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ORIGINAL ARTICLE

The Impact of Subway Station Proximity on Apartment Prices in Shiraz

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Abstract
Proximity to public transportation, such as subway stations is often considered as one of the main factors affecting urban land value and housing prices. However, the magnitude and direction of this impact may vary depending on the context and characteristics of each city. This paper aims to investigate the effect of subway station proximity on apartment prices in Shiraz, a major city in Iran with a population of over 1.8 million people. Using a hedonic price model and regression technique, we analyzed a dataset of 128 apartment transactions, controlling for apartment size, location, age, and other characteristics. The results differ from previous studies which suggested being closer to the transit station affects the property price due to accessibility. The findings suggest that distance to subway stations has an insignificant effect on apartment prices in Shiraz, with property size, location, and age being key determinants of apartment prices. The possible reasons for this result were discussed and recommendations were made for the development of further studies.

Keywords Subway accessibility · Proximity premium · Value capture · Apartment price · Hedonic price model · Shiraz

Introduction

The availability of transportation infrastructure is considered a crucial determinant of property value in urban areas. Proximity to public transportation, such as subway stations, can significantly affect residential property values [1, 2]. However, the magnitude and direction of this effect may vary depending on various factors, such as the characteristics of the subway system, housing market, and urban context. Investment in subway systems provides benefits beyond the public interest, including physical activity promotion [3], alleviation of traffic congestion [4], reduction of emissions [5], and expansion of consumer amenities [6].

Shiraz is the capital city of Fars Province in Iran, with a population of about 1.8 million people. In Shiraz, significant urbanization and population growth in recent years have led to an increased demand for housing. As a result, the housing market in Shiraz has become increasingly competitive, with prices varying greatly depending on location. One factor that has been suggested to impact apartment prices is proximity to subway stations. However, the extent of the influence of subway station proximity on apartment prices in Shiraz remains unclear.

Therefore, this study examines the impact of subway station proximity on apartment prices in Shiraz using a hedonic price model. Specifically, we analyzed data on apartment prices and characteristics, as well as subway station locations and accessibility, to provide insight into the relationship between subway station proximity and apartment prices in Shiraz.

Literature Review

Since the 1970s, numerous studies have examined the impact of rail station proximity on property values using various methods and data. These studies found that the relationship between rail station proximity and property values can vary based on several factors, such as distance from downtown,

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median income of the neighborhood, type of land use, type of rail service, rail system life cycle maturity, distance to stations, geographical location, accessibility to roads, methodological characteristics, and whether the impacted area is land or property [7].

While proximity to rail stations can have a positive impact on residential property values in some cases [8–11], it can also have insignificant or negative impacts in other cases [12, 13]. The decrease in property value can be attributed to externalities associated with rail transit systems, such as increased traffic congestion, higher crime rates, noise, vibrations, pollution, density, and modal preferences [7, 14].

The most commonly used method for investigating the relationship between rail station proximity and property values is the hedonic price model [15–18]. Other methods used the difference-in-differences (DID) approach [19, 20] and the Geographically Weighted Regression (GWR) method [21]. The DID approach can help control other factors that may affect property values and isolate the effect of the rail station, whereas the GWR method allows for the modeling of spatial non-stationarity, meaning that the relationship between rail station proximity and property values can vary across space. In addition, multiple studies have utilized repeat-sales methodology [22, 23]. This approach involves analyzing the sale prices of a particular property over two or more periods. Researchers using this approach compared the differences in sale prices of properties located near rail stations with the differences in sale prices of properties outside the predetermined station access zone.

The effect of proximity to rail stations on property values can also vary based on property type, with most studies focusing on residential properties [24, 25] and only a few acknowledging commercial or office property values [26, 27]. For instance, a meta-analysis by Debrezion et al. [28] found that commercial properties within the 1/4-mile range of a railway station were 12.2% more expensive than residential properties. At longer distances, the effect on residential property values dominates, with every 250 m a residence located closer to a station, resulting in a 2.3% higher price than commercial properties.

The impact of rail stations on property values can also vary according to the type of rail service. A meta-analysis by Rennert [29] found that factors such as rail type, transit cost, and transit network expansion significantly affect the magnitude of rail access uplift, ranging from depreciating effects of 7.4% points to appreciating effects of 9.6% points.

Studies conducted in Asian cities such as Bangkok, Thailand [30], Seoul, Korea [8]., Beijing, China [31], and Shanghai, China [23], have reported positive impacts on the value of properties located next to rail stations. Similarly, research conducted in European cities such as the Netherlands [17], Warsaw, Poland [9], and London, UK [32], found an increase in land value next to rail stations. In contrast to Asian and European cities, the influence of rail transit stations on land value is diminished in American cities, where there is a greater reliance on automobiles and a less established culture of trans-it-oriented development (TOD) [7, 28, 33]. However, to date, few studies have investigated the impact of rail station proximity on property values in Iran [24, 34, 35] and the Middle East. Therefore, this study aims to fill this gap by examining the impact of subway station proximity on apartment prices in Shiraz using a hedonic model.

Overall, the impact of rail station proximity on property values has been extensively studied using various methods and data, and the findings suggest that the relationship can vary based on several factors. While proximity to rail stations can have a positive impact on property values in some cases, negative impacts can also be attributed to the externalities associated with rail transit systems. The effect of proximity to rail stations on property values can also vary based on property type, geographical location, and type of rail service [36]. Table 1 provides a summary of the analytical techniques and outcomes of recent studies on the influence of rail transit access on property values.

Materials and Methods

The primary method used in this study is the Hedonic Pricing Model (HPM). The hedonic price model is a widely used method for estimating the implicit prices of housing characteristics, such as location, size, quality, and amenities. The model assumes that the housing price is determined by the marginal willingness to pay for each characteristic by buyers and sellers in the market. Using a hedonic price model, we can isolate the effect of subway station proximity from other factors that may affect apartment prices.

Case Study

Shiraz is a major city in Iran, serving as the capital of Fars province, with a population of approximately 1.8 million individuals. The city is comprised of eleven urban districts and covers an area of 240 square kilometers. Shiraz has a subway system consisting of six lines, with line 1 being the only operational line. This line covers six districts in Shiraz, including districts 1, 2, 6, 7, 8, and 11, spanning 24.5 km between Shiraz Airport and Ehsan Square, with 20 stations. The construction of the subway system commenced in 2001, with the first section opened in 2014, and the second section completed in 2017. Shiraz Metro is the third urban train system in Iran after Tehran and Mashhad Metro, serving millions of passengers each year and providing an efficient transportation option throughout the city. Figure 1 illustrates Shiraz's Subway Line 1 and its stations.

Table 1 Summary of previous studies on the impact of rail transit on property value

Authors	City	Rail type	Property type	Measure of property value	Findings
Bowes and Ihlanfeldt [37]	Atlanta	Metro	Single-family properties	Hedonic price model and auxiliary models	The effects vary with distance from downtown and the median income of the neighborhood
Gibbons and Machin [32]	London	Metro and LRT	Residential	Difference in differences (DID)	9.3% increase near rail stations
Hess and Almeida [16]	Buffalo, New York	LRT	Residential	Multivariate hedonic regression	$1300 to $3000 increase in house value within 1/2 miles of the station. Negative impacts in low-income neighborhoods
Duncan [15]	San Diego	Light and Commuter rail transit	Single-family housing and Condominium units	Hedonic pricing model	Increase in condominiums by 10% and decline in single-family housing By 10%
Dubé et al. [20]	Montreal, Quebec	Commuter rail transit	Residential	Spatial difference-in-difference and Hedonic model	5.2% increase for houses nearest the station (0–500 m)
Trojanek and Gluszak [9]	Warsaw	Metro	Residential	Hedonic pricing model	The new subway line (M2) in Warsaw influenced apartment prices even before it was completed. A steady price premium adjustment process related to the new subway line was observed
Mulley et al. [21]	Sydney	LRT	Residential	Geographically weighted regression (GWR)	Variation in the value of residential property, but the more impact was outside the central business district (CBD)
Acuña [22]	Suburb of Washington, DC	Metro	Residential	Hedonic and Repeat sales models	For properties at one mile from the nearest station, the preferred repeat sales model estimates a marginal price increase of 4.6 percent for a one-mile increase in distance

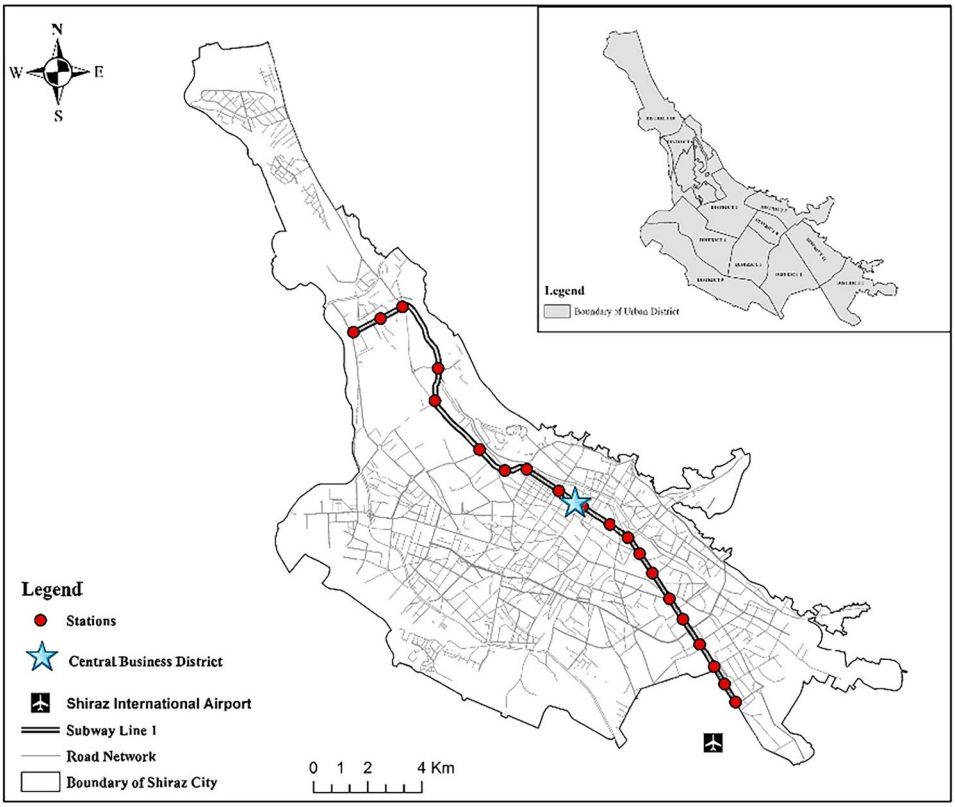

Fig. 1 Shiraz's subway line 1

Selection of Variables for the Model

The factors affecting the value of a property can be categorized into three groups: accessibility factors, neighborhood factors, and location factors. Since the average property price per square meter in the six districts covered by the Shiraz metro is significantly different from each other, we also considered the effect of location based on districts in the model. Therefore, a dummy variable was considered for each district. To avoid the dummy variable trap, District 6 was selected as the reference group. We chose the factors in Table 2 as the most important ones for apartment price changes based on the characteristics of Shiraz's property market.

Sphere of Influence

To analyze the effects of the subway on apartment prices, it was necessary to establish a boundary that defined the extent of the influence of the stations. The distance at which properties are evaluated for appraisal can vary depending on the density and location of the subway network. As there is no universal boundary for collecting data around stations, it is necessary to consider the local context and market conditions. Table 3 presents examples of studies that used different distances to estimate the effect of railway stations on property values in various cities. The distances range from 0.4 to 2 km, highlighting the variation in approaches taken in different contexts.

For this study, a 1000-m boundary was chosen around the stations to collect data. This distance was selected based on several factors, including the size and density of the subway system in Shiraz, the distribution of properties around the stations, and local real estate market conditions. The 1000-m boundary was deemed appropriate for capturing the effects of the subway stations on property values in the study area, while also minimizing any potential confounding factors that may arise from including properties outside of the sphere of influence.

Data Collection

Due to the lack of an official transaction data source in Iran, a questionnaire was used to collect data on apartment transactions in Shiraz. Real estate agents in the vicinity of subway stations were selected as the primary data sources for the study. Real estate agents were selected based on their knowledge of the local real estate market and their proximity to subway stations. The questionnaire was designed to collect information on property prices (in Toman Iran), age, size, location, and number of bedrooms. To ensure the accuracy and reliability of the data, the questionnaire was pretested with a sample of real estate agents, and any issues with the questions were addressed before the final version was

Table 2 Description of variables for modeling residential property values

Variable categories	Variables	Description	Data source
Accessibility variables	Distance to the nearest subway station	Euclidean distance to nearest subway station (m)	GIS
	Distance to CBD	Euclidean distance to CBD (m)	GIS
	Distance to the nearest park	Euclidean distance to nearest park (m)	GIS
	Distance to the nearest school	Euclidean distance to nearest school (m)	GIS
Structure variables	Size	The floor area of the housing unit (m^2)	Real estate marketplaces
	Age	Age of building (years)	Real estate marketplaces
	Number of bedrooms	Number of bedrooms in the housing unit	Real estate marketplaces
Location variables	District 1	Dummy variable indicating whether the apartment is located in District 1 or not (1: if located, 0: otherwise)	GIS
	District 2	Dummy variable indicating whether the apartment is located in District 2 or not (1: if located, 0: otherwise)	GIS
	District 7	Dummy variable indicating whether the apartment is located in District 7 or not (1: if located, 0: otherwise)	GIS
	District 8	Dummy variable indicating whether the apartment is located in District 8 or not (1: if located, 0: otherwise)	GIS
	District 11	Dummy variable indicating whether the apartment is located in District 11 or not (1: if located, 0: otherwise)	GIS

Table 3 Sphere of influence of stations from the point of view of different researchers

Study	City	Distance
Wen et al. [38]	Hangzhou, China	0.5 km and 1 km
Zhang et al. [39]	Beijing and Hangzhou, China	2 km
Trojanek and Gluszak [8]	Warsaw, Poland	1 km
Ma [40]	Beijing, China	1 km

distributed. The dataset contains transactions that occurred between January and May 2023. Finally, 128 transactions were collected within a 1000-m radius of subway stations in Shiraz.

Measuring Distance

To determine the location of each apartment, according to the address of the property in the questionnaire, the longitude and latitude of the property were extracted using Google Maps as an Excel sheet. Then, the Excel sheet was joined into ArcMap 10.5 software and based on the longitude and latitude of the property, the location of each property was determined in the form of a point feature. Consequently, we employed ArcMap 10.5 to measure the distances between apartments and the nearest subway station, CBD, park, and school. It is worth noting that distance was measured in meters for all variables. Table 4 presents the descriptive analysis of the variables, including the minimum, maximum, mean, and standard deviation.

Table 4 Sample descriptive statistics

Variables	N	Min	Max	Mean	STD. deviation
Price (Toman Iran)	128	1,800,000,000	40,300,000,000	6,520,148,437	4,657,717,409
Size (m^2)	128	60	250	134	40
Age	128	0	50	9.25	10
Number of bedrooms	128	1	4	2.31	0.684
Distance to subway station (m)	128	22	996	486	231
Distance to CBD (m)	128	218	10,972	6,245	3,527
Distance to park (m)	128	68	1925	696	377
Distance to school (m)	128	12	741	250	155

Model Description

The hedonic model is a widely used method in real estate economics to estimate the impact of various characteristics of a property on its value. This model assumes that the price of a property is determined by a combination of the values of its characteristics, such as location, size, amenities, and other features. The idea behind the hedonic model is that the price of a property can be considered a function of its attributes.

The Hedonic Pricing Model consists of three basic mathematical functions, where P represents housing prices, α_0 represents the constant term, β_K represents the coefficient of the variables ($K = 1, 2, 3, \ldots, n$, where n is the number of variables), and X_{aiK}, X_{njK}, and X_{stK} represent the i_{th} characteristic variable of accessibility variables, the j_{th} characteristic variable of neighborhood variables, and the t_{th} factor of structure variables, respectively. The three basic mathematical functions are as follows:

Linear function: Equation (1) shows the linear form of how housing prices are affected by various characteristics. The regression coefficients indicate how much housing prices change, on average, when the characteristics change by one unit.

$$P = \alpha_0 + \beta_K X_{aiK} + \beta_K X_{njK} + \beta_K X_{stK} + \varepsilon \quad (1)$$

Log-linear function: Equation (2) uses the logarithmic form of housing prices and their characteristics to estimate the price elasticity for each characteristic. This means that the regression coefficients measure how responsive the housing prices are to the percentage changes in the characteristics.

$$\ln P = \alpha_0 + \beta_K \ln X_{aiK} + \beta_K \ln X_{njK} + \beta_K \ln X_{stK} + \varepsilon \quad (2)$$

Semi-log function: Equation (3) uses the linear form of characteristics and the logarithmic form of housing prices to estimate the ratio of each characteristic price to the total price. This means that the regression coefficients measure how much the housing price changes in percentage terms when the characteristic price changes by one unit.

$$\ln P = \alpha_0 + \beta_K X_{aiK} + \beta_K X_{njK} + \beta_K X_{stK} + \varepsilon \quad (3)$$

The collected data near subway stations were used to test the three functional forms of the Hedonic Pricing Model through regression analysis. The results showed that the semi-logarithmic form produced the highest R^2 value, indicating the best statistical fit. As a result, the semi-logarithmic form of the Hedonic Pricing Model was chosen for the statistical analysis of residential values near Subway line 1. Thus, the equation regarding the effect of proximity to subway stations on apartment prices in the case study is as follows (4):

$$\begin{aligned}\ln(price) = {} & \beta_0 + \beta 1\,(\text{distance to subway}) + \beta 2(\text{distance to CBD}) + \beta 3(\text{distance to park}) \\ & + \beta 4(\text{distance to school}) + \beta 5(\text{size}) + \beta 6(\text{age}) + \beta 7\,(\text{number of bedrooms}) \\ & + \beta 8(\text{district 1 dummy variable}) + \beta 9(\text{district 2 dummy variable}) \\ & + \beta 10(\text{district 7 dummy variable}) + \beta 11(\text{district 8 dummy variable}) \\ & + \beta 12\,(district\ 11\ dummy\ variable).\end{aligned} \quad (4)$$

where ln (price) is the natural logarithm of the price of an apartment, distance to the subway is the distance from an apartment to the nearest subway station, distance to CBD is the distance from an apartment to the central business district, distance to park is the distance from an apartment to the nearest park, distance to school is the distance from an apartment to the nearest school, size is the size of an apartment in square meters, Age is the age of an apartment in years, number of bedrooms is the number of bedrooms in an apartment, and district i dummy variable is a binary variable that takes a value of 1 if an apartment is located in district i and 0 otherwise.

Results

To estimate the coefficients of the model, we used ordinary least squares (OLS) regression. The coefficients provide information on the magnitude and direction of the impact of each independent variable on apartment prices, including the impact of proximity to subway stations on apartment prices, controlling for other factors.

The normality of the data was tested using the Kolmogorov–Smirnov test. The test results were not significant ($p = 0.200$), indicating that the data did not deviate significantly from normal distribution. The value of R^2 for the regression model is 0.84, indicating that 84% of the price variation can be accounted for by the model. The degree of fit was good. Table 5 demonstrates the regression results for apartment prices near Shiraz's subway line 1.

The coefficient of the distance to the subway variable was not statistically significant ($p = 0.372$), indicating that there was no effect of distance to the subway on apartment prices, holding all other variables constant. This implies that proximity to subway stations is not a relevant factor in determining apartment prices in Shiraz.

Age has a negative and significant coefficient ($B = -0.010$, $p = 0.000$), indicating that older apartments have lower prices, holding all other variables constant. The size of apartments has a positive and significant coefficient ($B = 0.09$, $p = 0.000$), indicating that larger apartments have higher prices, holding all other variables constant. Surprisingly, the number of bedrooms has a negative and insignificant coefficient ($B = -0.087$, $p = 0.445$), indicating that it is not a relevant factor in determining apartment prices in

Table 5 Regression results of apartment prices near Shiraz's subway line 1

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig
		B	Std. error	Beta		
1	(Constant)	21.724	0.139		155.847	0.000
	D_SUB	− 8.320E–5	0.000	− 0.036	− 0.897	0.372
	AGE	− 0.010	0.002	− 0.196	− 4.506	0.000
	SIZE	0.009	0.001	0.676	10.020	0.000
	N_ROOM	− 0.087	0.050	− 0.111	− 0.767	0.445
	D_CBD	− 1.644E−5	0.000	− 0.109	0.262	0.794
	D_PARK	4.680E−5	0.000	0.033	0.689	0.492
	D_SCHOOL	0.000	0.000	− 0.049	− 1.119	0.266
	DIST_1	− 0.218	0.150	− 0.184	− 1.447	0.151
	DIST_2	− 0.555	0.106	− 0.293	− 5.227	0.000
	DIST_7	− 0.726	0.140	− 0.207	− 5.174	0.000
	DIST_8	− 0.676	0.203	− 0.326	− 3.326	0.001
	DIST_11	− 0.600	0.094	− 0.383	− 6.402	0.000

Shiraz. Distance to CBD, park, and school have insignificant coefficients, indicating that they do not affect apartment prices, holding all other variables constant.

The coefficients for the dummy variables for districts are interpreted as the percentage difference in the price of an apartment between each district and the reference group (District 6), holding other variables constant. The results of the dummy variables show that there are significant differences in apartment prices across different districts in Shiraz after controlling for other characteristics. Apartments in Districts 2, 7, 8, and 11 are cheaper than apartments in District 6, whereas apartments in District 1 are more expensive than apartments in District 6.

Discussion and Conclusion

Shiraz, the principal metropolitan center in the south of Iran, grapples with numerous transportation challenges, including inefficient public transport, heavy dependence on private cars and fossil fuels, limited accessibility for the elderly, and elevated rates of traffic accidents and environmental pollution [41–44]. Additionally, the advancement of smart and emerging technologies in the transportation sector, such as the manufacturing and utilization of electric cars, autonomous vehicles, and highly efficient rail systems, has encountered constraints due to national policies and restrictions, including international sanctions [45].

Our findings suggest that proximity to subway stations does not significantly influence apartment prices in Shiraz. This outcome contrasts with the majority of studies that typically identify a positive relationship between proximity to public transportation and residential property values. Interestingly, this finding aligns with some studies that examined the effect of rail transit proximity on property values. One study in Jakarta, Indonesia [26] also found that proximity to rail transit has an insignificant impact on commercial property value compared to other variables, such as building size, number of rooms, location, and hospitals. Similarly, another study carried out in Bayonne, New Jersey [12] concluded that the extension of the Hudson-Bergen Light Rail to the 8th Street did not have a statistically significant impact on the annual appreciation of house prices, indicating that properties closer to the station did not show more price appreciation than properties further away.

In the case of Shiraz, several factors could explain the lack of a significant relationship between subway station proximity and apartment prices. First, the relatively recent construction of Shiraz's Line 1 subway and the absence of an extensive subway network in the city may suggest that the subway has not had sufficient time to significantly impact residential property values. Additionally, the preferences and lifestyles of residents in Shiraz may not prioritize proximity to subway stations when considering apartment prices, focusing more on other factors such as location, size, or amenities. Moreover, the real estate market in Shiraz may be influenced by other factors that overshadow the impact of subway station proximity, such as economic conditions, market demand, or specific neighborhood characteristics.

However, it is crucial to note that the absence of a significant effect on apartment prices does not imply that public transportation is not important for residents or cities. Public transportation can offer numerous benefits beyond property value, such as reducing traffic congestion, improving air quality, and enhancing accessibility to employment opportunities and public amenities. Therefore, investing in public transportation infrastructure remains a sustainable

policy goal, irrespective of its immediate impact on property values.

The unexpected findings of this study highlight the need for further research in this field. This study faced significant limitations due to the lack of an official transaction data source, leading to reliance on data collected through questionnaires over two months. Despite these constraints. Future studies could explore the reasons behind the lack of a significant relationship between subway proximity and apartment prices in Shiraz and investigate whether similar patterns are observed in other cities or countries. Such research could provide valuable insights into the factors that mediate the relationship between subway proximity and property values, thereby contributing to more effective urban planning and transportation policies.

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Data availability The real estate data utilized for this study cannot be disclosed due to privacy and commercial considerations.

Declarations

Conflict of Interest The authors declare no conflict of interest.

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