowledge: This study shows that low-carbon knowledge positively influences low-carbon habit attitudes, indicating a need for educational programs focused on low-carbon knowledge. Knowledge is essential for behavior [75], particularly in environmental awareness, which positively impacts eco-friendly behaviors like responsible actions and green product purchases [75–77]. Campaigns and events should be conducted to enhance low-carbon knowledge. It is

important to tailor attitude change strategies to specific socio-demographic groups, as changes in attitudes lead to varying mode share adaptations for SPT based on group characteristics.

The second and third implications focus on promoting a mode shift to SPT through two types of investments: supply-oriented investments, such as expanding eco-friendly public transit modes and implementing intermodal transfer discounts, and investments aimed at changing individual attitudes, such as educational programs on low-carbon knowledge. Given potential resource limitations, it is crucial to carefully examine the effectiveness of policies relative to their investments and organize efficient strategies. Notably, reducing travel costs to 90% of the current level has a similar mode shift effect as perception change. Further research is needed to determine the impact of educational programs on pro-environmental attitudes.

6. Conclusions and Future Research

This study highlights the limitations of effectively reducing CO_2 emissions through the existing shift towards public transit and proposes a new combination of transportation modes called Sustainable Public Transit (SPT), which consists solely of environmentally friendly options. A Stated Preference (SP) survey was conducted, focusing on long-distance commuters in the Seoul metropolitan area.

The study aimed to explore variations in acceptance of SPT based on socio-demographic differences using the Integrated Choice and Latent Variable (ICLV) model. This model incorporated latent variables related to commuting attitudes (preference for transfers and punctuality) and low-carbon attitudes (knowledge and habits) into the discrete choice model. The mixed logit model was employed to account for heterogeneity in respondents' sensitivity to alternative attributes.

Key findings revealed significant differences in sensitivity to travel costs, with larger households being more sensitive, and older age groups showing resistance to transfers and lower levels of low-carbon knowledge and habits. CO_2 emissions were not a significant factor in mode choice, indicating that commuters may prioritize travel costs over CO_2 reductions.

The study's practical implications stress the need for clearer communication about the environmental and economic benefits of SPT to encourage its adoption. Expanding eco-friendly transport options and implementing transfer discount systems can help increase SPT's mode share. Additionally, targeted educational programs should enhance low-carbon knowledge and tailor interventions to specific demographic groups to promote a shift towards sustainable transportation.

However, this study has several limitations. First, the research was conducted with a limited sample, focusing mainly on long-distance commuting scenarios. Given that the characteristics of mode attributes may vary according to travel distance—such as differences in cost and time functions among transportation modes—future research should include surveys that consider a wider range of commuting situations. Also, future studies should take into account respondents' travel contexts, including factors such as weather conditions and the amount of baggage carried. Additionally, there is a limitation in that there may be some discrepancy between respondents' actual behavior and the survey results. First, in questions about individual preferences, the survey can only capture the level of declarative agreement regarding respondents' behavior, making it difficult to determine whether they actually behave as they responded. Furthermore, the survey did not incorporate information about what modes of transportation respondents actually use and how they use them in their commuting situations. As a result, there may be a gap when applying the survey results to real-world scenarios. To address this, future research should thoroughly consider the correlation between respondents' actual behavior and their stated preferences.

Finally, this study did not achieve significant statistical results related to CO_2 emissions as initially intended. Future research could explore alternative approaches, such as presenting CO_2 emission information differently or observing and comparing choice

behaviors after providing information on the various benefits of mode switching. These efforts are essential in identifying more effective strategies for promoting a modal shift towards SPT.

Author Contributions: Conceptualization, G.L. and S.C.; methodology, G.L.; software, G.L.; validation, G.L., S.K. and S.C.; formal analysis, G.L. and S.C.; investigation, S.K. and J.K.; resources, G.L. and S.K.; data curation, J.K.; writing—original draft preparation, G.L. and S.C.; writing—review and editing, G.L., S.K., J.K. and S.C.; visualization, G.L. and S.K.; supervision, S.C.; project administration, S.K. and S.C.; funding acquisition, S.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant RS-2023-00245871).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data are not publicly available because of privacy.

Conflicts of Interest: The authors declare no conflicts of interest.

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