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A Comparison into the Factors Affecting Urban Rail Systems: Local, Express, and High-Speed Rail in Tunnels at a Great Depth in a Metropolitan Area

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Abstract: In this study, the factors influencing the choice of the type of urban railroad transportation in the metropolitan areas of Korea were analyzed. As the populations of metropolitan areas are expanding, the importance of rail transportation, which has a high travel reliability in terms of travel time, has increased, and various types of railroad systems have emerged accordingly. This study was focused on the choice behavior of travelers on local and express trains that use the same track and differ only in the number of stations and operating times. To compare the choice behavior of travelers between local and express trains, factors such as the waiting time on the platform and the in-car travel time were considered. We also investigated the system choice behavior for an existing express subway and high-speed rail trains in tunnels at a great depth in terms of horizontal access time (walking), vertical access time, in-vehicle travel time, and travel fare. For a high-speed rail built underground at a great depth of 50 m, the stated preference survey was designed, and data were collected in consideration of the Great Train Express being promoted in the Seoul metropolitan area by the Korean government. The results of this study are expected to be considered important data for improving the rail system design from the user's perspective to increase the demand for urban rail transportation in metropolitan areas.

Keywords: choice behavior; urban rail; transfer; accessibility; express train

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Citation: Lee, K.; Kim, W.; Baek, J.; Kim, J. A Comparison into the Factors Affecting Urban Rail Systems: Local, Express, and High-Speed Rail in Tunnels at a Great Depth in a Metropolitan Area. *Sustainability* **2021**, *13*, 9527. https://doi.org/10.3390/su13179527

Academic Editor: Marco Guerrieri

Received: 20 July 2021
Accepted: 13 August 2021
Published: 24 August 2021

1. Introduction

In the past, South Korea implemented growth-oriented development policies to spur economic growth, which led to a rapid growth led by large cities and the metropolitan area of Seoul and urbanization triggered by population concentration. These are manifested in the data of the Korea National Statistical Office that show that the number of registered residents nationwide as of February 2017 stood at 517,000, with Seoul having 9.93 million residents, Gyeonggi having 17.24 million, and Incheon having 2.94 million, all of which accounted for 49.5% of the total population [1]. According to the report published by the Korea Research Institute of Human Settlement, the commuting population from Gyeonggi-do to Seoul increased from 570,000 in 1990 to 1,277,000 in 2015, which is an approximate increase of 2.2 times [2]. The report also indicated that the rate of inter-regional commuting in the Gyeonggi region in 2015 was 21.5%, which was much higher than the national average of 12.2%. Moreover, the population of Gyeonggi-do that had a job in Seoul significantly increased along with the new town development, thereby substantially increasing the commuting population from Gyeonggi-do to Seoul [2,3].

With the concentration of the population in a particular region, the spatial expansion of metropolitan areas has become accelerated, the majority of the metropolitan travel linked with Seoul has been related to job commuting, and the travel volume was higher from the Gyeonggi region to Seoul [2,3]. Such population migrations have caused problems, including a sharp increase in automobile traffic and an increase in home–work commute distances owing to a population shift from central urban areas to suburbs, which has resulted in an increase in the number of express trains in the urban railway system. The urban railway is the most effective method of transporting people in the metropolitan area; its network can be divided into the following two categories according to [4]: the first category comprises an integrated system, such as the New York City Subway, which provides greater flexibility in terms of conveniences for passengers, enabling them to transfer on the same platform without having to move to a different floor; the second category comprises an independent network that does not allow track sharing, wherein one physical track provides only one metro service. The latter comprises inconvenient transfer methods, which require passengers to use stairs or escalators. Korea's Seoul metropolitan railway belongs to the second category and comprises an independent network. In the early stage of the subway development in Seoul, the most important objective was to transport as many people as possible. However, the requirements of the system have changed, resulting in a shift in the top priority to flexible transit services that satisfy the various requirements of the passengers. In this study, a comparison analysis of the effects of the accessibility factors of subway travel, including transfer, on the selection of each type of railway is conducted.

Subway Line 9 and the great depth high-speed rail, which are expected to be operated, are targeted in this study. Subway Line 9 is the first urban railway to provide express train services in Korea, and its success has resulted in deliberation on whether to integrate express train services planned for different lines. Line 9 serves a crucial role in helping people move from the west to the east of Seoul, which is horizontally larger. The great-depth high-speed rail is included in the scope of this study to determine if the time required for transfer would affect passengers' decisions regarding the mode of transportation. As the Seoul metropolitan area has expanded, the Korean government is executing a plan to establish a deeper underground railway called the Great Train Express (GTX), which is presented in Figure 1 and enables passengers to move to the metropolitan area within 30 min. The construction of GTX with a three-line railroad network (tagged as A, B, and C) across the metropolitan area is expected to resolve the traffic congestion due to the commuting population of the greater metropolitan living area, raise the traffic welfare of long-distance commuters, strengthen global competitiveness, and improve quality of life by providing fast and comfortable transportation for residents in metropolitan regions by shortening the commute time [2]. Among the three lines, Line A is currently under construction as the route shown in Figure 1 with the goal of opening in 2024. GTX is intended to be an express railway system in a metropolitan area similar to France's RER (Réseau Express Régiona) and UK's Crossrail. This deep-level underground railway is expected to be laid in a tunnel built 50 m underground, which would possibly lengthen the time required to move from the ground to the deeper underground platform. It may take longer to transfer from the deep-level underground express train to a bus on the ground than from a regular subway train to the bus, which is the focus of this study.

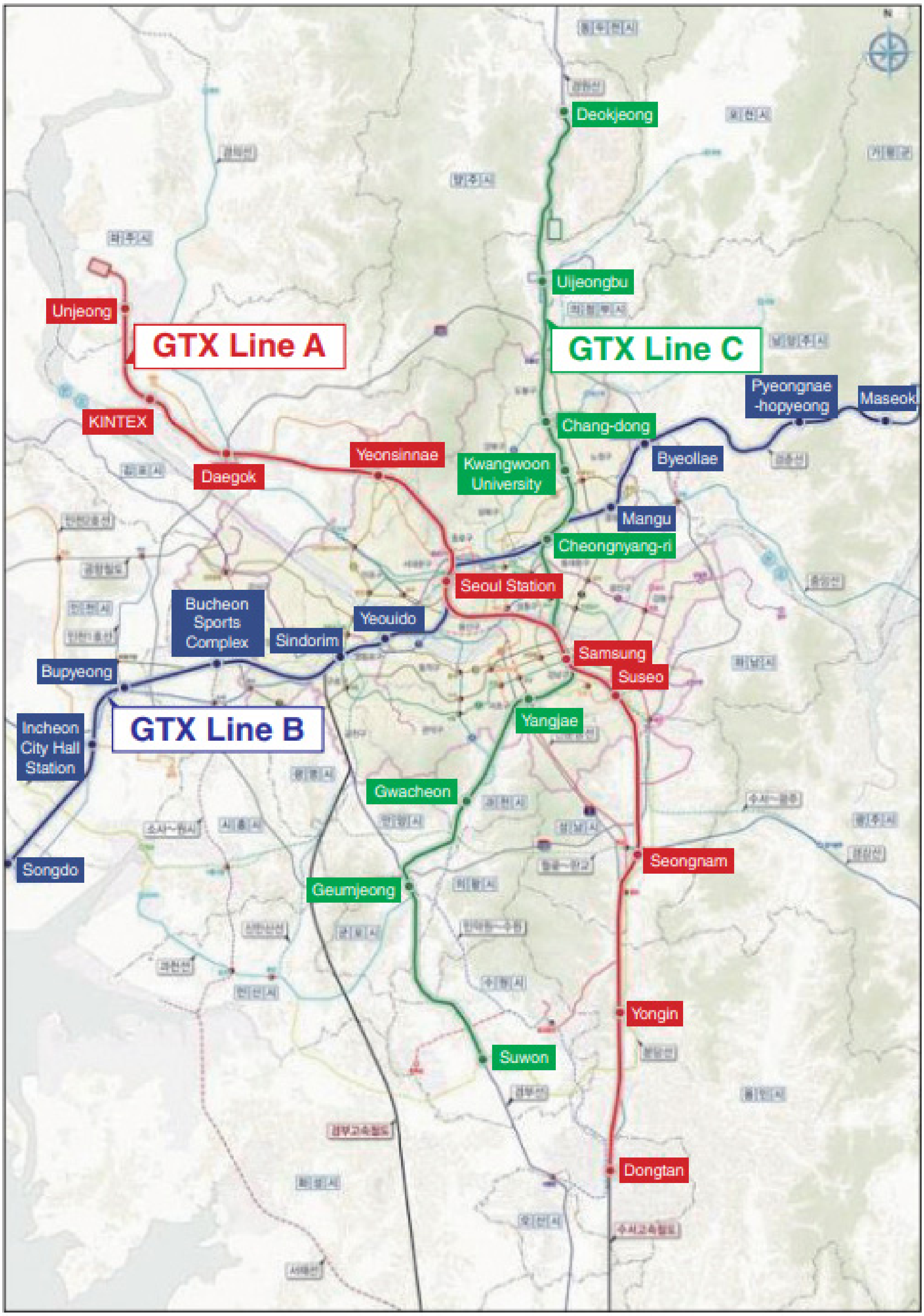

Figure 1. Prospective GTX line map (KRIHS, 2020).

2. Literature Review

A number of previous studies related to the service level and passenger behavior of the railway system have been conducted. D'Acierno et al. [5] conducted a simulation to predict passenger behavior on a railway platform. Here, they compared first-in-first-out (FIFO) and random-in-first-out (RIFO) and proved that the difference in results is clear as the congestion level increases. As a result of the analysis of the movement to the platform among the railway systems, it was confirmed that the behavior patterns of passengers varied according to the formation of the platform structure, which shows that the structures such as the presence or absence of escalators and stairs affect the behavior of passengers [6]. It was also found that passengers tend to move to the nearest exit point from their destination station if they have enough time before the train arrives [6–8]. Loon et al. [9] studied whether there is a change in demand using rail service as a variable, and the analysis result proved that the demand for use increases as the number of trains increases. Reduction of train travel time had a significant effect on demand, but it was investigated that the decrease in average delay did not have a significant effect on demand. In addition, there are studies confirming that the correlation between stations is affected by the routes through the flow of passengers who want to transfer to other subway lines by focusing on the existence of complex correlations between stations in urban subway networks [10]. Xie et al. [11] defined passenger flow as the amount, speed, and density of passenger flow and calculated a specific bottleneck of the railway system through simulation.

The research focused on investigating the factors affecting the choice of rail transportation is summarized as follows. Spiess [12] suggested that commuting via public transportation comprises "access," "waiting", "riding", "alighting", "transfer" (walking between two transit stops), and "egress." Herein, it was indicated that the factors other than waiting are easily quantified in terms of time or cost. Yang et al. [13] conducted a preference survey on subway users in Seoul to recognize transfers in public transportation as resistance to traffic and to examine how transfer-related factors affect route selection. The results revealed that the in-vehicle time, transfer time, number of transfers, and the presence or absence of escalators were the influencing factors. In a similar analysis conducted by [14], it was assumed that not only the route characteristic variables, such as the in-car time, transfer time, and number of transfers but also the characteristic variables of the transfer station, such as the horizontal travel distance, numbers of ascending and descending stairs, and escalator time, affect the selection of train routes. The results showed that the transfer time was not an influencing factor, but the number of transfers, horizontal movement distance, numbers of ascending and descending stairs, and the presence or absence of an escalator were the most influential factors.

The studies on local and express trains are divided as follows: a study based on the data of traffic counts between the first and last stations of a line, obtained using a face-to-face survey, and one comprising the usage data of transportation cards. First, the research comprising the use of data of traffic counts between the first and last stations of a certain line did not reflect individual attribute data but established a utility function with transit-related variables, such as time-relevant variables and transportation fares. Among the studies comprising the use of the data of traffic volume between the first and last stations, that of Lee et al. [15] comprised an estimation of the generalized cost including in-vehicle time, out-of-vehicle time, fares, and levels of congestion for the purpose of investigating the choice pattern of express trains in the Taiwan High Speed Rail, and transit assignments were completed using the logit model. As part of the generalized cost, the weight factors from previous studies were reflected in the in-vehicle and out-of-vehicle times, and the level of congestion was estimated based on a formula comprising the in-vehicle time, train capacity, and volume of passengers.

Actually, the choice among different public transport systems could be a sort of path choice model. Therefore, we also considered what factors affect system choice and what model is appropriated to explain a system choice behavior. Luo et al. [16] established a logit model for the choice between express and regular all-stop trains of the urban railway system in Shenzhen, China, that took into consideration the travel time and distance. The optimal operation pattern of the express and local train lines was created by associating the established logit model with a genetic algorithm, and the energy savings generated by the operation of the express trains were examined from the perspective of a manager. In the study comprising the use of face-to-face survey data, more subdivided variables were used to establish a utility function than in that comprising the use of the traffic volume between the stations, and the implications learned from an analysis of the estimated coefficient(s) of such variables and statistical significance were presented. Son et al. [17] did not focus on express trains but investigated the generalized cost for overall public transportation. Commuters in Seoul and between Seoul and Gyeonggi were informed of the in-vehicle time, waiting time, and transit time required for their current route and for an alternative route and asked to choose one of the routes. The results of such surveys were used to create a binomial logistic model, and the marginal rate of substitution was employed to suggest the relative weight factor of each variable compared to the in-vehicle time. As shown in Table 1, Baek et al. [18] analyzed the factors contributing to the popularity of express and local trains using a multinomial logistic model of Subway Line 9. In addition to the transit attributes, individual attributes such as age and annual salary were also considered while studying the factors that caused the commuters to choose express trains even though their occupancy was higher than local trains. Lastly, the study comprised the use of the transportation card data considered the boarding and alighting information of each individual. More detailed variables were used to create a utility function than those used in the traffic volume study, but individual attributes obtainable only from a survey were not considered as variables. Kim et al. [19] deduced whether the route chosen by passengers of Subway Line 9 comprised express, regular, or mixed commutes by using the boarding and alighting information at the first and last stations of the line and investigated changes in the commuters' choices between the express and local trains after the extension of the line. Kim et al. [20] focused on the Gyeongin Line to establish both linear and non-linear utility functions, with in-vehicle time and waiting time set as explanatory variables, and assessed the goodness-of-fit of the model based on the degree of explanation provided by the coefficient.

Table 1. Overview of the previous studies on the choice of express train using a utility function and logistic model.

Study	Line (Location)	Number of Samples	Data Source	Utility Function	Explanatory Variables	Study Purpose
Son et al. (2007)	Public Transportation (Seoul and Gyeonggi, Korea)	100	Survey (Revealed Preference, Stated Preference)	Linear	Walking time, waiting time, in-vehicle time, and transfer time	Weighting factor of walking time, waiting time, and transfer time compared to in-vehicle time
Baek and Sohn (2016)	Line 9 (Seoul, Korea)	255	Survey (Revealed Preference)	Linear	In-vehicle time, transfer time, waiting time, age, gender, travel purpose, other individual attributes	Analysis of factors contributing to choice of express trains
Kim et al. (2016a)	Line 9 (Seoul, Korea)	871,199	Smart card data (Revealed Preference)	Linear	In-vehicle time and transfer time	Creation of a choice model of express trains and altered pattern of choice between express and local trains upon the extension of Line 9
Kim et al. (2016b)	Gyeongin Line (Gyeonggi–Seoul, Korea)	38,041	Smart card data (Revealed Preference)	Linear; nonlinear	In-vehicle time and waiting time	Creation of a choice model of express and local trains on the Gyeongin Line

Table 1. *Cont.*

Study	Line (Location)	Number of Samples	Data Source	Utility Function	Explanatory Variables	Study Purpose
Lee & Hsieh (2000)	Taiwan High Speed Rail (Taiwan)	11,766	Predicted volume of passengers boarding/alighting at station (as of 2020)	Linear	In-vehicle time, out-of-vehicle time, fares, and congestion	Altered pattern of railway usage depending on a modification of each explanatory variable
Luo et al. (2018)	Shenzhen Metro (Shenzhen, China)	179,183	Data of passenger count boarding/alighting at the station at the peak time during the morning	Linear	Travel time and distance	Establishment of an optimal express and local train pattern from the perspective of the total travel time and energy savings

3. Study Objective

As a result of the literature review, it was confirmed that there was no research on the choice behavior in the railway system, and the main factors to be dealt with in this study were established through the related prior studies. Therefore, this study is aimed at investigating the factors that influence rail system choice depending on the urban rail system type. Herein, we considered local and express trains that have differences in waiting time at the platform and in-vehicle travel time, such as Subway Line 9, and furthermore, we attempted to compare the factors influencing the express rail and great-depth high-speed rail, GTX, such as the access time and fare level. To this end, we conducted a stated preference (SP) survey by randomly selecting users for Subway Line 9, which is already in operation, and suggesting a virtual choice alternative rather than a specific route used by each user. In addition, we tried to secure data through the SP survey for the GTX A route currently under construction as well. Through the collected data, we intend to proceed with the modeling analysis by applying logistic regression, which is widely used in the choice behavior model.

4. Data

A survey of the use of express trains and the great-depth high-speed rail was conducted with the objective of making the parameters applied in transit assignments more realistic by reflecting the respondents' opinions. In the case of the express trains, the aim was to estimate the weighting factor of out-of-vehicle time, which may be a more practical aspect that is considered when passengers choose between express and local trains among the urban subway train options, instead of the factor typically defined by the transfer. In the case of the great-depth high-speed rail, passengers may exhibit resistance to transfers owing to the vertical movements this mode entails, and the weighting factor of out-of-vehicle time was thus targeted, as it could be a more practical reason for people to choose this option.

Online surveys were implemented over 10 days from 8 to 17 January, 2020, with a total of 183 respondents who had experience using Subway Line 9 and were selected randomly to collect the data. As shown in Table 2, the respondents in their 20s and 30s accounted for more than 60% of the total respondents. In the case of the car ownership status, more than 60% of the participants owned a car. The responses to the question on the frequency of use of the urban railways were evenly distributed across all the given answers. More than 50% of the respondents used trains between 9:00 a.m. and 6:00 p.m., mainly to commute to and from work or to engage in leisure activities such as shopping.

Table 2. Respondents.

Personal Characteristics	Subjects (%)		Personal Characteristics	Subjects (%)	
Age			Hours of Use		
10s	1	0.55%	6:00–9:00 a.m.	34	18.58%
20s	59	32.24%	9:00 a.m.–6:00 p.m.	102	55.74%
30s	73	39.89%	6:00–9:00 p.m.	39	21.31%
40s	36	19.67%	9:00 p.m.–Dawn	8	4.37%
50s or older	14	7.65%			
			Purpose of Use		
Car Ownership			Commute	62	33.88%
Yes	115	62.84%	Business Trips	34	18.58%
No	68	37.16%	To and From School	5	2.73%
			Shopping and Leisure	82	44.81%
Frequency of Use					
1–2 Times a Year	42	22.95%			
1–2 Times a Month	51	27.87%			
1–2 Times a Week	49	26.78%			
1–2 Times a Day	41	22.40%			
Total Sample Size = 183 respondents					

The details of the survey, which comprised three sections, are presented in Table 3, and 183 respondents answered all sections. In terms of personal characteristics, the participants were asked about their age, vehicle ownership status, frequency of use of urban railway trains, and the time and purpose of use. Questions were asked regarding the difference in the waiting time on the platform and the travel time on the subway between the two options of the express and local trains in order to determine the transport mode preference of the commuters. For the questions relevant to the great-depth high-speed rail (in the GTX railway area), the deep underground trains and the ordinary subway trains were offered as options to choose from, with differences in the walking time to the entrance or exit of the station, walking time required to move to the underground platform, time required for trains to move between stations, and fares.

Table 3. Frame for survey.

Division	Contents
Personal Characteristics Section	Age, car ownership, frequency, hours of use, and purpose of use
Local and Express Rail Section	Local and express preference (travel time and waiting time comparison)
Common Express and Great-Depth Express Train Section	Great-depth express preference (travel time, horizontal transfer time, vertical transit time, and fare)

The choice of transport mode of the respondents after providing them with information regarding the variables reflecting the above-explained characteristics of the modes was studied. In terms of the express and local trains, the respondents were given two transport options comprising differences in waiting time and travel time on the subway. Figure 2 presents the actual example used during the survey to ask the respondents which one they would choose out of the two; the local train commute took a total of 25 min, with 5 min of waiting time on the platform and 20 min of travel time on the subway, whereas the express train took a total of 23 min, with 10 min of waiting time on the platform and 13 min of travel time on the subway combined.

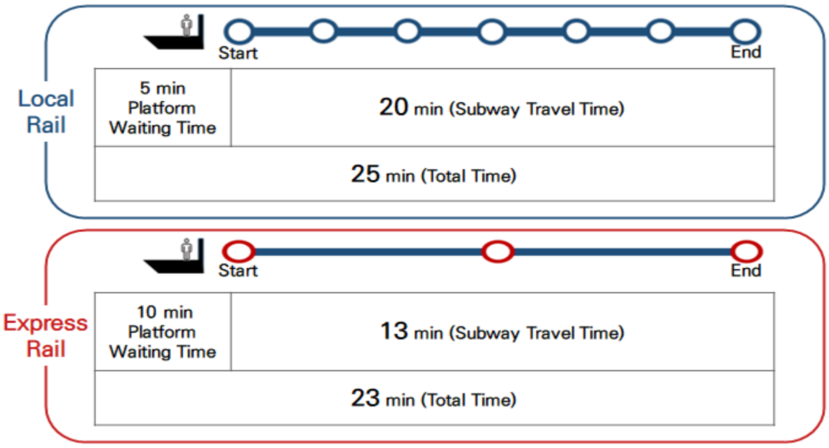

Figure 2. Example of local and express rail system choice section.

For the questions regarding the deeper underground GTX, the respondents were provided with information regarding the walking time to the platform of the ordinary subway train, walking time to the underground platform (stairs and escalator), time required for the subway train to move between stations, and fares, in addition to the equivalent GTX information, and they were then asked which of the two options they would choose. Figure 3 presents one of the examples shown to the respondents to provide them with the information regarding the ordinary subway train and to determine their choice between the express subway and GTX.

Division	Walking Time to the Subway Station	Underground Walking Time (Stairs, Escalator)	Arrival Time between Stations (Waiting Time + Travel Time)	Public Transportation Fare
Express	15 min	3 min	40 min	1500 KRW
	58 min			
GTX	18 min (+3 min)	7 Min (+4 min)	15 Min (−25 min)	2500 KRW (+1000 KRW)
	40 min (−18 min)			

Figure 3. Example of common express and great-depth express train choice section.

As a result of the user preference responses according to the age, rail-use frequency, main hours for rail use, and trip purpose, the number of respondents who said that they would use the express train rather than the local train was higher for those in their teens than those in their 50s. In contrast, those in their 10s and 30s were more likely to use the GTX than the general express trains, and the other age groups in their 20s, 40s, and 50s and over answered that they would use the general express trains rather than the GTX. In the result of the response regarding the frequency of use, the number of respondents who used the express train rather than the local train was higher for those who used it 1–2 times a year than those who used it 1–2 times a day. Except in the case of those who used it 1–2 times a day, more respondents used the general express trains than the GTX. In terms of main use hours, the number of respondents who said they would use the express train rather than the local train was greater. However, in the case of the choice between the GTX and express train, only the group who mainly used the railway from 9:00 a.m. to 6:00 p.m. had a greater preference for the GTX. As a result of the responses with respect to the frequency of use, the number of respondents who used the express railroad rather than the local train was higher in the case of those who used it once or twice a year than those who used it once or twice a day. In the express subway/GTX railroad sector, many respondents stated that they would use the subway rather than the GTX, except for those who used it 1–2 times a day. In the case of the response results with respect to the trip purpose, the number of respondents who stated that they would use the express train rather than the local train was higher for all purposes. However, the number of respondents who stated that they would use the general express rail was higher than those who stated they would use the GTX—with the exception of those using the train for business trips—as shown in Table 4.

Table 4. Comparison results for preference by railroad type according to individual-specific variables.

Individual-Specific Variables		**Choice Set 1**				**Choice Set 2**			
		Local		**Express**		**Express**		**GTX**	
		Subject (%)		**Subject (%)**		**Subject (%)**		**Subject (%)**	
Age	10s	2	0.18%	4	0.36%	1	0.11%	4	0.44%
	20s	132	12.02%	222	20.22%	159	17.38%	136	14.86%
	30s	158	14.39%	280	25.50%	173	18.91%	192	20.98%
	40s	97	8.83%	119	10.84%	106	11.58%	74	8.09%
	50s or more	22	2%	62	5.65%	36	3.93%	34	3.72%
Rail Use Frequency	1–2 Times a Year	107	9.74%	187	17.03%	136	14.86%	109	11.91%
	1–2 Times a Month	95	8.65%	151	13.75%	111	12.13%	94	10.27%
	1–2 Times a Week	101	9.20%	205	18.67%	140	15.30%	115	12.57%
	1–2 Times a Day	108	9.84%	144	13.12%	88	9.62%	122	13.33%
Main Hours for Rail Use	6:00–9:00 a.m.	82	7.47%	122	11.11%	95	10.38%	75	8.20%
	9:00–6:00 p.m.	217	19.76%	395	35.97%	255	27.87%	260	28.42%
	6:00–9:00 p.m.	98	8.93%	136	12.39%	104	11.37%	86	9.40%
	9:00 p.m.–Dawn	14	1.28%	34	3.10%	21	2.30%	19	2.08%
Trip Purpose	Commuting	152	13.84%	220	20.04%	171	18.69%	139	15.19%
	Business Trips	76	6.92%	128	11.66%	72	7.87%	98	10.71%
	To and From School	8	0.73%	22	2.00%	20	2.19%	5	0.55%
	Shopping and Leisure	175	15.94%	317	28.87%	212	23.17%	198	21.64%
Total Responses		411	37.43%	687	62.57%	475	51.91%	440	48.09%
		1098 (100%)				915 (100%)			

5. Methodology

In this study, mainly logistic regression was adopted to compare and analyze the factors affecting the decision of the form of transportation depending on the type of urban railway [21]. Logistic regression refers to a model that linearly expresses the relationship between the numerical explanatory variable x and the sequential dependent variable y. The general formula for multiple linear regression with p variables is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_p x_p + \varepsilon \tag{1}$$

On entering the blood-pressure levels per age into this formula, one can determine how much they increase or decrease annually. However, if y has the values of 0 or 1 (0 = normal; 1 = contracted a disease that indicates whether one has cancer, depending on their age), this data creates a significant error in the case of its application in the linear regression model. As the result values range from 0 to 1, the graph depicting these numbers cannot explain the correlations. This error is attributed to the value of y. In the case of the blood-pressure levels, y is sequential, whereas for the data regarding whether a cancer is developed, the y value is categorical. Therefore, a categorical y value is not applicable in the linear regression formula, which results in the proposal of using the logistic regression model.

Logistic regression is a statistical method used to predict the probability of an event based on a linear combination of independent variables. The following example can be used to obtain a better understanding of this method. This method can be used to determine whether a patient has a disease based on various variables. The logistic regression equation is presented below.

$$P = \frac{\exp(a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \cdots)}{1 + \exp(a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \cdots)} \tag{2}$$

The P value refers to the probability of the data belonging to a certain category, exp represents the exponential function, a denotes the constant of the equation, and b is a coefficient of the variable. In the logistic regression model, the logistic function and odds are essential [22,23]. The logistic function should be between 0 and 1, regardless of the number substituted for x. In other words, the function satisfies the requirement of the probability density function. The formula and shape of the graph are as follows:

$$y = \frac{1}{1 + e^{-x}} \tag{3}$$

The Odds is a value generated by dividing the probability of an event taking place by the chance that it does not happen. For example, when the probability of an item passing the test is 0.3, and the probability of it failing the test is 0.7, this value is calculated by dividing 0.7 by 0.3.

$$Odds = \frac{P(A)}{1 - P(A)} \tag{4}$$

Based on the above concept, this study was aimed at estimating two different models by applying binary logistic regression in order to analyze how different the factors contributing to the choice of express trains over local ones are—both of which share the rail lines but are operated in a different manner—from those contributing to the choice of a deeper underground high-speed rail over ordinary express trains. Binary logistic regression refers to a statistical technique that is used to estimate the causal relationship between the two dependent variables and independent variables based on a logistic function [24–26]. When a natural logarithmic function is placed (Formula (4)) on both sides, the following formula is obtained:

$$Ln\left(\frac{P(A)}{1 - P(A)}\right) \tag{5}$$

This is applicable even when there are more than two independent variables, and the formula of the binary logistic regression model [27,28] is indicated below:

$$Ln\left(\frac{P(A)}{1 - P(A)}\right) = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_3 + \cdots + \beta_px_p \tag{6}$$

In the case of binary logistic regression, there should not be any dependent variable other than the two dependent variable values, and the sum of the probability of them each being divided into two categories should be 1 in all cases. The targeted data should belong only to the two categories, and all the data must belong to either of the two categories. That is, it may belong either to the success or failure with no category of draw, which means that they cannot belong to a non-existent category of draw.

6. Model Estimation

6.1. Model Results for Local and Express Rail

The model estimation results show that, among the statistically significant variables included in the model, additional waiting time on the platform for express trains compared to local ones, additional travel time for express trains compared to local ones, age (10s, 30s, and 50s and over), the average frequency of usage, and purpose of usage (commuting or work-related, including business trips) are found to meet the significance level and are deemed to be the factors affecting the choice between express and local trains. In the above analysis, wherein the choice of express trains is set as 1, if B is positive—indicated by a plus sign—it is more likely to be included in the choice of express trains, whereas if it is negative—indicated by a minus sign—it is more likely to be included in the category of no choice. The Exp(B) value refers to the probability of selecting express trains depending on the variables listed in Table 5.

Table 5. Model estimation results for comparison between local and express trains.

Variables		B	S.E.	Wald	p-Value	Exp(B)
Additional waiting time on the platform for express trains compared to local trains		−0.283	0.031	85.815	0.000	0.753
Additional travel time for express trains compared to local trains		−0.202	0.018	120.385	0.000	0.817
Age	10s	-	-	9.545	0.049	-
	20s	−0.311	1.054	0.087	0.768	0.733
	30s	−0.614	0.301	4.158	0.041	0.541
	40s	−0.461	0.287	2.567	0.109	0.631
	50s or older	−0.879	0.309	8.101	0.004	0.415
Rail Use Frequency	1–2 times a day	-	-	13.815	0.003	-
	1–2 times a week	0.859	0.276	9.670	0.002	2.362
	1–2 times a month	0.424	0.219	3.769	0.052	1.528
	1–2 times a year	0.655	0.203	10.397	0.001	1.925
Trip Purpose	Commuting	-	-	9.193	0.027	-
	Work-related, including business trip	−0.607	0.224	7.329	0.007	0.545
	School commute	−0.136	0.203	0.445	0.505	0.873
	Personal leisure to shop or meet friends, etc.	0.278	0.507	0.301	0.583	1.321
Constant Term		0.679	0.363	3.494	0.062	1.972

B: Regression coefficient, S.E.: Standard error, Wald: $(B/S.E)^2$, Exp(B): Odds ratio.

The value of B in the variable of the additional waiting time on the platform for express trains as compared to local ones is negative and is more likely to be excluded from the choice of express trains, and an increase in the additional waiting time by 1 min causes the probability of selecting express trains to be 0.753. The value of B in the additional travel time required for express trains as compared to local trains is also negative and is more likely to be excluded from the choice of express trains, and the Exp(B) value is 0.817, which means that an increase in the additional travel time by 1 min causes the probability of selecting express trains to be 0.817. In terms of age groups, the value of B in the category of the respondents in their 30s is negative and is likely to be excluded from the choice of express trains, and the probability of the respondents in their 30s selecting express trains is 0.541. The value of B in the age group of 50s and above is negative as well, which increases the probability of being excluded from the choice of express trains, and the probability of selecting express trains is 0.415. In all the variables of the average usage frequency, B is positive, which translates into a high probability of being included in the choice of express trains. People who use express trains once or twice a week are 2.362 times more likely to choose express trains, and those who take them once or twice a month are 1.528 times more likely to choose express trains. Lastly, passengers who use the express trains once or twice a year are 1.925 times more likely to select express trains.

6.2. Model Results for Common Express and Great-Depth Express Train

As shown in Table 6, the factors affecting the choice of the form of transportation between ordinary express trains and the deeper underground GTX were analyzed based on the model estimation. Among the variables that belong to the estimated model, all of them, except for the work-related model, which includes business trips, satisfied the level of significance. In the above analysis, wherein the GTX choice is set as 1, a positive B value increases the probability of being included in the GTX choice, whereas a negative B value increases the probability of being included in the category of no choice. Exp(B) indicates the probability of selecting the GTX depending on the variables.

Table 6. Model estimation results for comparison between express and GTX trains.

Variables		B	S.E.	Wald	*p*-Value	Exp(B)
Additional walking time to the entrance of the GTX station compared to express subway		−0.140	0.049	8.037	0.005	0.870
Additional walking time to the deeper underground GTX platform		−0.150	0.074	4.130	0.042	0.861
Additional time for GTX to move between stations compared to express subway		−0.166	0.015	120.245	0.000	0.847
Additional GTX fares compared to express subway		−0.0004	0.000	8.124	0.004	0.999
Rail Use Frequency	1–2 times a day	-	-	12.538	0.006	-
	1–2 times a week	−0.463	0.281	2.711	0.100	0.629
	1–2 times a month	−0.564	0.224	6.332	0.012	0.569
	1–2 times a year	−0.727	0.212	11.741	0.001	0.483
Trip Purpose	Commuting	-	-	15.722	0.001	-
	Work-related, including business trips	−0.117	0.226	0.267	0.606	0.890
	School commute	0.542	0.206	6.912	0.009	1.720
	Personal leisure to shop or meet friends, etc.	−1.506	0.562	7.183	0.007	0.222
Constant		−1.379	0.475	8.446	0.004	0.252

B: Regression coefficient, S.E.: Standard error, Wald: $(B/S.E)^2$, Exp(B): Odds ratio.

The value of B in the additional walking time to the entrance of the GTX station compared to ordinary subway trains is negative and is more likely to be excluded from the GTX choice, and an increase in the additional walking time to the entrance of the station by 1 min causes the probability of selecting GTX trains to be 0.870. The value of B in the additional walking time to the deeper underground GTX platform compared to the ordinary ones is negative and is more likely to be excluded from the GTX choice, and an increase in the additional walking time to the deeper underground by 1 min causes the probability of selecting GTX trains to be 0.861. The value of B in the additional time required for the GTX to move between stations as compared to the ordinary ones is negative and is more likely to be excluded from the GTX choice, and when the time taken to move between stations increases by 1 min, the probability of selecting the GTX is 0.847. The value of B in the additional fares for the GTX compared to the ordinary ones is negative and is more likely to be excluded from the GTX choice, and the probability of selecting the GTX with an increase in the fare by 100 KRW (1 cent) decreases by 0.999 times.

In all the average frequency variables, B is negative and is more likely to be excluded from the GTX choice, and commuters who use the GTX once or twice a week are 0.629

as likely to select GTX. The probability of those who use the GTX once or twice a month choosing the GTX is 0.569, while passengers who use the GTX once or twice a year are 0.483 times as likely to select the GTX. The value of B in personal leisure among the various purposes of usage is negative and is more likely to be excluded from the GTX choice, while the value of B in a school commute is positive and is more likely to be included in the GTX choice. The probability of students commuting to and from school selecting GTX amounts to 1.720, whereas people using the trains for personal leisure to shop or to meet friends are 0.222 times as likely to select GTX trains.

7. Conclusions

In this study, the factors affecting the system choice behavior in terms of the type of urban railway system were investigated, and the differences were confirmed via a comparative analysis. We identified several factors that influence passenger rail choice. Among the individual variables, it was revealed through a model estimation that there may be differences in the choice of local and express trains for commuting and business trips regardless of the number of trains used by the respondents in their 10s, 30s, and 50s or older. It was confirmed that the frequency of train use did not influence the choice behavior of commuters between express trains and great-depth high-speed rail, and there could be significant differences in the purpose of travel, e.g., work, business trips, and shopping. Furthermore, in the choice between local and express trains, both the platform waiting time for the express train compared to that of the local train and the additional travel time for the express train compared to the local train were found to be statistically significant influencing factors. The results obtained for the express and great-depth high-speed rail showed that the influencing factors included the "additional walking time to the entrance of the GTX station compared to the existing general subway system", "additional walking time to the deeper underground GTX platform compared to the existing general subway system", "additional in-vehicle travel time of the GTX compared to the express subway system", and "higher GTX fares compared to those of the express subway system".

Our findings showed that, when selecting an express or a local train, the influence of the waiting time on the platform tends to be evaluated with the high sensitivity compared to the additional travel time in the car. This result would be a useful guideline for designing a new express service for the city subway. It will be necessary to optimize the waiting time on the platform of express users by adjusting the operating schedules of the express and local trains. However, if it is difficult to adjust the operating hours in this manner, it may be necessary to design a station such that the waiting time at the platform is not psychologically boring for commuters. There exist some cases wherein media screening and entertainment elements were designed and implemented at subway stations for this purpose. In the case of the great-depth high-speed rail, it was confirmed that the in-vehicle travel time factor was the most influential, as compared to that of the express train, and it was investigated as a related factor that had the least influence on the fare. Moreover, as out-of-vehicle time, the vertical approach time (time required to go underground) was confirmed as a factor that had a greater influence than the horizontal approach time (the time required to walk from the ground to the GTX station). This result suggests very important implications for planned great-depth high-speed rail construction. In the case of a railway built deep underground, if the vertical access takes a long time, the results show that even a railway system with a short in-vehicle travel time can have reduced attractiveness in rail transit choice. The design of a facility that can quickly transport a large number of people to an underground platform is a very important factor and should be considered during the initial planning stage. In particular, as the demand for users increases during commuting hours, it is necessary to ensure the safety if the users in the context of the high population of commuters crowding the platform, and in-depth consideration and appropriate countermeasures are required to minimize the underground access time.

By comparing the factors affecting the three types of railroads, it was confirmed that the out-of-vehicle travel time had a greater influence on the commute to work and business trips than the in-vehicle travel time in the choice of railroad system. This also indirectly implies that the connection with other transportation systems and the convenience of transfer facilities are very important from the user's point of view in a railroad system. Although there is a limitation of this study, in that it comprised a comparative analysis of the stated preference survey on Subway Line 9, which is already in operation, and the GTX, which is under construction, we expect our findings to function as a useful guideline for designing various types of rail transit systems. In addition, there probably is a weak point where the use of data for a small number of respondents is compared to the population size of the metropolitan area. Further research is required to be conducted in the future to suggest methods of increasing the transport mode utility by approaching them as a different transportation system and taking into consideration differences in characteristics, even in the same form of railroad.

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

Funding: This research received no external funding.

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 presented in this study are available on request from the corresponding author.

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

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