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Article

Is It Possible to Compete With Car Use? How Buses Can Facilitate Sustainable Transport

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Abstract
The need to prioritise the development of bus transport has attracted widespread attention in the literature. This study aims to investigate how buses can be used to facilitate a sustainable transport system, using Heze, in China, as a case study. Our results show that older people, unemployed residents, and those whose points of departure or arrival are within the city centre are more likely to travel by bus. In addition, compared to other travel modes, travel by bus tends to become more popular as travel time and distance increase. We predict the probabilities of people using buses for journeys of different travel times and over varying distances and rank them in order. The results suggest that bus travel could potentially replace car travel when the travel time is between 15 and 30 minutes or the travel distance is more than 9 km. In terms of policy implications, governments and planners should pay more attention to creating additional bus lanes, extending the bus network and its infrastructure, optimising bus-related facilities and services, particularly for older adults, and increasing the punctuality and reliability of bus travel.

Keywords
bus travel; car dependency; sustainable mobility; transport planning; travel behaviour

Issue
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1. Introduction

Currently, many countries are making strenuous efforts to provide better public transport services to encourage the public to use them, in order to reduce traffic congestion (Yao et al., 2021). Buses are often the only form of public transport available in small- and/or medium-sized cities in China. Since 2004, the Chinese government has issued a series of documents to promote the development of public transport (Zhang et al., 2016). Although the length of bus routes increased fivefold and the number of buses doubled between 2004 and 2017 (Yao et al., 2020), the number of private cars on the roads increased by a factor of almost 14 from 2005 to 2019 (National Bureau of Statistics of China, 2020). Car dependency and its impacts remain a serious problem in China. The potential of public transport for easing traffic congestion in China has therefore not yet been realised, especially with regard to replacing car travel with bus travel.

Existing studies on bus travel can be roughly divided into two types: first, those investigating factors affecting the use of buses (Brechan, 2017; Buehler, 2011; Chakrabarti & Joh, 2019; Chng et al., 2016; Ding et al., 2017; Ha et al., 2020; Ng & Acker, 2018; O'Fallon et al., 2004; Paulley et al., 2006; Rachele et al., 2015; Rasca & Saeed, 2022), and second, studies exploring the relationship between car ownership and bus use (Balcombe et al., 2004; Chakrabarti, 2017; Eriksson et al., 2008; Lee et al., 2003; Liu & Cirillo, 2015; Yao et al., 2021). Although some studies have considered the effect of car ownership and car use on bus travel (Rasca & Saeed, 2022; Yao et al., 2021), few have examined the influence of other travel modes, such as walking and cycling. Additionally, previous studies have paid scant attention to discussing the possibility of using buses for journeys of different travel times or over different distances. Furthermore, previous studies have primarily focused on large cities and metropolises rather than medium or small cities, meaning that the resulting policy implications may not be transferable to different types of cities. Our research, therefore, aims to address these gaps.

The rest of our article is organised as follows. Section 2 presents a review of the existing literature regarding bus service planning and bus travel. Section 3 explains the case study context, the data collection process, and the methodology. The key findings and a discussion of the empirical research are provided in Section 4. The final section presents the conclusions of our study together with policy implications.

2. Literature Review

2.1. Factors Affecting the Use of Buses

While various strategies for increasing the use of public transport have been studied in different contexts around the world, no standardised solution has yet been agreed on (Rasca & Saeed, 2022). Lanzendorf (2002) used the "mobility style" model to clarify the relationship between individuals' travel mode choices and a range of factors. Vij et al. (2013, p. 164) developed the concept further to encompass what they referred to as "'modality styles,' or behavioural predispositions, characterized by a certain travel mode or set of travel modes that an individual habitually uses."

For nearly seven decades, researchers have been closely studying the factors that affect human daily mobility behaviour and travel mode choices (Reeder, 1956). Demographic factors can affect the use of public transport. Several existing studies have demonstrated that younger (under 25) and older adults tend to use public transport to a greater extent (Coogan et al., 2018; Ding et al., 2017; Ha et al., 2020; Litman, 2004; O'Fallon et al., 2004), while middle-aged people appear to be more dependent on cars (Ding et al., 2017). Research from Buehler (2011) and Ng and Acker (2018) found that there is an association between gender and the use of public transport: Females tend to use public transport more than males. A link has also been found between educational levels and the use of public transport. Individuals with higher educational levels are more likely to use public transport (Rachele et al., 2015).

Ding et al. (2017) and Rasca and Saeed (2022) found that higher levels of accessibility can increase public transport use. According to the definitions provided by Litman (2008) and Saghapour et al. (2016), bus accessibility encompasses several factors: access to bus stops, travel time and distance by bus, frequency of the buses, and ticket prices. Having to travel a longer distance from home to the nearest bus stop has a negative impact on bus use (Rasca & Saeed, 2022). Rasca and Saeed (2022) found that travellers living within a comfortable walking distance (e.g., five minutes or less) of bus stops are more willing and likely to use the bus. The only current international sustainable urban development standard, the ISO Standard No. 37120:2018 Sustainable Cities and Communities—Indicators for City Services and Quality of Life specified a benchmark of the "percentage of population living within 0.5 km of public transit running at least every 20 minutes during peak periods" for public transport provision (International Organization for Standardization, 2018, p. 70). Yao et al. (2021) found that the quality of bus services has a significantly positive impact on bus use. Balcombe et al. (2004), Ha et al. (2020), and Kawabata (2009) have all produced evidence to show that very long travel times have a negative impact on public transport use. By comparing bus travellers making journeys of different travel times, Rasca and Saeed (2022) found that people are more likely to use buses when the travel time is between 15 minutes and 60 minutes; when the travel time is more than 60 minutes, people are least likely to make their journeys by bus. Hagenauer and Helbich (2017) claimed that travel distance is the most significant variable in determining travel mode use. Rasca and Saeed (2022) found that bus use increases with travel distance, which is in line with the findings from Chng et al.'s (2016) research. By exploring 24 experimental cases in Norway, Brechan (2017) found that both reducing prices and increasing the frequency of services can have positive effects on public transport use. Numerous other studies have also confirmed this finding (Ha et al., 2020; Paulley et al., 2006; Rasca & Saeed, 2022).

It is worth noting that existing studies have largely focused on global large cities and metropolises; only Rasca and Saeed (2022) targeted small cities and towns in Norway as case studies. However, Rasca and Saeed (2022) did not consider the effects of other transport modes (e.g., walking and cycling) on bus use. In this study, data on travelling by bus, car, active travel, and electric bicycle, in Heze, a medium-sized city in China, is used in an attempt to fill the existing research gap.

2.2. Car Dependency and the Shift to Sustainable Travel Modes

Nordfjærn et al. (2014) found that there is a weak relationship between habitual car use and the intention to use public transport. Existing research has demonstrated that a high rate of car ownership leads to a reduction in active travel and public transport use (Balcombe et al., 2004; Chng et al., 2016; Paulley et al., 2006). Car ownership influences both car use (Van et al., 2014) and bus use (Ding et al., 2018). Rasca and Saeed (2022) produced evidence to show that car ownership has a negative impact on bus use. Car owners rarely use public transport, and bus use is primarily driven by the absence of cars (Chakrabarti, 2017). Some studies have shed light on the relationships between the quality of bus services, bus use, car ownership, and car use. On the one hand, a higher quality of bus services has a significantly negative effect on car ownership (Fairhurst, 1975; Goodwin, 1993; Lee et al., 2003; Liu & Cirillo, 2015; Yao et al., 2021). On the other hand, a better quality of bus services leads to an increase in bus use, which in turn causes a reduction in car use (Eriksson et al., 2008; Lee et al., 2003; Liu & Cirillo, 2015; Yao et al., 2021). Furthermore, by surveying residents who commuted by car in Shanghai, Wang et al. (2013) found that enhancing the punctuality and comfort of public transport could reduce car use. In short, car ownership and car use decrease as bus use increases (Yao et al., 2021). However, the increase in car use caused by car ownership is much greater than the decrease in car use caused by improved bus services and the increase in bus use, which helps to explain why traffic congestion in China is so severe (Yao et al., 2021).

Several studies have investigated car users' subjective attitudes to explore how they could be persuaded to use cars less and buses more. Improving bus services may result in travellers developing a more negative attitude towards car use and/or perceiving bus travel in a more positive light (Cullinane, 2002; Eriksson et al., 2010; Kingham et al., 2001; Mackett, 2001). Fiorio and Percoco (2007) found that faster public transport services could encourage as many as 25.41% of car user respondents to use public transport. Similarly, Kingham et al. (2001) found that promoting greater reliability and convenience and better connections, as well as offering discounted tickets, could persuade 40% of car commuting respondents to switch to buses.

Kim and Kim (2004), Li et al. (2011), and Yao et al. (2021) pointed out that car ownership and car use usually increase in line with income. Conversely, those facing financial pressures are more likely to travel by bus (Yao et al., 2021). Ha et al. (2020) demonstrated that travel time could also give an indication of the competitiveness of public transport in relation to other travel modes. Public transport may be able to offer shorter travel times than cars during peak periods, but the reverse is true outside of peak periods (Guan et al., 2020; Ha et al., 2020). Collins and Chambers (2005) discovered that, when the travel time of a journey by public transport is 1.25 times as long or longer than that of travelling by car, people's preference for using public transport decreases significantly. Kawabata (2009) found that commuters travelling by car had a much higher rate of job accessibility for a 30-minute threshold than commuters travelling by public transport. Travel distance, as the most significant variable in determining travel mode use (Hagenauer & Helbich, 2017), has received widespread attention, but previous studies have produced differing results. Rasca and Saeed (2022) found that bus use tends to increase with travel distance; however, Yao et al. (2021) showed that bus use decreases while car use increases when the travel distance is more than 10 km. Scheiner (2010) also found that travellers are more likely to switch to using cars as travel distance increases. However, few empirical studies have investigated users' preferences for buses or cars for journeys of different travel times and distances. Therefore, by comparing the probabilities of travelling by bus or car for different travel times and distances, we explore whether bus travel can decrease car dependency. Our study provides new evidence that bus travel has the potential to replace car use when travel times and distances are taken into account, and thus contributes to addressing the research gap in the existing literature.

2.3. Summary

The existing literature has paid considerable attention to bus travel, primarily focusing on two aspects, as shown in Table 1: (a) factors affecting bus use and (b) the relationship between car ownership and bus use. The findings suggest that some socio-demographic factors (e.g., age, gender, education) and travel behaviour factors (e.g., access to the bus stop, travel time and distance, service frequency, and ticket prices) have a significant impact on bus use. In addition, an increase in bus use leads to a reduction in car ownership and car use; in turn, car ownership has a negative impact on bus use. Moreover,

Table 1. Summary of the existing literature.

Research topics	Key ideas	Key indicators	Key references	Key findings
Factors affecting bus use	1. Socio-demographic factors	Age	Coogan et al. (2018); Ding et al. (2017); Ha et al. (2020); Litman (2004); O'Fallon et al. (2004)	Younger (under 25) and older adults tend to be bigger users of public transport.
		Gender	Buehler (2011); Ng and Acker (2018)	Females tend to use public transport more than males.
		Education	Rachele et al. (2015)	Individuals with higher educational levels are more likely to use public transport.

Table 1. (Cont.) Summary of the existing literature.

Research topics	Key ideas	Key indicators	Key references	Key findings
Factors affecting bus use	2. Travel behaviour factors	Quality of bus services	Yao et al. (2021)	A higher quality of bus services has a significantly positive impact on bus use.
		Access to bus stops	Rasca and Saeed (2022)	A longer distance from home to the nearest bus stop has a negative impact on bus use.
			Ding et al. (2017); Rasca and Saeed (2022)	Higher levels of accessibility are positively related to public transport use.
		Travel time	Rasca and Saeed (2022)	Travellers who have a maximum travel time of one hour are more likely to use buses when the travel time is longer. When travel times are more than one hour, the probability of travellers using buses is lower than for journeys with a maximum travel time of one hour.
			Balcombe et al. (2004); Ha et al. (2020); Kawabata (2009)	Very long travel times have a negative impact on public transport use.
			Ha et al. (2020)	Travel time could give an indication of the competitiveness of public transport services compared with other transport modes.
		Travel distance	Chng et al. (2016); Rasca and Saeed (2022)	Bus use increases as travel distance increases.
		Service frequency and ticket prices	Balcombe et al. (2004); Brechan (2017); Ha et al. (2020); Paulley et al., (2006); Rasca and Saeed (2022)	Increasing the frequency of services and reducing prices can have positive effects on public transport use.
Car ownership and bus use		Car ownership	Balcombe et al. (2004); Chng et al. (2016); Paulley et al. (2006); Rasca and Saeed (2022)	Car ownership is negatively associated with public transport usage.
		Car use	Yao et al. (2021)	Bus use negatively affects car use.
		Bus services	Eriksson et al. (2008); Fairhurst (1975); Goodwin (1993); Kim and Kim (2004); Lee et al. (2003); Liu and Cirillo (2015); Wang et al. (2013); Yao et al. (2021)	High-quality bus services can reduce car ownership and car use.
			Cullinane (2002); Eriksson et al. (2010); Kingham et al. (2001); Mackett (2001)	Improving bus services may result in travellers showing more negative attitudes towards car use or more positive attitudes towards travelling by bus.
			Fiorio and Percoco (2007)	Faster public transport services could encourage as many as 25.41% of car users to use public transport.

Table 1. (Cont.) Summary of the existing literature.

Research topics	Key ideas	Key indicators	Key references	Key findings
Car ownership and bus use		Bus services	Kingham et al. (2001)	Promoting greater reliability and convenience and better connections, as well as offering discounted tickets, could persuade 40% of people who currently commute by car to switch to buses.
		Financial considerations	Yao et al. (2021)	Car ownership and car use increase as people's income increases. Travellers facing economic constraints are more likely to travel by bus.
		Travel time	Collins and Chambers (2005)	When the travel time of a journey by public transport is 1.25 times as long or longer than that of travelling by car, people have a significantly lower preference for public transport.
			Guan et al. (2020); Ha et al. (2020)	Public transport may be able to offer shorter travel times than cars during peak periods, but the reverse is true outside of peak periods.
			Kawabata (2009)	Commuters travelling by car have a much higher level of job accessibility for a 30-minute threshold than commuters travelling by public transport.
		Travel distance	Yao et al. (2021)	Car use increases and bus use decreases when the travel distance is more than 10 km.
			Scheiner (2010)	Travellers are more likely to switch to using cars as travel distance increases.

financial considerations, travel time, and distance may affect travellers' decisions about whether to travel by bus or car. However, current studies have mainly considered the effect of car use on buses and ignored the influence of other travel modes, such as walking and cycling. Additionally, previous studies have paid scant attention to investigating the likelihood of travelling by bus for different travel times or distances. Furthermore, existing studies have focused less on small or medium-sized cities. Therefore, to try to fill these gaps, this article investigates the feasibility of bus travel replacing car travel by comparing the possibility of using different travel modes for different travel times or distances, using Heze in China as a case study.

3. Case Study, Data, and Methodology

3.1. Case Study

The developing and medium-sized city of Heze, located in the southwest region of Shandong Province, was chosen as the case study city for this research. Three districts and seven counties comprise the entire administrative planning region of Heze, with a total land area of 12,239 km^2 and 8.8 million permanent residents in 2020. The data used in this study were obtained from the Heze local authority's Urban Residents' Travel Behaviour Survey (Heze Urban Planning and Design Institute, 2021). The survey was conducted from June to July 2021, mainly on weekdays. After data screening, 1,785 valid samples remained out of a total of 1,971. The Heze Urban Residents' Travel Behaviour Survey mainly focused on the downtown and urban fringe areas of the city, as shown in Figure 1, which we analyse and discuss in this article.

3.2. Logistic Regression Model

Logistic regression is one of the most popular methods used in transport studies, particularly to analyse individuals' travel behaviour and travel mode choices (Rasca & Saeed, 2022). The following studies have used binary logistic regression: Chakrabarti and Joh (2019), Collins and Chambers (2005), Ha et al. (2020), and Lanzendorf (2002), while other logistic regression models adopted in existing studies cited in Section 2 include: ordered logistic regression (Rasca & Saeed, 2022; Saghapour et al.,

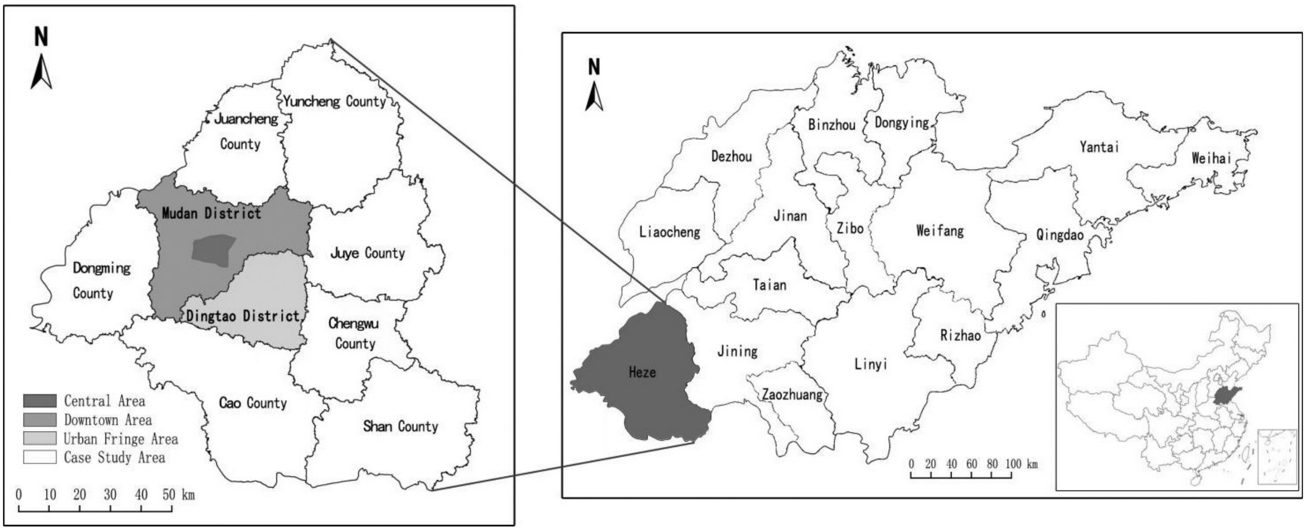

Figure 1. Case study map of Heze.

2016) and multinomial logistic regression (Chng et al., 2016; O'Fallon et al., 2004). Rasca and Saeed (2022) used logistic regression to explore the impacts of individual factors on bus use and investigate the probability of travelling by bus at different times and over different distances. In this study, we used binary logistic regression to analyse the relationship between individual factors and bus use and multinomial logistic regression to compare the probabilities of people using different travel modes to make journeys of different travel times and over different distances.

In the binary logistic regression model used in our study, the dependent variable 1 denotes the decision to *travel by bus* while 0 represents the decision to *not travel by bus*. A total of 11 independent variables relating to socio-demographics (gender, age, and employment status) and travel behaviour (travel time, travel distance, departure time, arrival time, departure area, arrival area, travel purpose, and number of travellers) were examined. More details can be found in Section 3.3.

Because this study aimed to explore how travel time and distance are associated with the choice of travel mode, we ran two multinomial logistic models. The dependent variable was the mode choice. Each of the multinomial logistic models contained 10 independent variables relating to socio-demographics and travel behaviour. Unlike the binary logistic regression model which included all 11 independent variables, one multinomial logistic model was run without the travel distance variable, while the other omitted the travel time variable, so as to avoid any effects resulting from the interrelationship between travel time and distance. More details are provided in the following sections.

3.3. Survey and Data Collection

All the information and data used in this study were taken from the Heze Urban Residents' Travel Behaviour Survey, which collected information on the following 13 categories from every respondent, as shown in Table 2:

1. Individual socio-demographic attributes: Gender, age, occupation, and employment status;
2. Travel time and travel distance: These were divided into two separate classifications for the respective quantitative analyses;
3. Departure/arrival time and departure/arrival area: Peak periods were defined as 5:00–9:00 and 17:00–19:00, and all other time periods were classified as off-peak;
4. Travel purpose: There were a total of 11 possible purposes, under the broader categories of commuting and leisure;
5. Number of travellers: Travelling alone or with others;
6. Travel mode: The following four kinds of primary travel mode choices were offered as options—active travel (walking and cycling), bus, car, and electric bicycle.

According to the 2020 Chinese census (Shandong Provincial Bureau of Statistics, 2021), males accounted for 50.78% of Heze's population, and females accounted for 49.22%. In our study, the respondents comprised 50.98% males and 49.02 females. Out of all the transport modes, the number of respondents who used active travel accounted for only around 7.79% of the total, while the proportion of respondents who travelled by bus was 25.15%, and 25.10% of respondents travelled by car. Respondents who travelled by electric bicycle accounted for the largest proportion of the total at 41.96%. Levy (2013) showed that some individual factors, such as financial, cultural, physical, locational, and gender-related factors, may affect people's choice of transport mode. A total of 27.28% of the respondents travelled for journeys lasting 20 to 30 minutes,

Table 2. Descriptive statistics (n = 1,785).

	Categories	Frequency	Percentage
Gender	Male	910	50.98%
	Female	875	49.02%
Age	<25	233	13.05%
	25–44	1,045	58.54%
	45–64	449	25.15%
	≥65	58	3.25%
Occupation	Managers, directors, and senior officials	127	7.11%
	Professional occupations	547	30.64%
	Skilled trades	434	24.31%
	Freelance or businessman/woman	352	19.72%
	Student	184	10.31%
	Retired/unemployed	141	7.90%
Employment status	Employed	1,460	81.79%
	Unemployed	325	18.21%
Travel time (min)	≤10	288	16.13%
	10–15	257	14.40%
	15–20	336	18.82%
	20–30	487	27.28%
	>30	417	23.36%
Travel distance (km)	≤3	447	25.04%
	3–6	556	31.15%
	6–9	278	15.57%
	9–12	218	12.21%
	>12	286	16.02%
Departure time	Peak period	1,223	68.52%
	Off-peak period	562	31.48%
Arrival time	Peak period	1,163	65.15%
	Off-peak period	622	34.85%
Departure area	Central area	1,196	67.00%
	Others	589	33.00%
Arrival area	Central area	1,220	68.35%
	Others	565	31.65%
Travel purpose	Commuting	955	53.50%
	Leisure	830	46.50%
Number of travellers	One	1,462	81.90%
	More than one	323	18.10%
Travel mode	Active travel	139	7.79%
	Bus	449	25.15%
	Car	448	25.10%
	Electric bicycle	749	41.96%

accounting for the largest proportion of the total. The most common travel distance was between 3 and 6 km, accounting for 31.15% of respondents' journeys.

Based on the descriptive statistics, the variables and corresponding measurements are shown in Table 3. These variables were regarded as the independent variables analysed in the binary logistic regression and multinomial logistic regression models. In the binary logistic regression model, the other variables were all binary variables, except age, which is a continuous variable. We ran multinomial logistic models to explore how travel time and distance influence the choice of transport mode. When we analysed the relationship between travel time and the choice of transport mode, we omitted travel

Table 3. Independent variables included in the models.

Category	Variable	Explanation and measurement
Socio-demographics	Gender	Binary variable (1 = *female*, 0 = *male*)
	Age	Continuous variables
	Employment status	Binary variable (1 = *employed*, 0 = *unemployed*)
Travel behaviour	Travel time	Binary variable (1 = *travel time > 30 mins*, 0 = *travel time ≤ 30 mins*)
	Travel distance	Binary variable (1 = *travel distance > 6 km*, 0 = *travel distance ≤ 6 km*)
	Departure time	Binary variable (1 = *departure in the peak period*, 0 = *departure in the off-peak period*)
	Arrival time	Binary variable (1 = *arrival in the peak period*, 0 = *arrival in the off-peak period)*
	Departure area	Binary variable (1 = *departure from the central area of Heze*, 0 = *others*)
	Arrival area	Binary variable (1 = *arrival in the central area of Heze*, 0 = *others*)
	Travel purpose	Binary variable (1 = *commuting*, 0 = *leisure*)
	Number of travellers	Binary variable (1 = *travelling alone*, 0 = *travelling with other people*)

distance from the independent variables, and travel time was regarded as a categorical variable containing five categories: (a) travel time ≤ 10mins, (b) 10 mins < travel time ≤ 15 mins, (c) 15 mins < travel time ≤ 20 mins, (d) 20 mins < travel time ≤ 30 mins, and (e) travel time > 30 mins. When we analysed the relationship between travel distance and the choice of transport mode, travel time was not included among the independent variables, and travel distance was regarded as a categorical variable containing the following five categories: (a) travel distance ≤ 3 km, (b) 3 km < travel distance ≤ 6 km, (c) 6 km < travel distance ≤ 9 km, (d) 9 km < travel distance ≤ 12 km, and (e) travel distance > 12 km.

4. Key Findings and Discussion

We used the binary logistic regression model to investigate how the socio-demographic and travel behaviour variables are associated with the choice of whether to travel by bus. The multinomial logistic regression model was then constructed to explore how travel time and distance are associated with the choice of travel mode.

4.1. Binary Logistic Regression

Table 4 shows the binary logistic regression results for how decisions about bus travel are associated with different variables. Age, employment status, travel time/distance, and departure/arrival area all had a significant influence on the intention to travel by bus ($p < 0.05$), while the other factors, namely gender, departure/arrival time, travel purpose, and number of travellers, did not significantly influence the intention to travel by bus ($p > 0.05$). First, we investigated whether demographic factors are associated with bus use. Residents were more likely to travel by bus as they got older. Our results are in line with several existing studies which found that older adults tend to be bigger users of public transport (Coogan et al., 2018; Ding et al., 2017; Ha et al., 2020; Litman, 2004; O'Fallon et al., 2004). Furthermore, according to our analysis, the relationship between gender and bus use is insignificant, contrary to the findings of studies by Buehler (2011) and Ng and Acker (2018). Second, unemployed residents were found to be more likely to travel by bus than employed residents. Yao et al. (2021) highlighted that people who were experiencing financial constraints were more likely to travel by bus. Third, residents whose points of departure/arrival were not located in the central area of the city were less likely to travel by bus, which means that, conversely, those whose points of departure/arrival were inside the city centre tended to be more frequent bus travellers. Regarding whether easy access to bus stops impacts bus use because there are fewer bus stops within the non-central area of the city than in the central area, travellers within the non-central area find it more difficult to access bus stops. In other words, residents whose points of departure/arrival were not in the central area had to walk a longer distance to bus stops. Correspondingly, Rasca and Saeed (2022) proved that long walking distances to bus stops were negatively related to public transport use. In turn, easier access to bus stops usually leads to higher levels of bus use (Ding et al., 2017; Rasca & Saeed, 2022); therefore, residents whose points of departure/arrival were located in the central area of the city were more likely to travel by bus. Finally, Table 4 shows that two further variables made residents less likely to travel by bus—if the travel time was less than or equal to 30 minutes or the travel distance was less than or equal to 6 km. In other words, residents making journeys of relatively longer travel times (>30 mins) or distances (>6 km) were more likely to travel by bus. Previous research found that travellers whose journey time lasted up to a maximum of one hour are more likely to use

Table 4. Results of the binary logistic regression (1 = *travelled by bus*, 0 = *otherwise*; *n* = 1,785).

Variable	*B*	Standard Error	Sig.	Exp(*B*)	95% CI for Exp(*B*) Lower	95% CI for Exp(*B*) Upper
Socio-demographics						
Male	–0.050	0.116	0.671	0.952	0.757	1.196
Age	**0.214**	0.083	**0.010***	1.238	1.053	1.456
Unemployed	**1.314**	0.147	**0.000****	3.720	2.788	4.963
Travel behaviour						
Travel time ≤ 30 mins	**–0.922**	0.138	**0.000****	0.398	0.304	0.521
Travel distance ≤ 6 km	**–0.380**	0.134	**0.004****	0.684	0.526	0.889
Departure in the off-peak period	0.134	0.229	0.557	1.144	0.731	1.790
Arrival in the off-peak period	0.162	0.230	0.480	1.176	0.750	1.845
Departure from the non-central area	**–0.278**	0.136	**0.040***	0.757	0.580	0.988
Arrival in the non-central area	**–0.377**	0.139	**0.007****	0.686	0.522	0.901
Leisure	0.196	0.130	0.130	1.217	0.944	1.569
Not travelling alone	0.207	0.149	0.166	1.230	0.918	1.648

Notes: Pseudo R^2 = 0.150; * *p*-value < 0.05, ** *p*-value < 0.01.

the bus (Rasca & Saeed, 2022), while very long travel times (i.e., more than one hour) have a negative impact on public transport use (Balcombe et al., 2004; Ha et al., 2020; Kawabata, 2009; Rasca & Saeed, 2022). Rasca and Saeed (2022) also found that bus use is positively associated with travel distance, which is in accordance with the research by Chng et al. (2016). However, Yao et al. (2021) pointed out that bus use decreases when the travel distance is more than 10 km, which is contrary to our results. In light of this finding, a further, more detailed classification of travel time and distance was used in the multinomial logistic model to explore how travel time and/or distance influences the choice of travel mode.

4.2. Multinomial Logistic Regression

Multinomial logistic regression was used to investigate how travel time and distance influence the choice of travel mode. The control group was comprised of those who travel by bus while people travelling by means of active travel, electric bicycles, and cars were the experimental groups. In order to achieve more accurate outcomes, travel time and distance were respectively treated as the independent variables. So as obtain the best results from the multinomial logistic regression, five different classifications of travel time and five different classifications of travel distance were used. Each classification was run through the multinomial logistic regression model and the best classifications for travel time and distance are shown in Table 5. After determining the best classifications for travel time and distance, four multinomial logistic regression analyses were conducted—two analyses each for travel time and distance, respectively. As shown in Table 5, the travel time analyses treated "≤10 mins" and ">30 mins" separately as the control groups, while in the travel distance analyses, "≤3 km" and ">12 km" were each treated as the control groups.

By comparing the coefficient *B* for different categories of travel time and distance, we were able to compare the probability of travelling by different transport modes for different travel times and distances (Rasca & Saeed, 2022). For example, with regard to car travel, when we treated ">30 mins" as the control group, the *p*-values for the other intervals of travel time were less than 0.05; therefore, we could compare the probability of travelling by car for different travel times by comparing the coefficient *B* of each of these travel time intervals. As shown in Table 5, we ascertained that residents are most likely to travel by active modes of travel such as walking, cycling, and electric bicycle, when the travel time is ≤10 mins or the travel distance is ≤3 km; residents are most likely to travel by car when the travel time is between 10 and 15 minutes or the travel distance is between 9 and 12 km. The following section shows the probability of using different travel modes for different travel times and distances in ranking order.

4.3. Comparison of Different Transport Modes

According to the results obtained from the multinomial logistic regression, the probabilities of making journeys by active travel, electric bicycle, and car for different time periods and over different distances are shown in Table 5. In addition, to determine the probability of people travelling by bus for different time periods and over different distances, another binary logistic regression was run, in which travel time and distance were treated as continuous variables and corresponded to the classifications of

Table 5. Results of the multinomial logistic regression (n = 1,785).

Categories		Active travel			Electric bicycle			Car		
		B	Sig.	Exp(B)	B	Sig.	Exp(B)	B	Sig.	Exp(B)
Travel time (min)	≤10	Control group								
	10 < x ≤ 15	−1.058	**0.004*****	0.347	−0.184	0.477	0.832	0.605	0.053*	1.831
	15 < x ≤ 20	−1.122	**0.000*****	0.326	−0.761	**0.001*****	0.467	0.218	0.439	1.244
	20 < x ≤ 30	−1.589	**0.000*****	0.204	−1.191	**0.000*****	0.304	0.058	0.825	1.060
	>30	−2.186	**0.000*****	0.112	−1.858	**0.000*****	0.156	−0.632	**0.018****	0.531
	≤10	2.186	**0.000*****	8.896	1.858	**0.000*****	6.409	0.632	**0.018****	1.882
	10 < x ≤ 15	1.128	**0.003*****	3.089	1.674	**0.000*****	5.333	1.237	**0.000*****	3.446
	15 < x ≤ 20	1.064	**0.001*****	2.897	1.097	**0.000*****	2.995	0.851	**0.000*****	2.341
	20 < x ≤ 30	0.596	0.055*	1.815	0.667	**0.000*****	1.948	0.691	**0.000*****	1.995
	>30	Control group								
Pseudo R^2 = 0.158										
Travel distance (km)	≤3	Control group								
	3 < x ≤ 6	−1.675	**0.000*****	0.187	−0.567	**0.001*****	0.567	0.711	**0.004*****	2.036
	6 < x ≤ 9	−2.668	**0.000*****	0.069	−1.139	**0.000*****	0.320	0.626	**0.020****	1.870
	9 < x ≤ 12	−2.527	**0.000*****	0.080	−0.864	**0.000*****	0.421	1.275	**0.000*****	3.579
	>12	−5.181	**0.000*****	0.006	−1.902	**0.000*****	0.149	0.721	**0.008*****	2.056
	≤3	5.181	**0.000*****	177.929	1.902	**0.000*****	6.698	−0.721	**0.008*****	0.486
	3 < x ≤ 6	3.506	**0.001*****	33.311	1.335	**0.000*****	3.799	−0.010	0.963	0.990
	6 < x ≤ 9	2.514	**0.020****	12.353	0.763	**0.001*****	2.144	−0.095	0.678	0.910
	9 < x ≤ 12	2.654	**0.018****	14.214	1.038	**0.000*****	2.823	0.554	**0.026****	1.741
	>12	Control group								
Pseudo R^2 = 0.298										

Notes: * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

travel time and distance used in the multinomial logistic regression, as shown in Table 6. The coefficient B of travel time was 0.424 when $p = 0.000 < 0.05$, and the coefficient B of travel distance was 0.265 when $p = 0.000 < 0.05$. Therefore, compared with other travel modes, residents of Heze were more likely to travel by bus as travel time and/or distance increased. It is worth noting that several studies have found that very long travel times negatively affect public transport use (Balcombe et al., 2004; Ha et al., 2020; Kawabata, 2009). Our results confirm Rasca and Saeed's (2022) findings, namely that travellers with a longer travel distance have a higher probability of making their journeys by bus. The results obtained from this binary logistic regression were in line with those discussed in Section 4.1.

In order to make it easier to compare the probabilities of using different travel modes for different travel times and distances, we have included Table 7 and Figures 2 and 3, which are based on Tables 5 and 6. Figure 2 shows that residents are more likely to travel by car when the travel time is between 10 and 30 minutes and more likely to travel by bus when the travel time is more than 15 minutes. Figure 3 shows that residents are more likely to travel by car when the travel distance is between 3 km and 6 km or more than 9 km and more likely to make their journeys by bus when the

Table 6. Results of the binary logistic regression (1 = *travelled by bus*, 0 = *otherwise*; n = 1,785).

Variable	B	Standard Error	Sig.	Exp(B)	95% CI for Exp(B) Lower	Upper
Travel time (continuous)	**0.424**	0.047	**0.000***	1.528	1.393	1.677
Travel distance (continuous)	**0.265**	0.045	**0.000***	1.304	1.193	1.425

Notes: * p-value < 0.01. This table only shows the results for travel time and travel distance; other indicators are omitted.

Table 7. The probability of using different travel modes for different travel times/distances.

Probability ranking	Active travel	Electric bicycle	Car	Bus
Travel time (min)				
1	≤10	≤10	10 < x ≤ 15	>30
2	10 < x ≤ 15	10 < x ≤ 15	15 < x ≤ 20	20 < x ≤ 30
3	15 < x ≤ 20	15 < x ≤ 20	20 < x ≤ 30	15 < x ≤ 20
4	20 < x ≤ 30	20 < x ≤ 30	≤10	10 < x ≤ 15
5	>30	>30	>30	≤10
Travel distance (km)				
1	≤3	≤3	9 < x ≤ 12	>12
2	3 < x ≤ 6	3 < x ≤ 6	> 12	9 < x ≤ 12
3	9 < x ≤ 12	9 < x ≤ 12	3 < x ≤ 6	6 < x ≤ 9
4	6 < x ≤ 9	6 < x ≤ 9	6 < x ≤ 9	3 < x ≤ 6
5	>12	>12	≤3	≤3

Notes: Binary logistic regression was used to produce the results for bus travel; multinomial logistic regression was used to produce the results for active travel, electric bicycles, and cars.

travel distance is more than 6 km. Therefore, it is possible for bus travel to replace car travel when the travel time is between 15 and 30 minutes or the travel distance is more than 9 km. Previous studies have discussed the impacts of travel time and travel distance on bus use and car use. Collins and Chambers (2005) determined that travellers' preference for public transport decreased significantly when the travel time of their journeys by public transport was 1.25 times as long or longer than that of travelling by car. Yao et al. (2021) found that bus use decreases while car use increases when the travel distance is more than 10 km. Similarly, Scheiner (2010) claimed that an increase in travel distance will make travellers more likely to switch to using cars. Although our findings are not entirely aligned with some previous studies, we complement them by producing empirical evidence to explain the impacts of travel time and distance on bus use and car use. Several existing studies have found that increasing bus use can have the effect of decreasing car use (Eriksson et al., 2008; Lee et al., 2003;

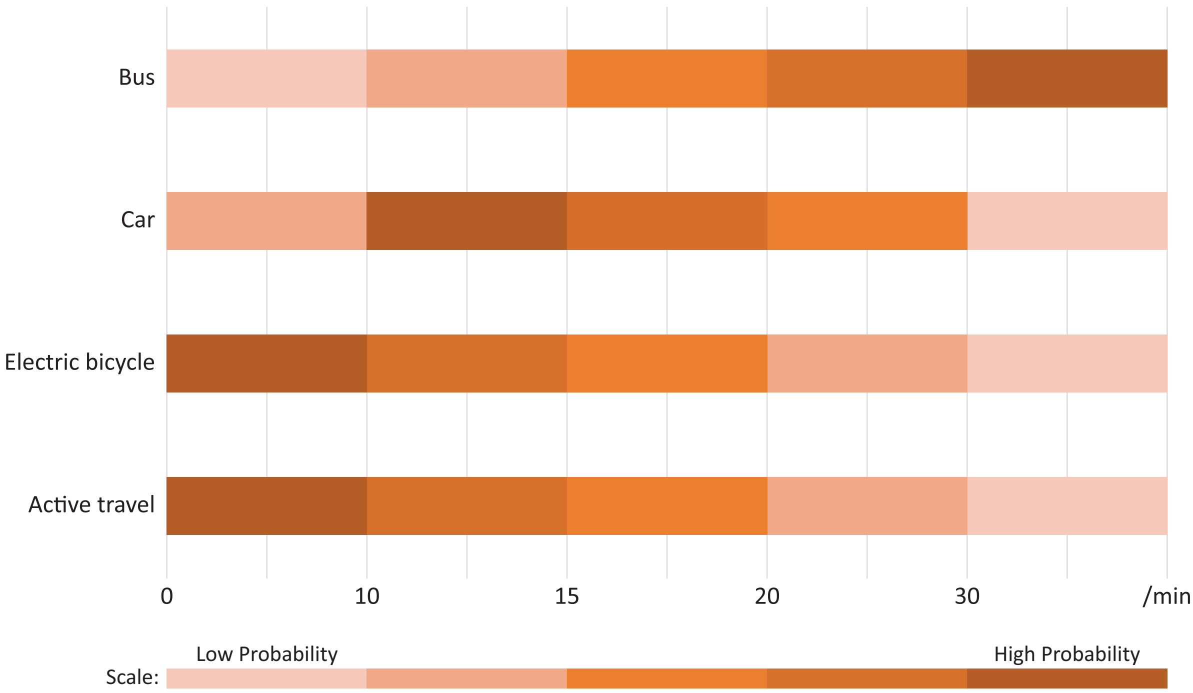

Figure 2. The probabilities of using different travel modes for different travel times.

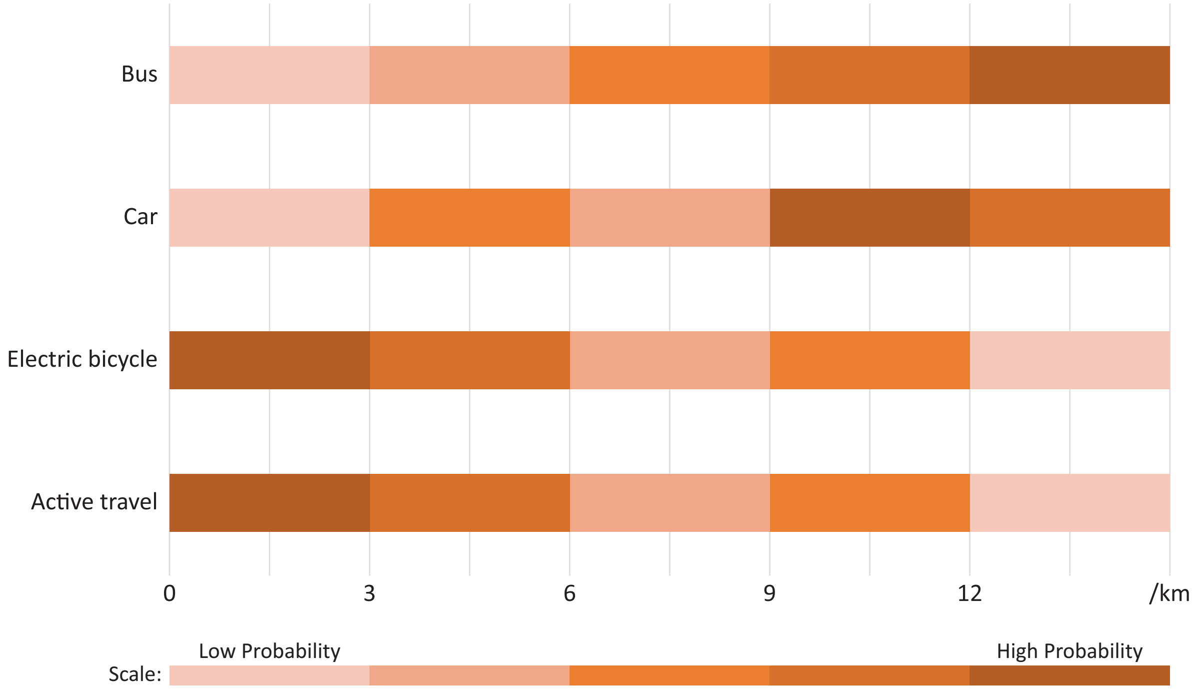

Figure 3. The probabilities of using different travel modes for different travel distances.

Liu & Cirillo, 2015; Yao et al., 2021). From the perspective of different travel times and distances, we discussed the likelihood of replacing car travel with bus travel.

5. Conclusions

In this study, we used data from the Heze Urban Residents' Travel Behaviour Survey comprising 1,785 valid samples and ran binary and multinomial logistic regressions to investigate the factors associated with bus use and explore the potential for bus travel to replace car travel.

Our study produced three key findings. First, we explored the relationship between individual/demographic factors and residents' daily bus use. Age, employment status, travel time/distance, and departure/arrival area all significantly affected whether people choose to travel by bus. Older and unemployed residents were more likely to travel by bus. Residents who have a relatively longer travel time (>30 mins) or longer travel distance (>6 km) were more likely to travel by bus. Furthermore, residents whose points of departure/arrival were located in the central area of the city were also more likely to travel by bus. Second, we investigated the likelihood of people travelling by different travel modes (bus, car, active travel, and electric bicycle) for different travel times and over different distances. Third, we discussed whether bus travel had the potential to replace car travel for various travel times and distances. It was found to be equally likely that people would travel by bus and car when the travel time was between 15 and 30 minutes or the travel distance was more than 9 km. In other words, there is the potential for bus travel to replace car travel to some extent in order to reduce car ownership and ease traffic congestion.

Our study makes two main contributions which attempt to fill previous research gaps. On the one hand, existing studies have mainly considered the effect of car use on bus travel and ignored the influence of other travel modes, such as walking and cycling (Yao et al., 2021); therefore, we analysed and discussed the possibility of using buses for different travel times or distances compared with other transport modes, including active travel, electric bicycles, and cars. On the other hand, only a few studies have investigated the possibility of travelling by bus at different travel times or over different distances (Rasca & Saeed, 2022), and rarely have they compared the likelihood of travelling by bus with other transport modes. We found that people had a similar probability of travelling by bus or car when the travel time was between 15 and 30 minutes or the travel distance was more than 9 km. In short, we provided empirical evidence for the potential of bus travel to replace car travel for journeys of these time and distance intervals, which could help to reduce car ownership and ease traffic congestion. Therefore, we identified the following relevant policy implications which could promote and improve bus transport in small and medium-sized Chinese cities. First, older adults are more likely to use public transport (Coogan et al., 2018; Ding et al., 2017; Ha et al., 2020; Litman, 2004; O'Fallon et al., 2004); thus, Heze's transport system should be developed with a focus on making bus travel more accessible for older adults. Second, given that unemployed residents are usually financially constrained, it would seem reasonable to reduce ticket prices for them as well, as offering discounted fares has been shown to positively affect public transport use (Brechan, 2017; Paulley et al., 2006; Rasca & Saeed, 2022). Third, given that easier access to bus stops tends to increase bus use (Ding et al., 2017; Rasca & Saeed, 2022), the government should address the problems caused by the inadequate bus infrastructure in the non-central area of Heze. Fourth, Redman et al. (2013) and Yao et al. (2021) provided evidence to show that enhancing the punctuality and reliability of buses can help to attract more travellers and increase bus use. Therefore, improving the punctuality and reliability of bus travel is another key area for the future development of bus services. Finally, the government should continue to prioritise buses alongside other policies aimed at reducing car use and ownership, as well as encouraging residents to opt for buses instead of cars when making medium- and long-distance journeys.

Because of the data set that we used, the results of our study are necessarily limited to Heze. Thus, the extent to which the findings of the research can be applied to other small and medium-sized Chinese cities is limited, because we used a single survey location. However, future research could seek to combine surveys and data from small and medium-sized cities in China to further develop the research findings and policy implications.

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Conflict of Interests

The authors declare no conflict of interests.

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