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Evaluating measures of jobs–housing proximity and their commuting impacts in Shanghai

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A long-running controversy arises over the magnitude of the effect of jobs–housing proximity on commuting length. Different views may stem in part from the inconsistency of the selection of jobs–housing proximity measures. Job–worker ratio, minimum commuting, and job accessibility are three common proxies for jobs–housing proximity. This paper analyzed and compared the magnitude of these measures on average commuting distance for all workers and five occupational worker subgroups, based on the national 1% Population Sample Survey in Shanghai. The results indicate that, in contrast to studies in developed countries, job accessibility has the strongest explanatory power for average commuting distance, and job–worker ratio is the weakest one, followed by minimum commuting. Residential location follows patterns of average job location rather than that of the closest available job location in Shanghai. Each measure is valuable in characterizing the spatial proximity between jobs and housing and can provide important information and guidance to policymakers on jobs–housing proximity. This study highlights that improving the jobs–housing balance is an effective way to reduce commuting length, but the magnitude of the impact varies with the category of measures and worker subgroups. In order to make the jobs–housing balance an effective planning tool with which to shorten commuting, land use patterns at the local and regional levels must be spatially linked and coordinated.

KEYWORDS

jobs–housing balance, job accessibility, minimum commuting, commuting distance, Shanghai

1 Introduction

For decades, the interaction between travel and urban land use has been one of the most studied in urban geography and urban planning (Cervero and Kockelman, 1997; Ewing and Cervero, 2010; Schwanen et al., 2016; Niedzielski et al., 2020; Yue et al., 2024; Ling et al., 2024). Although the significant impacts of urban land use on travel mode options have been identified, a long controversy arose over the magnitude of its effects on travel length (Horner, 2007; Chowdhury et al., 2012; Stevens, 2017; Zhou et al., 2022). There is no consensus on the extent to which jobs and housing are balanced and the potential for this to reduce commuting in the existing literature. Some scholars have provided much evidence to prove urban land use strongly influences commuting (Cervero and Wu, 1997; Sultana, 2002), while others found its impact is fairly small or has no effects on commuting (Giuliano and Small, 1993; Zhou et al., 2022; Li et al., 2022).

One of the potential explanations for the controversy is that different studies use different measures for urban land use in terms of the jobs–housing relationship and produce different quantitative diagnoses (Yang and Ferreira, 2005; Watts, 2009). However, which measure can better characterize urban land use and has superior explanatory power for commuting length remains less studied. This kind of comparative analysis is important because an inferior proxy could lead to a weak quantitative relationship between commuting and the jobs–housing proximity and then largely undermine the role of jobs–housing proximity in informing spatial policymaking.

With differences in spatial and socioeconomic structure (Cao, 2017), the jobs–housing relationship and its impact on commuting in China may be different from that in developed countries. A study in the Chinese context could provide new insights into the relationship between urban land use and commuting, which has primarily been based on low-density sprawl cities in developed countries. Shanghai, one of the world's leading megacities, faces increasing traffic congestion and long commuting costs (Yue and O'Kelly, 2023a). To fill the abovementioned research gaps, this paper presents a comparative empirical evaluation of three categories of measures in Shanghai. Using the 2015 1% National Population Sample Survey (*NPSS*), we first characterize jobs–housing proximity represented by three categories of measures for all workers and examine their impacts on average commuting distance. Then, we compare the magnitude of the commuting effects of the three measures across different occupational worker subgroups.

In the following, we first review the literature on three categories of jobs–housing proximity measures and their impacts on commuting. Next, we introduce the study area and survey data. Then, the comparative empirical analysis results for all and each occupational worker subgroup in Shanghai are presented. The final section concludes.

2 Literature review

2.1 Jobs–housing proximity and commuting

The job–worker ratio (*JWR*) (Cervero, 1991), minimum commute (*MC*) (Horner, 2002), and gravity-type job accessibility (*JA*) (Shen, 1998) are the three most common proxies for jobs–housing proximity in existing commuting studies. Different measures belong to different conceptual frameworks and quantify jobs–housing proximity based on different geographical spatial scopes (Horner, 2004; Yang and Ferreira, 2008).

Job–worker ratio (*JWR*) refers to the relative quantitative relationship of jobs and workers in a given geographical analysis unit, which is the most common measure used to capture the jobs–housing proximity or balance. Giuliano and Small (1993) found that *JWR* had a statistically significant but not very large influence on average commuting time for the Los Angeles region in 1980. Peng (1997) measured *JWR* within floating catchment areas of 5–7 miles and came to a similar conclusion that *JWR* has little impact on vehicle miles traveled in the Portland area. Watts (2009) found that *JWR* is an inadequate proxy for urban form, and the relationship between *JWR* and average commuting distance is not significant in the Sydney Metropolitan Area. Zhou et al. (2022) examined the scale and zoning issues of *JWR* in Shanghai and verified that *JWR* has a significant but very slight influence on commuting distance. However, Cervero (1989) came to the opposite conclusion. He argued that *JWR* significantly influences commuting for over 40 major suburban employment centers in the United States. Suburban workplaces with severe jobs–housing imbalances tend to have low shares of non-motorized travel and high levels of freeway congestion. Sultana (2002) measured *JWR* within a commuting catchment area having a 7-mile radius and also highlighted the fact that *JWR* is the most important determinant for longer commuting in the Atlanta metropolitan area.

Minimum commute (*MC*) is sensitive to the local spatial distribution of jobs and workers and is also often used to characterize the degree of jobs–housing balance at the local level (Horner, 2002). Giuliano and Small (1993) found a weak positive relationship between the actual commuting time and *MC* in the Los Angeles region. Yang (2008) used minimum commute and random commute to represent local and regional aspects of the jobs–housing relationship, and empirical results suggest that average commuting distance decreases following *MC* in Atlanta and Boston. However, Chen (2000) explored the relationship between commuting and urban form in the Taipei metropolitan region and found that *MC* is highly significant in an ordinary least squares estimation of average commuting distance. Watts (2009) suggested that *MC* has superior explanatory power for average commuting distance in the Sydney Metropolitan Area.

Wachs and Kumagai (1973) said, "Accessibility is perhaps the most important concept in defining and explaining regional form and function." A number of empirical studies suggested that job accessibility (*JA*) contributes much to the explanatory power for the variation of commuting length. For example, Levinson (1998) modeled the determinants of commuting time in metropolitan Washington, DC. The results suggested that workers in job-rich areas are associated with shorter commutes, and 17–38% of the variation of commuting time can be explained by *JA*. Wang (2000) measured urban form by *JA* and *JWR* defined in a floating catchment area and found that the former could better explain how far workers commute than the latter in Chicago. Wang (2001) came to the similar conclusion that intraurban variations of commuting are explainable to a large extent by *JA* in Columbus, Ohio.

The two most directly comparable studies are those by Yang and Ferreira (2005), who qualitatively and quantitatively assessed three categories of urban form measures and compared their relationship to average commuting length in Boston, United States, and Watts (2009), who utilized a number of proxies for urban form to analyze the determinants of average commuting distance in Sydney, Australia. The former study identified that *MC* is the most consistent measure to characterize urban form in terms of the jobs–housing relationship, while the latter, using a spatial econometric model, only found that both the *MC* and *JA* have superior explanatory power but could not distinguish which is better. Furthermore, neither study compared the magnitude of the commuting impacts across different socioeconomic worker subgroups. Lastly, there is no evidence of any study in developing countries, especially high-density compact Chinese cities.

2.2 Socioeconomic characteristics and commuting

Another notable strand of literature, disaggregate commuting studies, focuses on commuting length in relation to commuters' socioeconomic characteristics, including gender (Ta et al., 2022; Kwan and Kotsev, 2015), occupation (Sang et al., 2011), education (Zhou et al., 2022), and income (Ángel et al., 2013; Hu, 2021). Some studies suggest that the impacts of commuters' socioeconomic characteristics are even greater than those of the jobs–housing spatial relationship (Sultana, 2002). Affected by economic/time bearing capacity and location preference, different commuters have great variations in the demand and use characteristics of the jobs–housing space, leading to different commuting behavior and performance. Previous disaggregate commuting studies have found that highly educated workers and high-skilled employment make longer commutes (Yue et al., 2022; Shen, 2000). This may be because well-educated or high-skilled workers must search a large area for suitable jobs and housing opportunities (Lee and McDonald, 2003). Yue et al. (2023) found that for well-educated workers, the selection of residential location follows patterns of average job location rather than that of the closest job location.

Given that there is still a debate on whether the jobs–housing balance is an effective tool to optimize commuting and improve commuting performance, it is necessary to consider socioeconomic attributes for accurately assessing the interaction between the jobs–housing relationship and commuting length.

3 Methodology

3.1 Study area

Shanghai is one of the most densely populated and compact cities in China. It covers an area of 6800 km^2, and its population increased from 16.09 million in 2000 to 24.87 million in 2020. The central urban area (CUA) is chosen as the study area for the following reasons (Figure 1). First, although recent years have witnessed the increasing urban suburbanization and decentralization, the CUA still agglomerates many jobs and workers. It accounts for only about 10% of the city's territory (1125 km^2) but approximately 50% of the total workers (6.73 million) in 2015. Thus, we can capture a distinctive employment and commuting pattern in the CUA. Reducing the impact of the modifiable area unit problem is another reason. The spatial analysis unit in this research is the sub-district, similar to a census tract in the United States. It is the basic unit of the urban management system in China, and the statistical unit in economic and population censuses (Zhao et al., 2011). In Shanghai, there are 196 sub-districts. Their sizes in the suburbs are larger than those in CUA. The CUA contains 120 sub-districts, and 76% of them have an area of less than 10 square kilometers.

3.2 Data sources

Three major sources of data are used in this research. First, the 1% National Population Sample Survey (*NPSS*) in 2015, obtained from the Municipal Bureau of Statistics in Shanghai, provides commuting flows and the origin and destination totals for each occupation subgroup. It defines seven categories of occupation types. This research focuses on the first five occupation types in Table 1 because the count of the latter two is too small[1]. Second, the measure of inter-zonal commuting cost is the road network distance between sub-district centroids, computed using ArcGIS. It is assumed that a sub-district has a circular shape such that the intra-zonal commuting cost can be calculated as a function of the radius of the sub-district (Frost et al., 1998; Horner, 2002).

3.3 Measurements for jobs–housing proximity

3.3.1 Job–worker ratio (JWR)

JWR is the most common and easiest of the three categories of urban form measures. It represents the jobs–housing relationship with a simple ratio of jobs to workers and has the following formulation (Equation 1):

$$JWR_i = \frac{J_i}{W_i}, \tag{1}$$

$$AJWR_i = \frac{J_i - W_i}{J_i + W_i}, \tag{2}$$

where J_i represents the total number of jobs in zone i, and W_i represents the total number of workers in zone i. A *JWR* value greater than 1 indicates a jobs-rich zone, while a value less than 1 indicates a housing-rich zone. When the *JWR* value is equal to 1, the zone is in quantitative balance. Due to its asymmetric value, Horner and Marion (2009) proposed another metric named adjusted job–worker ratio (*AJWR*) in Equation 2, ranging between −1 and 1. It has a value of 1 when W_i reaches 0 and J_i equals any nonzero value. The *AJWR* becomes −1 when J_i is 0 and W_i has any nonzero value. A positive value demonstrates a jobs-rich zone, while a negative *AJWR* value demonstrates a housing-rich zone. Jobs-rich areas might be expected to account for a heavy level of attraction and "in-commuting."

3.3.2 Minimum commute (MC)

MC is the theoretical minimum commuting cost within a given urban form, first introduced by White (1988). The system-wide *MC* is the solution to the linear programming problem, and origin-specific minimum commuting (MC_i) for each zone can be obtained based on an optimal commuting matrix and a distance matrix (Niedzielski, 2006). Mathematically, they can be defined as Equations 3–5

$$Minimize\, MC = \frac{1}{N}\sum_i \sum_j x_{ij} d_{ij}. \tag{3}$$

Subject to:

$$\sum\nolimits_{j=1}^{n} x_{ij} = W_i, \sum_{i=1}^{m} x_{ij} = J_j, x_{ij} \geq 0, \tag{4}$$

$$MC_i = \frac{\sum_j x_{ij} d_{ij}}{W_i}, \tag{5}$$

1 Inconvenience classification and primary industry-related personnel account for 0.23% and 0.16%.

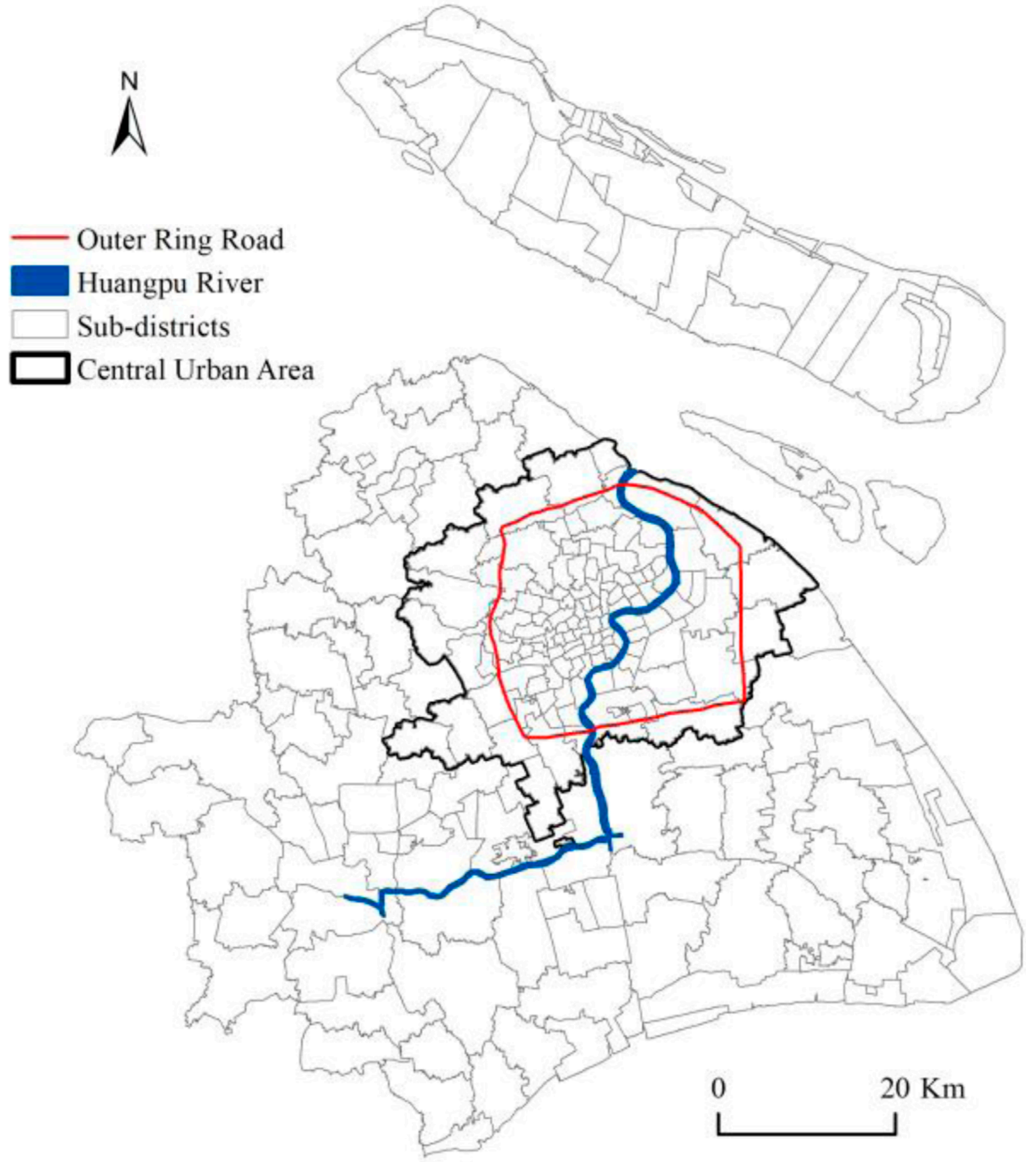

FIGURE 1
Study area.

TABLE 1 The number of workers and β values for each occupation type in CUA.

Occupation sector	Percentage of total (%)	Observed travel distance (km)
Total	100	7.046
Social production service and life service personnel [Soci]	47.08	6.334
Professional and technical personnel [Tech]	20.89	8.858
Manufacturing and related personnel [Manu]	13.19	5.606
Clerks and related personnel [Clerk]	11.86	8.122
Persons in charge of state organs, enterprises, and institutions [Head]	6.60	7.468

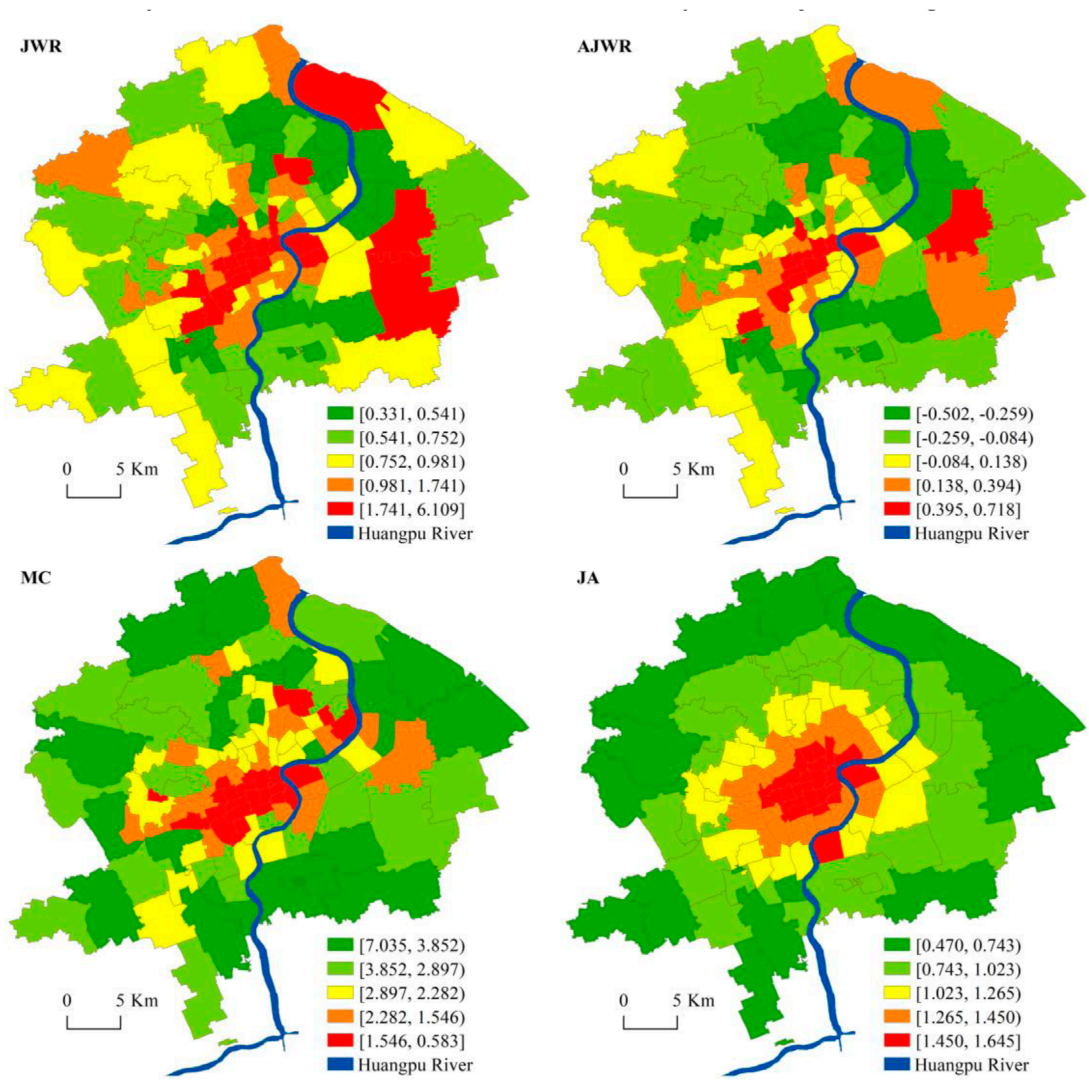

FIGURE 2
Spatial patterns of different jobs–housing relationship measures (all workers).

TABLE 2 Correlation coefficients of four measures.

Variables	JWR	AJWR	MC	JA
JWR	1			
AJWR	0.903***	1		
MC	−0.485***	−0.556***	1	
JA	0.687***	0.667***	−0.251***	1

where x_{ij} is the optimal number of commuters living in zone i and working in zone j, d_{ij} is the commuting distance between zone i and j, N is the total number of commuters, W_i is the total number of workers living in zone i, J_i is the total number of jobs in zone j, and W_i is the total number of workers living in zone i. A lower MC value indicates a more balanced distribution of jobs and workers, and *vice versa*.

3.3.3 Job accessibility (JA)

Potential accessibility measures (also called gravity-based measures) have been widely used in urban and geographical studies since they were invented by Hansen (1959). Due to the exclusion of competition effects, a number of studies tried to refine the measures by incorporating the effects of competition on opportunities, for example, Shen (1998). Consistent with other studies (Watts, 2009; Yang and Ferreira, 2005), here, we choose Shen's job accessibility measure with the following formulas in Equations 6–8:

$$JA_i = \sum_j \frac{J_j f(d_{ij})}{WA_j}, \tag{6}$$

$$WA_j = \sum_i W_i f(d_{ij}), \tag{7}$$

$$f(d_{ij}) = \exp(-\beta d_{ij}), \tag{8}$$

TABLE 3 Model results using different jobs–housing relationship measures for all workers.

Variables	Univariate linear regression				Multiple linear regression			
	Model1		Model2	Model3	Model4		Model5	Model6
JWR	−0.585***				−0.524***			
AJWR		−0.679***				−0.627***		
MC			0.584***				0.628***	
JA				−0.704***				−0.886***
Edu					0.136	0.227**	0.089	0.218***
Head					−0.295***	−0.249***	−0.244***	−0.079*
Hukou					0.127	0.020	0.394***	0.425***
R^2	0.342	0.461	0.341	0.495	0.447	0.546	0.561	0.816
N	120	120	120	120	120	120	120	120

Notes: The table shows the standardized regression coefficients (Beta) of the explanatory variable. * denotes statistical significance at 0.1, ** at 0.05, and *** at 0.01.

TABLE 4 Multiple linear regression results for each occupational worker subgroup.

Variables	Soci	Manu	Tech	Clerk	Head
JWR	−0.496***	−0.167**	−0.428***	−0.254***	−0.134
Edu	0.140	0.520***	−0.254***	0.021	0.436***
Hukou	−0.194**	−0.231***	0.158*	0.112	0.142
R^2	0.390	0.471	0.261	0.085	0.132
AJWR	−0.628***	−0.233***	−0.639***	−0.621***	−0.417***
Edu	0.210**	0.533***	−0.232**	0.004	0.394***
Hukou	−0.081	−0.235**	0.169*	0.125	0.133
R^2	0.503	0.497	0.490	0.406	0.288
MC	0.661***	0.237***	0.695***	0.623***	0.583***
Edu	0.030	0.526***	−0.143**	0.052	0.363***
Hukou	−0.403***	−0.288***	−0.008	0.036	−0.038
R^2	0.604	0.494	0.522	0.395	0.428
JA	−0.841***	−0.131*	−0.998***	−0.907***	−0.832***
Edu	0.209***	0.521***	0.097**	0.148**	0.470***
Hukou	−0.410***	−0.262**	−0.155***	−0.128**	−0.128*
R^2	0.839	0.459	0.822	0.726	0.703
N	120	120	120	120	120

Notes: The table shows the standardized regression coefficients (Beta) of the explanatory variable. * denotes statistical significance at 0.1, ** at 0.05, and *** at 0.01.

where JA_i is the demand-adjusted job accessibility for zone i, WA_i is the labor accessibility for zone j, β is the spatial decay parameter, and other notations are the same as previously stated. The spatial decay parameter β equals one over the average commuting distance of a city (Hu et al., 2017). The average commuting distance was 7.04 km in 2015. Therefore, the decay parameter in the job accessibility model is 0.1419 (=1/7.04).

3.4 Regression analysis

In this study, we focus on the effects of the jobs–housing relationship on origin-specific average commuting distance. Thus, the average commuting distance (Co_i) of workers living in each sub-district i is taken as the dependent variable. Following most existing studies, we first examine the results for all workers. To compare the magnitude of the effect of the three measures, four simple regression models are established as follows in Equations 9–12:

$$Co_i = \beta_0 + \beta_1 JWR_i + \varepsilon_i \tag{9}$$

$$Co_i = \beta_0 + \beta_1 AJWR_i + \varepsilon_i \tag{10}$$

$$Co_i = \beta_0 + \beta_1 MC_i + \varepsilon_i \tag{11}$$

$$Co_i = \beta_0 + \beta_1 JA_i + \varepsilon_i. \tag{12}$$

Socio-demographic attributes also play an important role in commuting distance. A number of studies have found that the well-educated or high-skilled workers must make a long commute to find suitable living and employment opportunities (Yue et al., 2022; Hu et al., 2017; O'Kelly and Lee, 2005; O'Kelly et al., 2011; Zhang et al., 2023). Additionally, *Hukou* is another important factor that must be considered (Yue and O'Kelly, 2023b; Li and Liu, 2016; Zhao and Howden-Chapman, 2010). The *Hukou* system classifies people into locals and migrants. Compared with the locals, most migrants live in factory dormitories and rental houses. They cannot afford a long commute in terms of both money and time costs. So, in this study, occupation type, education level, and *Hukou* are introduced into the model as control variables. Multiple linear regression models are established as follows in Equations 13–16:

$$Co_i = \beta_0 + \beta_1 JWR_i + \beta_2 Hukou_i + \beta_3 Edu_i + \beta_4 Head_i + \varepsilon_i \tag{13}$$

$$Co_i = \beta_0 + \beta_1 AJWR_i + \beta_2 Hukou_i + \beta_3 Edu_i + \beta_4 Head_i + \varepsilon_i \tag{14}$$

$$Co_i = \beta_0 + \beta_1 MC_i + \beta_2 Hukou_i + \beta_3 Edu_i + \beta_4 Head_i + \varepsilon_i \tag{15}$$

$$Co_i = \beta_0 + \beta_1 JA_i + \beta_2 Hukou_i + \beta_3 Edu_i + \beta_4 Head_i + \varepsilon_i, \tag{16}$$

JWR_i, $AJWR_i$, MC_i, and JA_i are the job–worker ratio, average minimum commuting distance, and job accessibility in the sub-district *i*, respectively. $Hukou_i$ is the proportion of local workers in the sub-district *i*, Edu_i is the proportion of residents with a bachelor's degree or above, and $Head_i$ is the proportion of management workers in the sub-district *i*.

Workers attach different importance to commuting costs when making a location decision. Thus, we also examine the magnitude of the effect of the jobs–housing relationship across different occupational worker subgroups by establishing the above simple and multiple regression models. The only difference is that in multiple regression models for each occupational worker subgroup, there is no need to include the variable $Head_i$.

4 Results and discussion

4.1 Spatial pattern of three measures

Figure 2 maps four measures at the sub-district level. Their values characterize the jobs–housing relationship from different aspects for each residential sub-district. Each legend represents a quintile. All three jobs–housing relationship measures suggest that the urban core has more job opportunities than the marginal area, but there are significant differences between the spatial distribution of the three jobs–housing relationship measures. The *JA* has an ordered spatial distribution, but *JWR* and *MC* are subject to more local variation. This is because *JA* is dependent on the regional jobs–housing distribution at the whole study area, while *JWR* and *MC* are more determined by the local jobs–housing distribution.

To see whether these four measures are essentially different, we also examine the correlation between them (Table 2). *MC* is negatively associated with *JWR, AJWR*, and *JA* (r = −0.485, −0.556, and −0.663, respectively) because a lower *MC* indicates a better job supply, and lower *JA* and *JWR* values denote a worse job supply. *JA* is positively correlated with *JWR* and *AJWR* (r = 0.563 and 0.618). However, except for the correlation between *JWR* and *AJWR*, all the absolute values of correlation coefficients between the four measures are less than 0.7, which means that they are significantly different from each other in representing the jobs–housing relationship. Thus, this finding, to some extent, explains why empirical studies using different categories of measures send different messages about the impacts of the jobs–housing relationship on commuting.

4.2 Aggregate results for all workers

Table 3 shows the results of linear regression models. In order to compare the magnitude of effects of three jobs–housing relationship measures on average commuting distance, we report the standardized regression coefficients (Beta).

First, we model the univariate regression only including the jobs–housing relationship measure. The results suggest that the jobs–housing relationship explains the spatial variation of commuting distance well, whether it is represented by *JWR*, *AJWR*, *MC*, or *JA*. A high level of jobs–housing balance or job accessibility would reduce workers' commuting distance. The R^2 values for three univariate regression models are 0.342, 0.461, 0.341, and 0.666, which means that 34.2%, 46.1%, 34.1%, and 66.6% of the spatial variation of average commuting distance at the sub-district can be explained by the change in *JWR*, *AJWR*, *MC*, and *JA*, respectively. Their standardized regression coefficients are −0.585, −0.679, 0.584, and −0.816, respectively. Thus, the results suggest that *JA* is the most adequate proxy for the jobs–housing relationship and has the best superior explanatory power for average commuting distance. *JWR* is slightly better than *MC*.

In addition to the jobs–housing relationship, socio-demographic attributes such as the ratio of local workers and the ratio of well-educated workers at each sub-district are introduced into multiple linear regression models. However, the results show that the effects of the jobs–housing relationship on average commuting distance are more significant than all socioeconomic factors, as the proxy variables of the jobs–housing relationship (*JWR*, *AJWR*, *MC*, and *JA*) have a greater standardized regression coefficient value. After controlling for the socio-demographic attributes, the model results also reveal that the impact of the three measures on average commuting distance changes differently. *JA* and *MC* exhibit more impacts, and *JWR* shows less. The standardized regression coefficients of *JA* and *MC* change from −0.816 and 0.584 to −0.913 and 0.598, and that of JWR changes from −0.585 to −0.465.

The improvement of explanatory power (R^2) suggests that workers' socioeconomic characteristics can explain, to some extent, the spatial variations in commuting distance. A higher *Hukou* value contributes to a longer commuting distance. In China, *Hukou* plays an important role in structuring residents' life chances, including where to live and work (Yue and O'Kelly, 2023b). Compared with a local person, a migrant faces an inferior situation in the jobs and housing market, and they are less likely to own homes or cars due to a lower income (Li and Liu, 2016). To save time and money on commuting, they usually find a job close to their place of residence or live near their place of employment. A higher *Edu* value is associated with a longer commuting distance. Well-educated workers must search a large area to find suitable employment opportunities and meet the demand for housing space and neighborhood environment, which leads to a long commuting distance (Shen, 2000; Yue et al., 2022; Zhou et al., 2022). A higher *Head* ratio leads to shorter commuting distances. Management workers have higher wages and the ability to adjust the location of housing with reference to their workplace to make shorter commuting (Zhao et al., 2011).

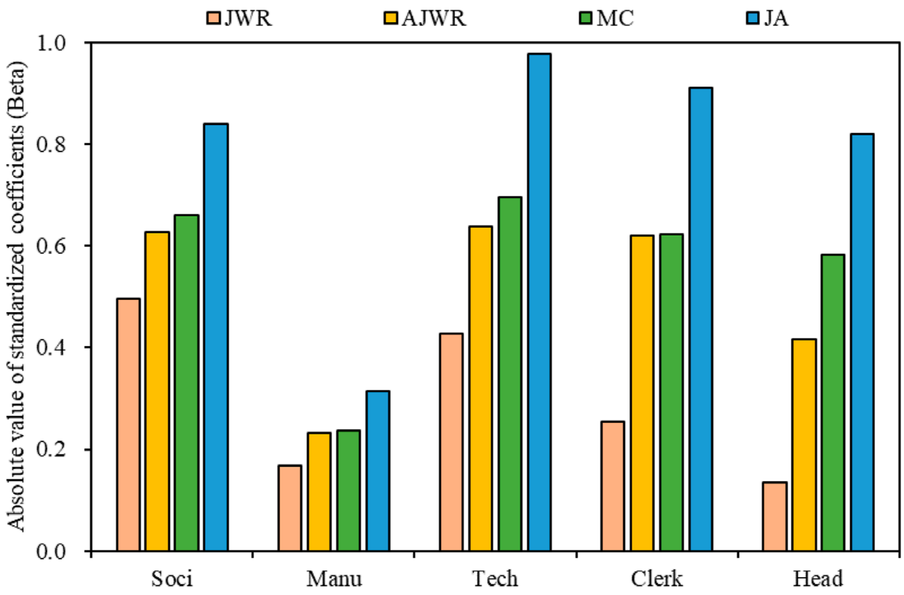

FIGURE 3
The magnitude of the commuting effects of different jobs−housing relationship measures.

4.3 Disaggregated results for different occupational subgroups

The regression analysis for all workers reveals that occupation is a major determinant of commuting distance. In this section, five separate multiple linear regression analyses are carried out to provide insights into the magnitude of the commuting impacts of three jobs–housing relationship measures for different occupational worker subgroups in Table 4. The results add evidence to the results drawn from the data in Table 3, indicating the magnitude of the commuting impacts of three jobs–housing relationship measures for each occupational worker subgroup: *JWR* < *AJWR* < *MC* < *JA*. *JA* has the greatest impact on commuting distance. For example, for the social service sector, the Beta values of *JWR* and *AJWR* are −0.496 and −0.628; that of *MC* is 0.661, but that of *JA* is −0.840.

Table 4, Figure 3 suggest that using different categories of jobs–housing relationship measures comes to a different conclusion about the magnitude of commuting impacts across occupational worker subgroups. When the jobs–housing relationship is measured by *JWR*, the magnitude of its impact is Soci > Tech > Clerk > Manu > Head. When the jobs–housing relationship is measured by *MC*, the magnitude of its impact is Tech > Soci > Clerk > Head > Manu. When the jobs–housing relationship is measured by *JA*, the magnitude of its impact is Tech > Clerk > Soci > Head > Manu. Existing studies find that skilled workers must search for jobs in a larger space in order to find satisfactory jobs, they have the ability to bear higher time and money costs, and commuting distance is not the primary consideration (Yue and O'Kelly, 2023a).

The above empirical analysis in Shanghai suggests a negative relationship between *JWR*, *JA*, and average commuting distance and a positive relationship between *MC* and average commuting distance, which is consistent with some previous commuting studies (Wang, 2001; Zhou et al., 2022; Yang and Ferreira, 2008). For all workers and five occupational worker subgroups, commuting distance has the least correlation with *JWR* and the most correlation with *JA*. One potential explanation is that with the increase of the geographical scope measuring the jobs–housing relationship, the relationship between average commuting distance and *JA* increases. The coefficient of variation (CV) of three measures (*JWR*, *MC*, and *JA*) is 0.838, 0.493, and 0.337, respectively. Therefore, it contributes to the increase in regression coefficients. This is similar to the modifiable areal unit problem (MAUP). Zhou et al. (2022) find that with the increase of the analysis unit size, the correlations between commuting distance and the adjusted jobs-workers ratio (*AJWR*) increased. These different findings with various jobs–housing relationship measures may explain, to some extent, inconsistent conclusions about the commuting impacts of jobs–housing relationship in the existing literature.

We find that *JA* has the greatest impact on commuting distance in Shanghai, while Yang and Ferreira (2005) came to the inconsistent conclusion that *MC* has the greatest impact on commuting distance in Boston, United States. This may be related to social norms and urban spatial structures. Distance from the CBD has been proved that it can explain the spatial variations of commuting length to some extent (Wang, 2000; Wang, 2001). We also introduce the distance from CBD as an explanatory variable into the model and found that its commuting impact (Beta value) is much larger than *MC*. There is still a marked rent gradient over the distance from the CBD in Shanghai (Yue and O'Kelly, 2023b). Therefore, commuting length is more related to *JA* than *MC* in Shanghai, because *JA* captures the jobs–housing relationship in the whole area, especially the CBD, while *MC* only captures the neighborhood area. Another reason may be related to a spatial decay parameter, which is subjectively set at 0.1 for Boston. However, O'Kelly and Niedzielski (2008) set a spatial decay parameter for Boston at 0.24 derived from the doubly constrained spatial interaction model. Unreasonable parameter settings may produce misleading results because they affect the calculation of *JA* and its spatial pattern.

5 Conclusion and discussion

To shorten commuting and mitigate traffic congestion, balancing jobs and housing has become a common land use policy tool in academic and policy circles. This tactic would backfire, of course, if people chose to live far from their jobs, or if jobs attracted workers from well beyond the ideal local range. We would like to know if and to what extent balanced residential and job location leads to greatly improved commuting. This work attempts to quantify and compare the commuting impacts of urban land use in Shanghai, China, using different proxies to measure jobs–housing proximity.

JWR indicates the labor quantity supply–demand relationship within given geographical analysis units, such as census tracts. *MC* considers the local effects of jobs–housing distribution to minimize the system-wide commuting cost. *JA* measures the job opportunity potential following a certain distance attenuation law in the whole region. We chose them as proxies for jobs–housing proximity and compared the magnitude of their commuting impacts. It is found that all indicators significantly influence commuting distance, but *JA* is superior to others in terms of explanatory power, especially for skilled workers. Although existing studies have explored the interaction between commuting and jobs–housing proximity, different empirical studies send different messages (Sultana, 2002; Giuliano and Small, 1993). This study highlights that improving the jobs–housing balance is an effective way to reduce commuting length, but the magnitude of its commuting impacts varies with the category of measures and worker subgroups. Therefore, in order to make the jobs–housing balance an effective planning tool with which to shorten commuting, land use patterns at the local and regional levels must be spatially linked and coordinated. On the other hand, especially for skilled workers, their selection of residential location follows patterns of average job location rather than that of the closest available job location (Ommeren et al., 1997). Urban planners should pay more attention to the integration of transportation and urban land use, aiming to improve job accessibility in the whole area.

Our intention is not to criticize all use of these common measures but to help identify better methods for interpreting the interaction between commuting length and jobs–housing proximity. Each measure is valuable in characterizing the spatial proximity between jobs and housing. Each measure is valuable in characterizing the spatial proximity between jobs and housing and can provide important information and guidance to policymakers on the jobs–housing proximity.

This research has some limitations. First, due to data limitations, we cannot include more control variables that might affect commuting length, such as income and travel mode, in the models. Second, taking the sub-district as the spatial analysis unit could lead to a modifiable areal unit problem. Future studies should focus on the impacts of travel modes to accurately analyze and compare the interaction between jobs–housing proximity and commuting in all of Shanghai, based on high-resolution data.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

LY: conceptualization, formal analysis, methodology, and writing – original draft. KL: formal analysis, software, visualization, and writing – review and editing. YZ: writing – review and editing, data-curation, validation, funding-acquisition, resources.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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