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RESEARCH ARTICLE

Factors Affecting Public Transportation Ridership in a High-income Developing Country

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Abstract:

Background:

In rich developing countries, the increased rate of car use has major implications in terms of pollution, noise, and congestion problems. One of the main solutions to these problems is to find ways to promote the use of other transportation modes. The first step in this process is identifying the factors affecting the use of these modes.

Aim:

In Qatar, a major bus service was introduced to address the fast-growing transportation demands in urban areas. This study was initiated to explore the factors influencing public bus ridership in Qatar. The goal is to understand the influence of various attributes at the stop-level of the existing public buses.

Methods:

Multiple linear regression models were developed to identify the parameters significantly influencing stop-level boarding and alighting.

Results:

The results indicate that land use and population parameters significantly affected the existing bus ridership in Qatar. The population parameters include the number of persons available in the catchment area for residing, working, visiting restaurants, and shopping. Land use parameters include the number of shopping places, the number of restaurants, and the number of mosques.

Conclusion:

This information can help policymakers and public authorities to develop policies and plans to increase bus usage in Qatar.

Keywords: Public transportation, Bus service, Developing country, Ridership, Noise, Car.

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1. INTRODUCTION

Qatar is one of the fastest-growing countries in the world, resulting in substantially larger private vehicle usage and congestion [1, 2]. One of the suggested solutions to reduce private car usage is introducing a public transportation system that provides reasonable service and accessibility to the population. Qatar's population in 2005 was approximately 821,000, and due to many factors, including economic growth and the country's oil and gas boom, the population has grown to approximately three million people in 2022. In 2005, to accommodate this growth and reduce the rate of car usage in Qatar, Mowasalat, a company owned by the Qatari government, launched its first bus service, the Karwa public bus. In 2008, Mowasalat initiated the Karwa Smart Card to be used as a quick and easy way to pay for the Karwa public bus. The Kentkart system, a tracking system, was then initiated to monitor the operation of the bus service and to record the number of passengers and revenues per cardholder per line and stop. This study aims to understand the influence of various attributes at the stop-level of public buses in Qatar using data obtained from the Kentkart system. The results can help policymakers and public authorities to develop policies and

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plans to increase bus usage in the country.

Many research efforts in transportation worldwide have been focusing on promoting public transportation use. Toward this end, studies focused on understanding the primary determinants of public transit system usage from two perspectives: (1) user perspective – What makes individuals opt for transit mode, and (2) transit system perspective – What attribute at a system-level contributes to transit usage. The first group of studies examines how individual-level socio-demographics, transit accessibility measures, and the built environment affect transit ridership choice. In the second group, the emphasis is on a systems perspective, where transit ridership is studied from the perspective of the transit provider [3 - 8].

The use of different transport modes is affected by several factors, such as economic, sociological, and geographical factors [9 - 16]. Some studies focused on weather-related factors. For example, Arana *et al*. investigated the influence of weather conditions on the number of public bus trips made for leisure, shopping, and personal business. The results indicated that bus trips decreased in the case of rain and wind, especially leisure trips. In addition, the number of trips increased in direct proportion to the increase in temperature. Also, regular users with smart cards are less affected by weather conditions than other users [17]. Singhal *et al*. examined the weather impact on ridership based on the day of the week and time of day combinations. The results showed that the weather's impact on transit ridership varies based on the time of day and location. The results show significant differences in how the daily, hourly, and individual weather variables can account for transit users' ridership variability and travel patterns [18].

Previous research has also examined other factors such as land use, built environment, transit attributes, and socioeconomic characteristics [19 - 21]. Some studies focused on understanding several factors that affect transit ridership at a nationwide level. For example, Taylor *et al*. have undertaken a countrywide study of 265 urbanized areas in the United States and concluded that transit ridership is influenced by regional geography, metropolitan economy, population characteristics, and roadway system characteristics. Their study has classified the factors that affect transit ridership as internal (fare, level of service) or external (income, parking policies, development, employment, fuel prices, car ownership, and density levels) variables. They observed that external factors generally affect ridership more than internal factors [22].

Other studies focused on the land use impact and other parameters on the station-level ridership [8, 23, 24]. For example, Sung *et al*. [24] investigated the impacts of land use, rail service coverage, and rail station accessibility on rail transit ridership in Seoul and the surrounding metropolitan region. They employed different regression models to analyze the impact of land use by service coverage and station-level accessibility on rail transit ridership. The relationship was empirically analyzed between rail transit ridership and locational characteristics of rail transit stations in terms of land use density and diversity and station accessibility based on service distances of 250 m, 500 m, 750 m, 1 km, and 1.5 km. The findings showed that the 500 m boundary for rail station service coverage is the most important when considering transit-oriented development. The results also identified development density and station-level accessibility as the most important measures for rail transit promotion.

Chakour and Eluru [8] investigated the influence of transit system operational attributes, transportation system infrastructure attributes, and built environment attributes on the stop level boarding and descending by the time of day for the bus transit system in the Montreal region. The involved estimating the effect of the built environment and urban design on ridership at a stop level using ordered regression models. The study examined ridership for three categories of stops: high, medium, and low ridership. For each of these, boarding and alighting were modeled separately. In addition, the peak and off-peak periods (am peak, pm peak, off-peak day, and off-peak night) were analyzed individually.

This study investigated the effect of different factors on bus ridership in Qatar at the stop level. Some of these factors were related to existing infrastructure around the bus stops, including roads, footpaths, shoulders, parking, and bike lanes. Other factors were related to land use, including the availability of businesses, shopping, religious facilities, universities, restaurants, and other shopping facilities.

2. METHODS

2.1. Data Collection

Several agencies were approached to collect the relevant data for this study and approach. The Karwa bus data were collected from Mowasalat. The data included the bus routes and stops, boarding and alighting data for 2016, frequency, timetable, and the stops' attributes. The Public Works Authority was approached to collect the most recent geodatabase for the built infrastructure data. For the land use and population data, the Ministry of Transport was approached, and the relevant land use and population data were extracted from the Qatar Strategic Transport Model (QSTM). The QSTM is used in Qatar to forecast traffic demand utilizing census data, population, land uses, and relevant growth factors. A Geographic Information System (GIS) map was created to overlay Qatar's relevant layers. This step was completed after collecting the relevant information, including the roads, footpaths, shoulders, bike lanes, and land-use layers. A buffer of 500 m was then developed around each bus stop to create the catchment area.

2.2. Boarding and Alighting Data

Before requesting the boarding and alighting data, a review of previously used data in previous studies was conducted, as shown in Table **1**.

Table 1. Different data used in previous studies.

System	Data Used	Operation*	Level	Refs
LRT	Average Weekday	Boarding	Stop Level	[19]
Transit	Average Daily	Boarding/Alighting	Station Level	[25]
Metro	Average Weekday	Ridership	Station Level	[26]
Transit	Average Daily	Ridership	Station Level	[27]
Metro Bus	Average per Hour	Boarding	Stop Level	[28]
Subway	Daily	Ridership	Stop Level	[18]
Transit	Monthly	Ridership	Stop Level	[29]
BRT	Daily	Boarding	Stop Level	[30]
Bus	Daily	Boarding/Alighting	Stop Level	[31]
Bus	Hourly	Boarding/Alighting	Stop Level	[8]
Metro	Average Weekday	Boarding	Station Level	[32]
Transit	Daily	Ridership	Statewide Level	[33]
Subway	Daily	Ridership	Stop Level	[23]
Rail	Average Daily	Ridership	Station Level	[24]
Metro	Annual Average Weekday	Ridership	Station Level	[34]
Bus	Average Weekday	Ridership	Route Level	[35]
Bus	Total Daily per Year	Boarding and Alighting	Stop Level	[36]
Rail	Total Daily per Year	Ridership	Station Level	[37]
Transit	Total Daily per Year	Ridership	System-wide Level	[38]

Note: *Ridership is defined as total boarding and alighting.

Table 2. List of parameters used.

Type	Parameters	Units
Bus Data	Average Daily Boarding	Average number of daily boarding passengers
	Average Daily Alighting	Average number of daily alighting passengers
	Average Weekday Boarding	Average number of boarding passengers during the weekday (Saturday to Thursday)
	Average Weekend Boarding	Average number of boarding passengers during the weekend (Friday)
	Average Weekday Alighting	Average number of alighting passengers during the weekday (Saturday to Thursday)
	Average Weekend Alighting	Average number of alighting passengers during the weekend (Friday)
	Average AM Boarding	Total number of boarding passengers during the AM peak period
	Average PM Boarding	Total number of boarding passengers during the PM peak period
	Average AM Alighting	Total number of alighting passengers during the AM peak period
	Average PM Alighting	Total number of alighting passengers during the PM peak period
Infrastructure Data	Road Length	Length (m)
	Footpath	Length (m)
	Shoulder Length/Parking	Length (m)
	Bike Lane	Length (m)
Land Use and Population Data	Employer Business	Number of persons available within the catchment areas for work-related business.
	Employees	Number of persons available within the catchment area for work purposes.
	Leisure Commuters	Number of persons available within the catchment areas for leisure purposes (hotels, hospitality, etc.)
	Mosques	Number of Mosques (buildings) within the catchment area.
	Personal Business	Number of persons available within the catchment areas for personal-related business.
	Adults	Number of persons available within the catchment areas.
	Restaurants	Number of persons within catchment areas for restaurants only
	Schools Students	Number of school students within the catchment areas that include schools in the land use category
	University	Number of university students within the catchment areas that include universities in the land use category.
	Shopping	Number of persons within catchment areas for shopping purposes
	Total Population	Number of persons, including adults and inhabitants.

It was found that most of the previous studies used the average daily and average weekday ridership of boarding and alighting, while limited studies used the total daily per year ridership. Therefore, this study obtained and used the average daily boarding and alighting, average weekday and weekend boarding and alighting, and total morning (AM) and evening (PM) peak periods. Table **2** tabulates all parameters used in the study with their definition and units.

3. RESULTS AND DISCUSSION

Regression models were developed, with a prediction goal, to estimate boarding and alight on different levels based on the bus infrastructure, population, and planning-related attributes. Multiple linear regression (MLR) analysis was chosen as it is a robust technique that can model the effect of continuous and categorical variables. The mathematical formulation of the MLR model (Equation **1**) and various measures (Equations **2** to **4**) are shown next. The analysis was conducted using a confidence interval of 95%.

$$Y = \beta_0 + \beta_1 \times X_1 + \beta_2 \times X_2 + \ldots\ldots + \beta_p \times X_p + \ldots + \beta_k \times X_k + E \quad \textbf{(1)}$$

$$R_p^2 = 1 - \frac{SSE(p)}{SSY} \quad \textbf{(2)}$$

$$R_{Adj}^2 = 1 - \left[\frac{(1-R^2)(n-1)}{(n-p-1)}\right] \quad \textbf{(3)}$$

$$SSY = \sum_{i=1}^{n} (Y_i - \overline{Y})^2 \quad \textbf{(4)}$$

Where,

R^2_p = Predictive ability of model with p variables

R^2_{Adj} = Adjusted R^2 for the number of predictors in the model

SSE(p) = error sum of squares of the model with p variables

SSY = Total (corrected) sum of squares for the response Y

n = total number of observations

p = no of variables in selected model

k = total number of variables considered in the maximum model

Forward, backward, and stepwise selection methodologies were assessed. The stepwise selection procedure explained the data set better. The stepwise regression model development procedure first considered all the variables to see if their significance has been reduced below the specified tolerance level. The variables were eliminated one at a time, starting with the one that had the lowest correlation with the dependent variable. Elimination continued until only statistically significant variables were left in the model. The coefficients and t-statistic for the initial and best models developed using different input variables and selected using selection criteria are shown in Tables **3** to **6**.

Table 3. Multiple linear regression analysis for average hourly boarding and alighting.

Dependent Variable: Average Hourly Boarding							
	Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Sig.**	**95.0% Confidence Interval for B**	
Variables	**B**	**Std. Error**	**Beta**			**Lower Bound**	**Upper Bound**
(Constant)	-153.084	186.289		-0.822	0.411	-518.753	212.586
Number of Shopping Places	273.408	38.208	0.266	7.156	0	198.41	348.407
Personal Business (Number)	0.101	0.026	0.141	3.878	0	0.05	0.153
Shopping Commuters	0.121	0.019	0.38	6.243	0	0.083	0.159
Total Residents	-0.147	0.03	-0.216	-4.89	0	-0.206	-0.088
Number of Restaurant Commuters	-0.232	0.093	-0.132	-2.49	0.013	-0.415	-0.049
R^2	0.210						
Adj. R^2	0.205						
Dependent Variable: Average Hourly Alighting							
	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Variables	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	420.533	171.743		2.449	0.015	83.415	757.65
Shopping Commuters	0.101	0.012	0.512	8.714	0	0.078	0.124
Number of Shopping Places	165.667	23.221	0.266	7.134	0	120.086	211.248
Total Residents	-0.062	0.02	-0.153	-3.144	0.002	-0.101	-0.023
Personal Business (Number)	0.071	0.016	0.162	4.477	0	0.04	0.102
Number of Restaurant Commuters	-0.22	0.054	-0.207	-4.074	0	-0.327	-0.114
Number of Mosques	-118.766	42.68	-0.103	-2.783	0.006	-202.543	-34.989
Parking (m2)	-0.009	0.005	-0.071	-2.021	0.044	-0.018	0

(Table 3) contd.....

R^2	0.275
Adj. R^2	0.269

Table 4. Multiple linear regression analysis for average daily boarding and alighting.

Dependent Variable: Average Daily Boarding							
	Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Sig.**	**95.0% Confidence Interval for B**	
Variables	**B**	**Std. Error**	**Beta**			**Lower Bound**	**Upper Bound**
(Constant)	-9.765	-9.765		-0.853	0.394	-32.245	12.715
Number of Shopping Places	16.637	2.338	0.258	7.116	0	12.049	21.226
Personal Business (Number)	0.006	0.002	0.139	3.902	0	0.003	0.009
Shopping Commuters	0.008	0.001	0.384	6.512	0	0.005	0.01
Total Residents	-0.009	0.002	-0.212	-4.888	0	-0.013	-0.005
Number of Restaurant Commuters	-0.014	0.006	-0.129	-2.504	0.012	-0.026	-0.003
R^2	0.206						
Adj. R^2	0.201						
Dependent Variable: Average Daily Alighting							
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
Variables	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	13.895	9.148		1.519	0.129	-4.06	31.85
Shopping Commuters	0.006	0.001	0.452	7.7	0	0.004	0.007
Number of Shopping Places	10.2	1.527	0.251	6.681	0	7.203	13.197
Total Residents	-0.003	0.001	-0.116	-2.413	0.016	-0.006	-0.001
Personal Business (Number)	0.004	0.001	0.124	3.538	0	0.002	0.005
Number of Restaurant Commuters	-0.014	0.004	-0.197	-3.87	0	-0.021	-0.007
Number of Mosques	-7.477	2.81	-0.098	-2.661	0.008	-12.992	-1.962
R^2	0.239						
Adj. R^2	0.234						

Table 5. Multiple linear regression analysis for average weekday boarding and alighting.

Dependent Variable: Average Weekday Boarding							
	Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Sig.**	**95.0% Confidence Interval for B**	
Variables	**B**	**Std. Error**	**Beta**			**Lower Bound**	**Upper Bound**
(Constant)	-9.409	10.333		-0.911	0.363	-29.69	10.871
Number of Shopping Places	15.052	2.109	0.258	7.137	0	10.913	19.192
Personal Business (Number)	0.006	0.001	0.145	4.083	0	0.003	0.009
Shopping Commuters	0.007	0.001	0.39	6.634	0	0.005	0.009
Total Residents	-0.008	0.002	-0.204	-4.72	0	-0.011	-0.005
Number of Restaurant Commuters	-0.014	0.005	-0.134	-2.61	0.009	-0.024	-0.003
R2	0.213						
Adj. R2	0.208						
Dependent Variable: Average Weekday Alighting							
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
Variables	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	12.759	8.518		1.498	0.135	-3.96	29.478
Shopping Commuters	0.005	0.001	0.458	7.824	0	0.004	0.007
Number of Shopping Places	9.402	1.422	0.248	6.614	0	6.612	12.193
Total Residents	-0.003	0.001	-0.11	-2.295	0.022	-0.005	0
Personal Business (Number)	0.003	0.001	0.128	3.672	0	0.002	0.005
Number of Restaurant Commuters	-0.013	0.003	-0.2	-3.941	0	-0.02	-0.007

(Table 5) contd.....

Number of Mosques	-6.98	2.616	-0.098	-2.668	0.008	-12.116	-1.845
R2	0.245						
Adj. R2	0.239						

Table 6. Multiple linear regression analysis for average weekend boarding and alighting.

Dependent Variable: Average Weekend Boarding							
	Unstandardized Coefficients		**Standardized Coefficients**			**95.0% Confidence Interval for B**	
Variables	**B**	**Std. Error**	**Beta**	**t**	**Sig.**	**Lower Bound**	**Upper Bound**
(Constant)	-12.905	18.35		-0.703	0.482	-48.922	23.111
Number of Shopping Places	23.791	3.909	0.234	6.085	0	16.117	31.464
Personal Business (Number)	0.009	0.003	0.132	3.558	0	0.004	0.015
Shopping Commuters	0.011	0.002	0.345	6.185	0	0.008	0.015
Total Residents	-0.016	0.003	-0.229	-5.097	0	-0.022	-0.01
Number of Employees	-0.006	0.003	-0.105	-2.147	0.032	-0.011	-0.001
R^2	0.180						
Adj. R^2	0.175						
Dependent Variable: Average Weekend Alighting							
	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Variables	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	20.643	13.041		1.583	0.114	-4.953	46.239
Shopping Commuters	0.008	0.001	0.426	7.13	0	0.006	0.01
Number of Shopping Places	14.94	2.176	0.262	6.864	0	10.668	19.212
Total Residents	-0.005	0.002	-0.139	-2.841	0.005	-0.009	-0.002
Number of Restaurant Commuters	-0.018	0.005	-0.184	-3.553	0	-0.028	-0.008
Personal Business (Number)	0.004	0.001	0.106	2.977	0.003	0.001	0.007
Number of Mosques	-10.426	4.005	-0.098	-2.603	0.009	-18.288	-2.564
R^2	0.215						
Adj. R^2	0.210						

The analysis results revealed that the land use and population parameters were the most significant in terms of impact on the stop-level ridership. The most significant parameters were the number of shopping places, personal businesses, shopping commuters, total residents, number of restaurant commuters, and number of mosques. The most significant parameters against the average hourly, daily, and weekday boarding were the number of shopping places, personal businesses, shopping commuters, total residents, and restaurant commuters.

The shopping commuters, number of shopping places, number of residents, personal businesses, number of restaurant commuters, and number of mosques were the most significant parameters on the average hourly and daily alighting. In terms of the average weekday alighting, the most significant parameters were shopping commuters, number of shopping places, total residents, personal business, number of restaurant commuters, and number of mosques. While for the average weekend alighting, the most significant parameters are shopping commuters, number of shopping places, total residents, number of restaurant commuters, personal business, and number of mosques. In general, the most common significant parameters were the shopping commuters and the number of shopping places.

CONCLUSION

In this study, boarding and alighting data were collected and analyzed to understand the factors affecting the ridership of the rail service in Qatar. MLR models were used to estimate boarding and alighting on different levels based on the bus infrastructure, population, and planning--related attributes. The models included different parameters, including infrastructure, population, land use, and bus operation parameters. The data were collected from several agencies and compiled on a GIS map to understand the correlation between the parameters and to achieve a better presentation of the data.

The results revealed that most land use and population parameters significantly affected stop-level boarding and alighting. The population parameters include the number of persons available in the catchment area for residing, working, visiting restaurants, and shopping. Land use parameters include the number of shopping places, restaurants, and mosques. The road length and parking area were the most significant from the infrastructure parameters. This can be because there is no other mode of transport in Qatar that integrates with the bus service; as such, the use of passenger cars and taxis is needed to allow for this integration.

One of the study's limitations was not including information about other transport modes along the corridor, such as taxis and the new metro service, due to the difficulty of obtaining. Such parameters could affect the ridership and the parameters included in the study. This can be further assessed when such information is collected in the future. Future studies should also focus on studying the effect of future network expansion. In this case, the effect of the newly added routes, the passengers' shift to these new routes, and passengers' behavior should be investigated. Finally, the impact of other transport modes on bus operation should be explored in the future. Despite the limitations discussed, the results from the study can help and guide policymakers in determining how to promote public transportation in Qatar and other rich developing countries, such as Saudia Arabia, Bahrain, Kuwait, Oman, and United Arab Emirates.

LIST OF ABBREVIATIONS

QSTM	=	Qatar Strategic Transport Model
GIS	=	Geographic Information System

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

Not applicable.

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CONFLICT OF INTEREST

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