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Research Article

Study on Influencing Factors of the Duration of Residential Leisure Travel to Urban Parks

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With the improvement of living standards, more and more residents in China choose short leisure travel at weekends. This study aims to model the leisure travel duration to investigate the relationship between travel time and residents' factors, which can provide guidance for the development of urban parks and improve the structure of transportation modes to promote low-carbon travel modes. The accelerated hazard model is applied to establish the model equation between travel time and various factors, to obtain the differences between weekend travel time in scenic spots and personal characteristics such as residents' playing time and travel mode choice. First, an analysis of variance was performed on the valid data which have been collected. Then, the Kaplan–Meier test proved that weekend activity types tend to follow different survival functions. Finally, this study established the lifespan regression equation of the travel time, and we found that the best fit is the Log-normal distribution. This study shows clearly that accelerated hazard models based on fixed parameters are better at evaluating the attractiveness of urban parks, and they can also get feedback travel characteristics of primary residents. So, we can build a lifespan analysis-based model for the travel time of urban residents, to help plan the urban parks. The result of this study can be used for predicting the flow of different travel modes at urban parks in cities, which can be helpful for regional traffic organization such as regional traffic flow guidance and signal timing.

1. Introduction

With the increase in global greenhouse gas emissions, many measures have been adopted by countries to achieve sustainable development [1]. The Chinese government formally put forward the goal of 'carbon neutralization and carbon compliance' at the 75th United Nations General Assembly in 2020 and strongly developed a low-carbon economy to reduce greenhouse gas emissions. Among many greenhouse gas emission pathways, transportation accounts for more than 20% of the total greenhouse gas emission [2–5], and the carbon emission of ground transportation is much higher than that of air transportation [6–9].

The decision-making process of travel purpose, travel time, and travel mode is carried out by urban residents before any travel [10–13]. For residents, avoiding the urban environment and seeking contact with the natural landscape are one of the important motivations for travel [14–17]. Urban parks are common travel destinations because entertainment in urban parks positively impacts people's health [18, 19]. There are great differences in travel time, travel mode, and residence time in urban parks between weekdays and weekends [8, 20, 21].

Due to the importance of residents' working days travel in the field of transportation, weekend travel is not representative of-transportation policy and transportation planning [22]. Previous studies focused on residents' workday travel rather than weekend travel [23–29]. But recent studies show that there are significant inter-relationships between weekdays and weekend days in activity-travel scheduling behavior [30]. Besides, travel frequency, activity duration, and some analogous features are not only the typical form of residents' travel behaviors but also for vehicles. All these aspects have a significant effect on the traffic condition directly or indirectly [31]. Travel patterns can be explored by analyzing the travel characteristics of moving objects (vehicles and humans), which reflects peoples' travel regularity, traffic congestion regularity, and social activity pattern [32].

With the improvement of the living standard of the Chinese people, more and more people choose leisure travel at weekends, and urban parks as one of the main destinations. The increase in weekend leisure travel has caused great pressure on the traffic around such urban parks. For example, as the largest lake park in Nanjing, the intersections near Xuanwu Lake are often congested and there is a serious shortage of parking spaces. Thus, it is necessary to accurately predict of traffic flow of different modes, which can help improve the traffic condition by adapting the traffic control strategy according to the prediction.

In terms of travel to urban parks, travel is affected by residents' characteristics, such as age, gender, and family size [33]. The previous literature suggested that the elderly travel to urban parks more frequently than young people, but the travel distance of the elderly is shorter [34]. Compared with men, women are less likely to travel to remote urban parks; one possible reason is that women tends to take their children, so they prefer short trips to urban parks [35]. In recent years, people have reduced the frequency of private car travel but adopted low-carbon travel modes such as nonmotor vehicles, public transport, and walking [36]. In a study conducted in Kunming, China, the acceptable commuting time is concerned and the study shows that the commuting time of public transport users is twice than that of car users [37]. People can tolerate a longer travel time before the EWB reaction becomes worse when taking a bus [38]. High pedestrian areas should reduce the use of personal cars and should increase pedestrian travel according to travel preferences or needs [39].

In terms of attracting residents to travel to urban parks, its service level is related to the accessibility of transportation and the way of transportation [40]. Public transport facilities can improve the attractiveness of urban parks, and increasing the number of bus stations can attract more residents to urban parks [41]. The convenience of travel also affects the attractiveness of urban parks, because the attractive radius of urban parks is mainly 1–3 km [42]. Residents living nearby are more convenient to travel to and are more likely to go to urban parks [43, 44].

The characteristics of age, gender, occupation, family size, and monthly travel frequency were investigated. The corresponding travel time, travel mode, and residence time in the park were obtained. In terms of model establishment, we considered the AFT model as the main research topic. The AFT model has been used extensively in the analysis of cancer patients' survival rates [45] and the analysis of permanent employment [38] but rarely used in the traffic field. Based on the accelerated risk model with fixed parameters, the travel time model of urban parks is generated to explore the travel characteristics and travel preferences of residents to urban parks at weekends. Reasonable suggestions were put forward for the planning of improving the attractiveness of urban parks and the planning of improving the public transport facilities around parks. A series of measures can then be taken to increase residents' willingness to travel to urban parks, which are conducive to their health, low-carbon travel, and sustainable human and environmental development.

In Section 2, we will introduce the progress of data preparation, division of statistic groups, and data processing by one-way ANOVA. In Section 3, the main data processing method will be introduced in detail. The modeling results will be discussed in Section 4, to confirm the rationality of the analysis results. In the process of data analysis, the significance of travel time and personal attributes is explored by using one-way ANOVA. According to that, we tried to explore the distribution relationship between travel time and personal attributes by survival analysis. After exploring the distribution relationship, we attempted to establish a regression equation to digitalize the distribution relationship, so we used the AFT model to gain the results. We will discuss the analysis results and the main focus of the study in Section 5. In Section 6, research meaning and planning suggestions will be given.

2. Data Preparation and Processing

In this study, Xuanwu Lake Park in Nanjing, Jiangsu Province, was selected to obtain the required information. Xuanwu Lake Park is a national 4A-level urban park and is the most famous park among many urban parks in Nanjing. Xuanwu Lake Park is located in the eastern part of the main city and is composed of five islands and three lakes. The landscaped environment is very good, it is free and open, and it can reach 100,000 passengers per day [46]. Xuanwu Lake Park is a rhombus, the perimeter is about 15 km, and the total area of the scenic area is 5.13 square kilometers, including 3.78 square kilometers of the lake area and 1.35 square kilometers of the land area. There are four subway lines around it, and a railway station near its north, so it can attract residents and external tourists at the same time. Xuanwu Lake Park forbids vehicles to enter, internal for walking behavior. There is much out-of-plan parking around Xuanwu Lake Park, so this study also has important value for the planning of public transport stations and parking around Xuanwu Lake Park.

We collected weekend resident travel data by questionnaires from Xuanwu Lake Park on 2021 November 14th and December 5th. We distributed 200 questionnaires by two group of members; question settings focused on gender, age, travel mode, family size, etc. We set two correlating questions to test whether the questionnaire is valid or not. After inspection, we deleted 11 questionnaires and obtained 189 valid questionnaires. Categorical simplification of the data resulted in pie charts are in Figure 2.

As can be seen from Figure 1, the proportion of female residents is 55% and male residents is 45%. Over 90% of residents traveled collectively, and 73% are in-service personnel. The ratio of public transport, private vehicles, walking, nonmotorized vehicles, and taxis is approximately 6 : 6:4 : 3 : 1. The sample is divided into seven parts depending on the subject's age, including ages 20–25 years old, ages 25–35 years old, ages 35–45 years old, ages 45–55 years old, ages 55–65 years old, and ages 65–75 years old. The male is

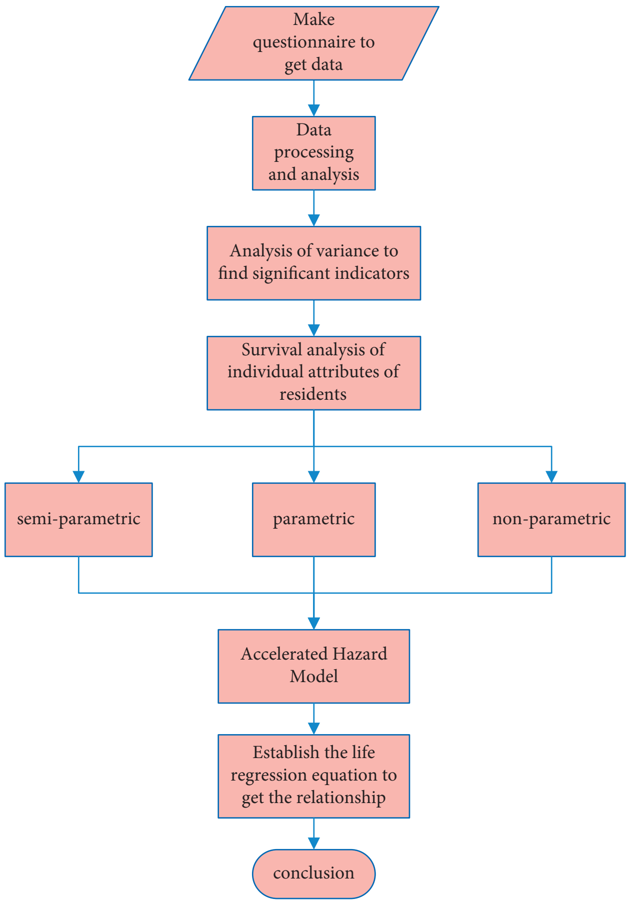

Figure 1: Article structure chart.

marked as 1, the female is marked as 2, and public transport, private vehicle, walking, nonmotorized vehicle, and taxi are marked as 1, 2, 3, 4, 5 individually. The counterpart of the job in this pie-chart marked the people who are on the job as 1, students as 2, the jobless and retired as 3.

After descriptive statistics of data, we performed a one-way ANOVA between travel time and personal attributes. Variance analysis is a statistical method to analyze the influence of category independent variables on numerical dependent variables. The method has been carried out to analyze robust estimation [47] and proposes an appropriate number of measurements [48].

One-way analysis of the variance model was used to analyze whether different levels of a control variable had a significant impact on the observed variables. The effect test expression of it is as follows:

$$\begin{aligned} \mathrm{SST} &= \mathrm{SSA} + \mathrm{SSE}, \\ \mathrm{SSA} &= \sum_{i=1}^{k} n_i \left(\overline{x}_i - \overline{x}\right)^2, \\ \mathrm{SSE} &= \sum_{i=1}^{k} \sum_{j=1}^{n_i} \left(x_{ij} - \overline{x}_i\right)^2. \end{aligned} \tag{1}$$

Here, k denotes the number of variable levels and n_i denotes the i^{th} of the control variable, n_i denotes the control variable sample size at the ith level of the variable individual levels, $\overline{x_i}$ denotes the sample means for observed variables at the i^{th} level of the variable. x_{ij} denotes the j^{th} observation at the i^{th} level of the variable. $\overline{x}$ denotes the observed variable means.

Statistic F is as follows:

$$F = \frac{SSA/(k-1)}{\mathrm{SSE}/(n-k)}. \tag{2}$$

Q is the total number of samples, F is the extent to which the variable affects the observed variable, $k-1$ is the freedom of SSA, and $n-k$ is the freedom of. SSE

We calculate the observed values and P values of the test statistics, that is, the visibility of the F value. For the given explicitness level, the value is generally 0.01 or 0.05. If $\mathrm{P} < \alpha$, it is considered that the influence of control variables on observation variables is not significant. On the contrary, if $P > \alpha$, it is considered that the influence of control variables on observation variables is not significant.

This paper selects age, gender, travel mode, travel time, family size, and monthly travel frequency as the main variables and analyzes the impact of various factors on travel time without considering the impact of other factors on the target variables.

The Variance Analysis Model is obtained using Minitab in this paper.

The analysis of the relationship between duration and travel time is as follows: through the variance analysis of data, the result can be seen in Table 1. Duration of stay can have a significant effect on travel time. This conclusion illustrates that after experiencing a long journey, residents prefer to stay in the park for a long time. For the Xuanwu Lake Park, there are some academic tourists and more distant residents, while this part of these tourists will stay for a longer time in the spot. And for this subset of residents, driving trips account for a larger proportion than that of the other travel mode, causing a shortage of surrounding parking facilities during the tourist season.

The analysis of the relationship between the travel mode and the travel time is as follows: through the variance analysis of data, the result can be seen in Table 2. Because the P value is less than 0.05, the travel mode can make a significant effect on travel time. There are several travel modes to reach the park, and there are differences among various travel modes. Such as the convenience of travel modes, length of time spent, and the travel mode's service level are all significant factors for the attractiveness of urban park.

The analysis of the relationship between family size and travel time is as follows: the analysis result can be seen in Table 3. Because the P value is less than 0.05, different family sizes can make a significant effect on travel time. Because family size has some connection with family structure, we took the family with two people as examples, and there were six groups of samples aged 55 years and older, who belonged to middle-aged and older categories. These people have more spare time, and in these samples, travel time was longer than the others. But for a family with three people, which is consisted of a couple with a child, because of the existence of a child, they prefer to drive to the park. So, they have a shorter travel time.

Table 1: Variance analysis table for duration and travel time.

Source	Freedom	Adj SS	Adj MS	F-value	P value
Duration of stay (hour)	3	6001	2000.2	3.49	0.017
Error	185	105984	572.9		
Total	188	111985			

Table 2: Variance analysis table for travel mode and travel time.

Source	Freedom	Adj SS	Adj MS	F-value	P value
Duration of stay (hour)	12	31.75	2.645	1.90	0.038
Error	176	245.69	1.396		
Total	188	277.44			

Table 3: Variance analysis table for family size and travel time.

Source	Freedom	Adj SS	Adj MS	F-value	P value
Duration of stay (hour)	3	6001	2000.2	3.49	0.017
Error	185	105984	572.9		
Total	188	111985			

3. Methodology

3.1. Survival Analysis Model. Statistical analysis of data on lifespan, survival time, or time to failure is referred to as duration modeling or hazard modeling. Most of such models have been applied to such aspects as the test of cancer hallmark genes [49], the clinical data analysis (In and Lee 2019), and the method to study topics in entrepreneurship [50]. For duration modeling, the key is in the determination of the hazard function. A hazard function represents the probability of its occurrence in a given time. However, the conditional probability of the start or the end of the duration plays a significant role [51].

Generally, there are three methods for survival analysis, which are parametric, nonparametric, and semiparametric. A parametric model can analyze the effect of risk factors on survival time and can also model the relationship between survival time and risk factors. But the distribution of survival times needs to be known in advance. The semiparametric method does not need to assume the distribution of survival time, but it allows the analysis of the distribution law of survival time and the effect of risk factors on survival time, using a model. Survival functions were estimated using nonparametric methods, allowing comparison of two or more groups of survival distribution functions and also analyzing the effect of risk factors on survival time. Although the nonparametric method did not require the distribution of survival time, the relationship between survival time and risk factors could not be modeled.

The risk function is defined as follows: let T be a non-negative random variable, and it means survival time.

The CDF of T is

$$F_T(t) = P(T \le t) = \int_0^t f_T(t)\mathrm{d}t. \tag{3}$$

Survival function is as follows:

$$S_{T(t)} = P(T > t) = 1 - F_T(t). \tag{4}$$

Failure function is as follows:

$$h_{T(t)} = \lim_{\Delta t \longrightarrow 0} \frac{\mathrm{p}(t \le T < t + \Delta t | T \ge t)}{\Delta t} = \frac{f_T(t)}{S_T(t)}. \tag{5}$$

The accelerated hazard model is as follows:

$$\mathrm{LnT} = \boldsymbol{\beta}\mathbf{X} + \varepsilon. \tag{6}$$

β is the vector of unknown coefficients associated with the covariate X, ε is the error variable, and different ε represents the different baseline distributions of survival times. The Weibull, Log-normal, exponential, gamma, and Log-Logistic distributions are commonly observed. Weibull, Log-normal, and Log-Logistic distributions were used to develop model equations between travel time and each factor in this study.

Let $p = (\ln t - \beta X)/\sigma$. Proportional parameters that need to be estimated are σ.

Weibull model is as follows: $f(p) = \exp(p - e^p)$.

Log-normal model is as follows: $f(t) = \phi(t)$, $\phi(x)$ is the PDF of Log-normal distribution.

Log-Logistic model is as follows: $f(p) = e^p(1 + e^p)^{-2}$.

Since there were no censored data in this study, the log-likelihood distribution for the N observations is

$$LnL(\beta, \sigma|\mathrm{data}) = \sum_{i=1}^{N} \ln\ f(\ln\ t_i | \mathbf{X}_i, \boldsymbol{\beta}, \sigma). \tag{7}$$

3.1.1. Log-Normal Distribution. A random variable X has lognormal distribution if its logarithm is normally distributed with the location parameter μ and scale parameter σ^2, which is usually denoted as $\ln(X) \sim N(\mu, \sigma^2)$.

3.1.2. Log-Logistic Distribution. A random variable X has log-logistic distribution if its logarithm has logistic distribution with the location parameter μ and scale parameter s, which is usually denoted as $\ln(X) \sim \mathrm{Logistic}(\mu, s)$.

3.1.3. Weibull Distribution. The probability density function of a Weibull random variable is as follows:

$$f(x|\lambda,k)=\begin{cases}\frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1}e^{-(x/\lambda)^{k}}\,x\geq 0,\\ 0,x<0\end{cases}\tag{8}$$

where $k>0$ is the shape parameter and $\lambda>0$ is the scale parameter. Weibull distribution is usually denoted as $X\sim \mathrm{Weibull}(k,\lambda)$.

4. Modeling Results

In this part, the data which were imported into Minitab will be applied to the methods which have been described in the methodology. Then, the factors in the data are evaluated and the extent of their effect on travel time is obtained. From these, the best fit model for travel time spent is the three-parameter logistic model, the best fit model for traffic mode is the logistic model, and the best fit model for the duration of stay is the Weibull distribution. Because the effect of a single factor was not enough to judge the whole model, the life-span regression equation was obtained after the AFT analysis, and the fitted distribution was lognormal.

4.1. Results of the Survival Analysis Model. Data included respondents' employment status (on-the-job or retired), age, gender, family size, travel time, travel pattern, and duration of activity. Travel times are significantly related to the duration, family size, and travel modes according to the analysis of variance. However, the magnitude of the effect of each influencing factor remains unknown, so the analysis is repeated using the duration model.

First, the Kaplan–Meier test is one of the nonparametric methods commonly used in survival analysis, as data for survival analysis are generally censored and skewed. So, this study uses the Kaplan–Meier test in data processing to examine the data on travel from the park. At the same time, we also used Log-rank, Wilcoxon, and Tarone statistics to test that. Wilcoxon test with Minitab yielded the following results: at the 95% confidence level, travel time is significantly affected by various influencing factors. The examination results are shown in Table 4.

The survival function image was generated after analysis of the time spent for each travel option in SPSS. We marked 1 as public transport, 2 as private vehicles, 3 as walking, 4 as nonmotorized vehicles, and 5 as taxis. From the function image, it can be estimated that when the travel time is 15 min, the utilization ratio of taxis is 80%, nonmotorized vehicles is 70%, walking is 50%, private vehicles is 70%, and public transport is 75%. But when travel time reaches 45 min, the utilization ratio of taxis is 30%, the nonmotorized vehicle is 0%, walking is less than 5%, the private vehicle is 10%, and the public transport is approximately 35%. According to the results, we can preliminarily evaluate that the travel time of weekend residents from Xuanwu Lake Park mostly concentrates within 30 min. According to the calculation, the farthest distance from Xuanwu Lake Park is approximately 10 km. Along with travel time growth, when travel time is over 60 min, the main travel modes are private vehicles and public transports, and all three statistical methods differed. The result is in Figure 2.

Results obtained from nonparametric methods of surface data can be used in survival analysis, and a parametric method was used to search for the best fit model. Eleven parametric duration models are available in Minitab; it contains Weibull distribution, Log-Logistic distribution, Log-normal distribution, etc. We tested the distribution from Minitab and then used the adjusted-Anderson–Darling method to test the goodness of fit of the AD value and COR value. The fitting criteria were to select the distribution with the lowest AD value or highest COR value as shown in Table 5.

The best fit parameterized model was identified after a fit search for each factor. The best fit model for travel time was a three-parameter logistic model, for travel mode was the logistic model, and for the duration was the Weibull model. Model fit was further demonstrated by contrasting the fitted line with the observed cumulative distribution function.

The probability distribution function and survival function can be seen in Figure 3; according to that, we can know the range of travel time is approximately from 30 min to 60 min. The maximum hazard rate at 30 min was approximately 0.06%, and the failure function shows a rapidly increasing trend from the onset to the peak. A rather flat decrement rate is presented after the peak. This high-frequency pattern suggests that the people whose travel time is less than 30 min will be more sensitive to the travel time. By contrast, the people whose travel time is more than 30 min will stay for a long time in the park. Figure 3 also shows a good fitting between theoretical function and observed data. To get the regression model for the survival analysis, the results are as follows.

According to Figure 4, the maximum probability density value of nonmotorized vehicles can be seen when the travel time is 20 min. But its failure function value reached its peak when the travel time is 40 min. It suggests that the utilization rate of nonmotorized vehicles is relatively high, but its failure rate is still high, which means the selection rate of nonmotorized vehicles is lower and they are paradoxical. Although the selection rate of walking is relatively lower than those of the other in total, according to Figure 5 of the survival function and the failure function, when travel time is approximately 10 min, the selection rate of walking is relatively high. From this analysis, travel time is affected by several factors; one way analysis of variance alone could not be performed for the parameters that were significant in the analysis of variance.

After selecting aft, we calculate the p value and Z-statistics of each attribute separately, the results are as follows:

The lifetime regression equation which has been built for travel time and was obtained different regression models' adjusted value, respectively, is shown in Table 6.

According to the goodness of fit, we can find that the Log-normal distribution outperforms other distributions.

Table 4: Wilcoxon test.

Sample	Median	Confidence interval	Confidence level (%)	P value
Age	33.0	(31.5, 34.5)	95.00	0.045
Travel mode	2.5	(2, 2.5)	95.00	0.000
Frequency	2.0	(2, 2)	95.00	0.000
Family size	3.5	(3.5, 3.5)	95.00	0.000
Employment	1.0	(1, 1.5)	95.00	0.000
Travel time (min)	25.0	(22.5, 25)	95.00	0.402
Duration of stay (min)	150	(2.5, 2.5)	95.00	0.000

Note: employment marked 1 as on-the-job, 2 as student, 3 as retired.

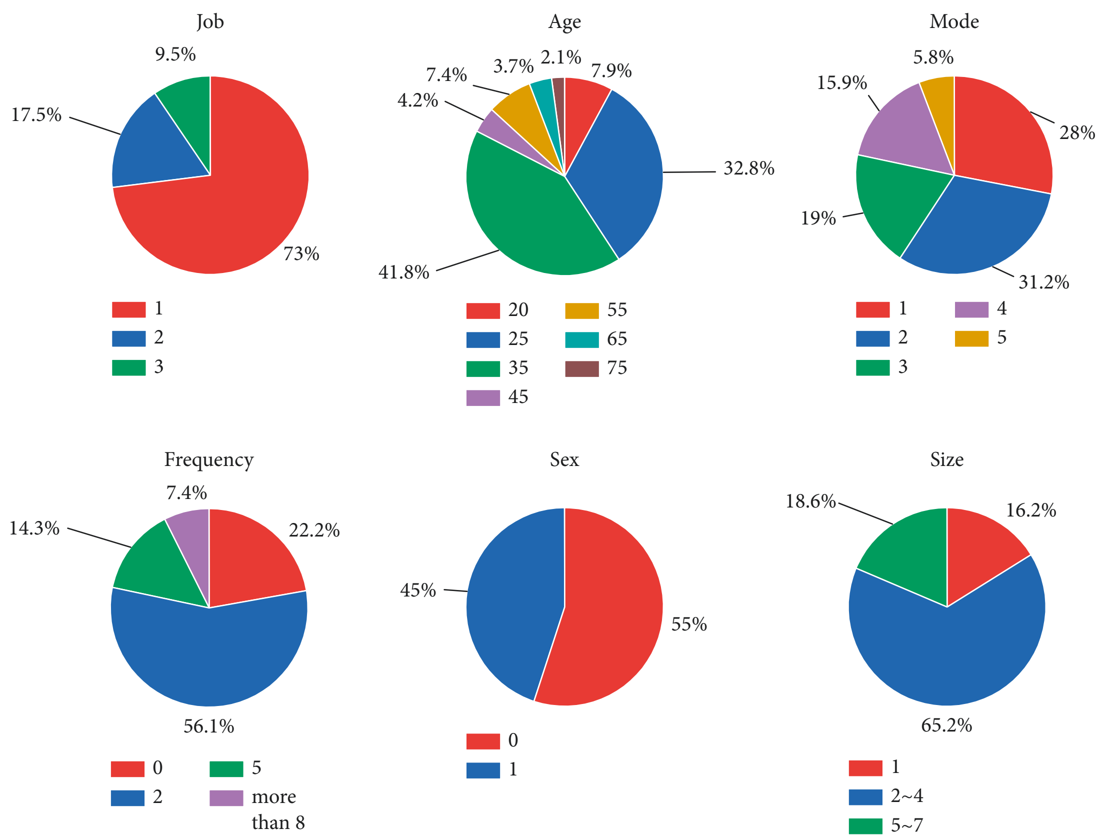

Figure 2: Percentage of different factors.

Table 5: AD value of different distributions.

Distribution	Travel time AD value	Travel mode COR value	Duration of stay AD value
Minimum value	32.396	9.821	14.155
Weibull	10.114	7.489	12.101
Three-parametric Weibull	9.322	44.720	11.914
Index	21.645	23.267	41.669
Two-parametric index	13.228	43.876	23.887
Normal	17.314	8.354	12.673
Log-normal	6.439	9.363	12.123
Three-parametric-log normal	6.643	39.836	12.105
Logistic	7.701	8.039	12.634
Log-Logistic	2.794	8.746	12.215
Three-parametric-Log-Logistic	2.791	37.495	12.215

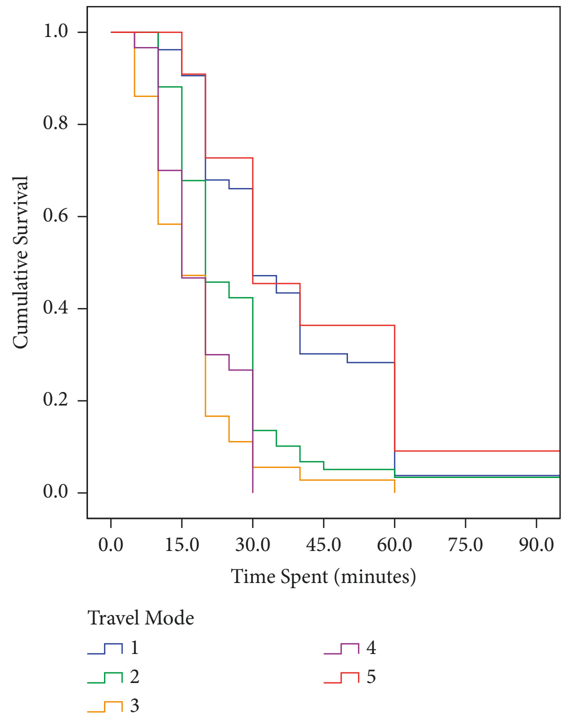

Figure 3: Survival function of the travel mode.

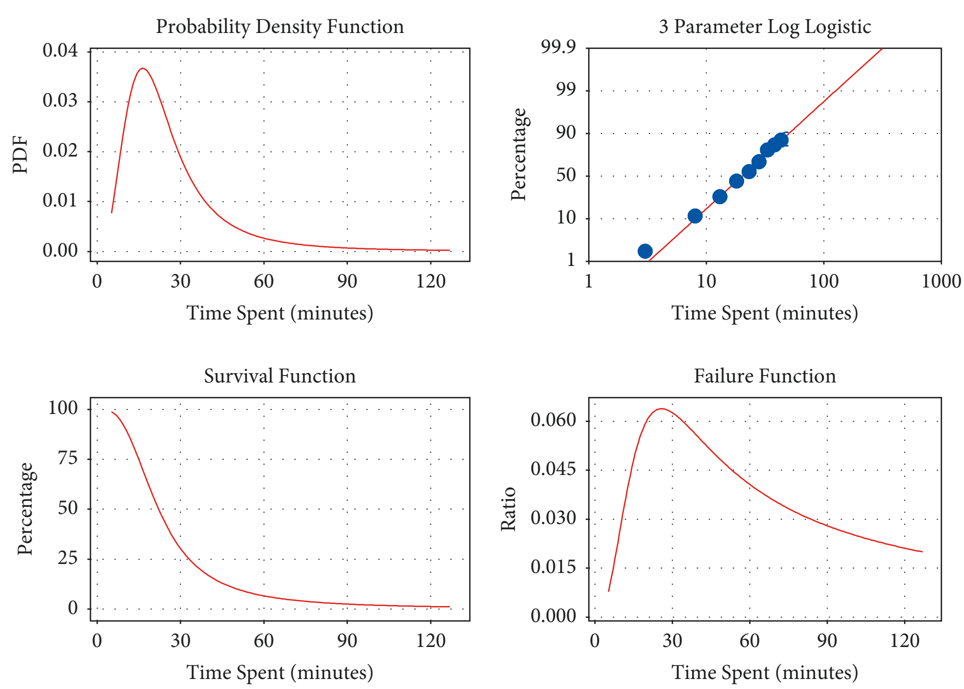

Figure 4: Distribution overview plot of time spent.

The life regression equation is as follows:

$$\begin{aligned} Y_{\mathrm{p}} = {} & 3.42449 + 0.0013242 * (\text{age}) \\ & - 0.225674 * (\text{frequency}) + 0.0483219 * (\text{sex}) \\ & + 0.340789 * (\text{size}) + \beta_i * (\text{job}) + \beta_j * (\text{mode}) + \sigma, \end{aligned} \tag{9}$$

σ is the scale parameter, β_i is employment situation, and β_j is travel mode.

We can make a further analysis of travel time by using this equation. As the p value can be seen in Table 7, the ages of residents did not make a significant impact on travel time. But according to the equation, with the same other variables and increasing travel times, the probability of still traveling

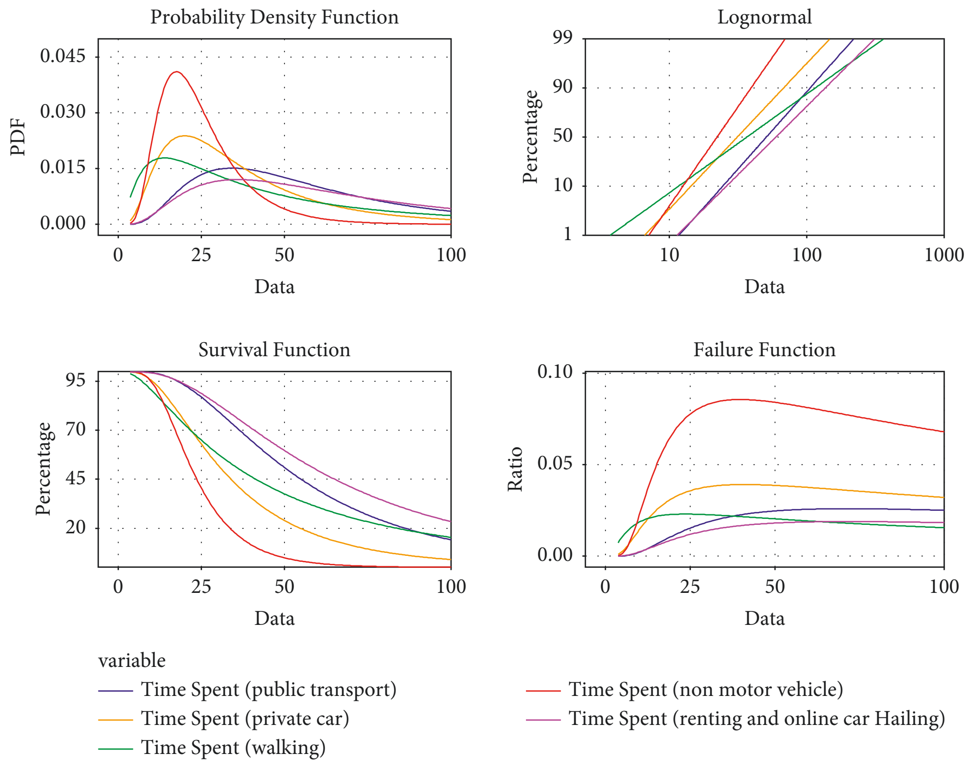

Figure 5: The distribution fitting of the travel mode.

Table 6: Different distributions' goodness of fit for the same model.

Model	Distribution	Standardized residual	Cox–Snell residuals
	Weibull	3.098	3.098
Fixed parameter model	Log-normal	0.722	0.733
	Log-Logistic	0.780	0.765

Table 7: Estimation results of the Log-normal model.

Variables	Coefficient	Z-statistics	P value
Constant	3.42449	15.27	0.000
Age	0.0013242	0.25	0.803
Frequency	−0.225674	−2.24	0.025
Sex	0.0483219	0.59	0.554
Family size	0.340789	1.03	0.305

to a destination increases by 1% for every 10-year increase in age. And this is consistent with the collected data (aged from 25 to 35) because the people whose age is from 25 to 35 years have various travel modes and stronger travel willingness. At the same time, the people whose age is from 55 to 65 years have more spare time and their travel willingness is strong too. As for frequency, if the monthly frequency of the park traveling is raised, the residents prefer the shorter travel time. The travel willingness will decrease by over 25% if the travel time grows. As for gender, the male residents are willing to spend more time going to the Xuanwu Lake Park than the female residents. As for family size, people prefer to go to Xuanwu Lake Park with their families, rather than going alone. These results are all consistent with the analysis of variance.

According to Table 8, as for the job, the probability that retired residents and students would be willing to spend more travel time than the working residents is 33% versus 14%, respectively.

As for the travel mode, public transport dominates the travel mode. If the travel time rises, public transport is associated with a 2.28-fold increase in walking, a 1.9-fold increase in walking compared with nonmotorized vehicles, and a 1.4-fold increase compared with private vehicles.

After the analysis of the equation, we can know that the effects among factors are mutual. The reason why the male residents are more willing to go to the park than the female residents is maybe the male residents decide to stay with their families and have a relaxing time, and their travel modes are more varied and their travel frequency is relatively low. So, the rise in travel time will make a little influence on their travel willingness. As for the retired, on the one hand, they have more spare time, and on the other hand, they prefer to walk for exercise. But their physical strength is limited. Thus, they will not walk to the park if the distance is too long. The dominance of public transport is the basis for the establishment of a park, but the coexistence of multiple modes of transport and the development of these are also important factors for the frequent visit of the park.

Table 8: Statistics of related variables in each class.

Variables	Class	Coefficient	Z-statistics	P value
Job	1	—	—	—
	2	0.132348	1.07	0.283
	3	0.283443	1.41	0.160
Mode	1	—	—	—
	2	−0.351649	−3.31	0.001
	3	−0.826044	−7.04	0.000
	4	−0.640463	−5.05	0.000
	5	−0.0223313	−0.12	0.902

Note: on the job, we marked 1 as on-the-job, 2 as the student, and 3 as the retired. In the mode, we marked 1 as public transport, 2 as private vehicles, 3 as walking, 4 as the nonmotorized vehicle, and 5 as the taxi.

5. Discussion

In this paper, we provide an in-depth analysis of the relationship between travel time and residents' characteristics at Xuanwu Lake Park in Nanjing. After collecting resident travel data from different locations and with different travel characteristics, we completed the establishment of the accelerated risk model. Our survey data are focused on resident travel modes, travel time, age, gender, family size, etc. It reflects the characteristics of the residents in Xuanwu Lake Park.

We treated travel time as the dependent variable and individual resident-related characteristics as independent variables. The model yields estimated parameters for independent variables, and then, we get the lifespan regression equation. This analysis found that women who were distant from a park rarely visited a park compared to men, which is consistent with previous empirical studies. Residents' willingness to travel to the park increases with age, the number of residents traveling alone is low, and their willingness to spend time going to the park is low. We found the fact that public transport occupies a major role in residents' travel patterns, and it is a key development factor in urban parks.

This study is an analysis of the effects of travel time and travel willingness on residents' characteristics in urban park travels. The center of research is through more rational planning of transportation facilities in urban parks, to increase the transport convenience of urban parks and rise residents' willingness to go to urban parks. Public transport travel modes in urban parks will be subdivided in the future, to make the transportation planning cater to the "Two-Carbon" policy.

6. Concluding Remarks

We analyzed the residents' travel time and travel mode by survival analysis andincreased credibility at the urban park planning level; prior urban park planning only considered geographic location but did not consider the travel time and the travel mode of residents. In this paper, we analyzed the travel time of residents in Xuanwu Lake Park preliminarily and compared the results of different travel modes selection of the residents. The best fit model for the travel time was determined, and this provides an important evaluation index for the attractiveness of this park. The attractiveness evaluation of an urban park is not simple for the number of residents, but whether residents are willing to spend some time visiting the park is also an important criterion. As for Xuanwu Lake Park, on the one hand, the park is a representative urban park in Nanjing; on the other hand, there are many schools and business areas around it. Therefore, there are many comprehensive evaluation indexes of this park, and variations in travel time are also large. We found that some personal attributes have manifested correlation through ANOVA, so we continue doing survival analysis to explore the relationships between travel time and personal attributes. After the accelerated survival analysis for each factor, the life span regression equation was established, and a Log-normal distribution was found to have a good fit.

After analyzing the effect of each factor on travel time, urban park planning can be evaluated initially. For residents of urban parks, public transport is the most significant travel mode. Therefore, the rationality and accessibility of the public transport site settings are the main factors to attract residents. But since tourists to urban parks are mainly residents, driving travel is also an important form of travel. It is also convenient to look after the children and take necessities, so we should pay attention to the number of parking facilities. The data including the number of car parks and types of parking vehicles at low and high seasons in the park should be analyzed statistically. We should also classify the vehicles in the park's parking lot and plan the number of parking facilities. Generally, the residents do not want to walk more than 300m after they parked and the old residents prefer walking and using nonmotorized vehicles to go to the park.

The results of this study can help improve the planning of urban parks. Furthermore, traffic management can also benefit from the study by adapting the traffic control strategies to accommodate to the traffic flows of different modes [52, 53].

Data Availability

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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