

Analyzing the parcel delivery pattern in the Global South: The case of Belo Horizonte, Brazil

Leise Kelli de Oliveira, Federal University of Rio Grande do Sul, leise.oliveira@ufrgs.br
Rui Colaço, CERIS, Instituto Superior Técnico, Universidade de Lisboa, r.colaco@tecnico.ulisboa.pt
Gracielle Gonçalves Ferreira de Araújo, Federal University of Pernambuco, gracielle.araujo@ufpe.br
João de Abreu e Silva, CERIS, Instituto Superior Técnico, Universidade de Lisboa, jabreu@tecnico.ulisboa.pt

Abstract: This study investigates parcel delivery patterns in Belo Horizonte, Brazil, to elucidate the influence of spatial inequalities, urban structure, socioeconomic factors, and retail diversity on delivery demand, employing spatial regression models. The results reveal that income and retail diversity positively impact parcel delivery, while food deserts drive increased reliance on e-commerce due to limited local options. In particular, the distance from the city center negatively affects delivery patterns, highlighting spatial inequities. Areas characterized by social inequalities exhibit greater delivery activity, highlighting e-commerce as a vital alternative where local services are scarce. These findings advocate for integrated urban planning policies that strategically leverage parcel delivery services to achieve more equitable access, address service gaps, and foster delivery expansion in marginalized areas.

Keywords: urban freight transport, e-commerce, parcel delivery, informal settlements, spatial inequality

1 Introduction

In recent decades, the rapid development of digital technologies, coupled with the ongoing process of globalization, has fundamentally transformed consumer shopping behaviors and market structures. The proliferation of online retail platforms has introduced new paradigms in consumption, characterized by increased convenience, greater product variety, and the ability to shop from virtually anywhere (Moon et al., 2021). Consequently, such changes have reshaped the retail and logistics landscape, leading to a significant increase in parcel deliveries (Dias et al., 2020; Mokhtarian, 2004; Mokhtarian et al., 2009; Zhen et al., 2018). However, this transformation is not without externalities; the increased prevalence of parcel deliveries, marked by their fragmented focus on the last-mile, has been associated with increased vehicle kilometers traveled, fuel consumption, and environmental degradation, particularly air pollution (Calabrò et al., 2022).

Although the adoption of e-commerce has garnered extensive scholarly attention, especially in the wake of the COVID-19 pandemic, which significantly accelerated online shopping behaviors, most existing research remains anchored at the individual or household level. These studies predominantly explore demographic and socio-economic factors such as age, income, education level, and gender (Beckers et al., 2018; Cao et al., 2012). For example, recurring findings underscore that younger populations and higher-

income, better-educated individuals tend to have a higher propensity to engage in online shopping, with variations observed across different national contexts and cultural settings (Beckers et al., 2018; Clarke et al., 2015; Farag et al., 2007; Pérez-Amaral et al., 2020). Moreover, some research has investigated how these patterns evolve post-pandemic, indicating shifts in user profiles and consumption behaviors (Colaço & de Abreu e Silva, 2023; Sousa, Oliveira, Santos Junior et al., 2023; van Wee & Witlox, 2021).

Despite these valuable insights, a significant research gap persists in relation to the spatial dimensions of parcel delivery demand and how urban land use and urban structure disparities influence delivery patterns within cities. Existing studies tend to focus on macroeconomic or demographic indicators, with limited integration of spatially explicit data or urban infrastructure variables that directly impact the accessibility and distribution of parcel delivery services. Only a few works, such as those by (Beckers et al., 2018), (Shin et al., 2023), and (Sousa, Oliveira, Santos Junior et al., 2023) have employed delivery data within analytical frameworks explicitly incorporating spatial dimensions. However, many of these investigations predominantly focus on high-income or developed country contexts, often overlooking the complex socio-spatial realities characteristic of many Latin American cities.

In addition, urban inequalities manifested through disparities in access to affordable, healthy food, quality housing, and basic infrastructure can significantly influence patterns of e-commerce adoption and parcel delivery demand. For example, areas classified as food deserts or food swamps, or neighborhoods characterized by informal settlements with precarious infrastructure, represent environments where traditional retail access is limited. These spatial inequalities can drive differential reliance on parcel services, either as a substitute for physical retail or due to accessibility barriers; yet their effects remain underexplored in empirical research. Understanding these dynamics is crucial, especially in emerging urban contexts where socio-economic disparities are often stark and infrastructure challenges are prominent.

In light of the rapid growth of e-commerce and the increasing reliance on parcel deliveries, this study addresses a critical gap in the understanding of how spatial inequalities affect delivery patterns, particularly in the informal settlements of Belo Horizonte, Brazil. While extensive research has been conducted on e-commerce adoption in the Global North, there remains a lack of empirical evidence on the unique socio-spatial challenges faced by urban areas in the Global South, where informal settlements often coexist with significant socio-economic disparities. This study seeks to fill this gap by investigating how the urban structure, socioeconomic factors, and retail diversity shape parcel delivery demand. By focusing on these unresolved dynamics, we aim to provide actionable insights for local policymakers and logistics providers to better design delivery systems that cater to the needs of underserved urban populations, particularly by uncovering how established patterns might differ or manifest uniquely within the socio-spatial complexities of Latin American cities and informal settlements.

This paper is structured as follows: Section 2 reviews the current literature on the socio-economic and spatial determinants of e-commerce and parcel delivery; Section 3 describes the case study, data sources, variables, and the research method; Section 4 presents the empirical results, their discussion, and policy recommendations; finally, Section 5 concludes with avenues for future research.

2 Literature review

Anderson et al. (2003) hypothesized more than two decades ago that “urban populations are more likely to adopt e-commerce because they are better educated and more likely to use the Internet.” Research on the relationship between socioeconomic characteristics and electronic commerce delivery emerged in the 1990s (Donthu &

Garcia, 1999). Since then, research results have shown that younger people have a higher probability of buying online (Clarke et al., 2015; Farag, Krizek et al., 2006; Farag, Weltevreden et al., 2006; Pérez-Amaral et al., 2020; Reiffer et al., 2023; Sousa, Oliveira, Oliveira et al., 2023), with ages ranging from 18 to 29 years in the United Kingdom (Clarke et al., 2015), 25 to 34 years in Belgium (Beckers et al., 2018) and 35 to 44 years in Spain (Pérez-Amaral et al., 2020). On the other hand, older people are still more prone to buying in physical stores (Colaço & de Abreu e Silva, 2022, 2023).

Furthermore, many studies have identified that higher income increases online shopping (Clarke et al., 2015; Colaço & de Abreu e Silva, 2022; Gong et al., 2013; Pérez-Amaral et al., 2020; Reiffer et al., 2023; Sousa, Oliveira, Oliveira et al., 2023). In contrast, Shin et al. (2023) identified a negative influence of the gross regional product per capita on the demand for parcel delivery. Associated with higher income, a higher education level also has a positive impact on online shopping (Beckers et al., 2018; Gong et al., 2013; Pérez-Amaral et al., 2020). Regarding gender, men buy more online in Belgium (Beckers et al., 2018), Spain (Pérez-Amaral et al., 2020), and South Korea (Shin et al., 2023). Hernández et al. (2011) found that age, gender, and income are of minor significance for e-shoppers after acquiring experience with the channel.

Anderson et al. (2003) also hypothesized that people in non-metropolitan areas with low retail accessibility could be early adopters of e-shopping due to the increased accessibility to goods offered by e-shopping. Some authors have explored this hypothesis by comparing the amount of parcel deliveries in urban and non-urban areas. Focusing on the Netherlands, Farag et al. (2006) found that urban residents shop more online than suburban residents. In Belo Horizonte (Brazil), the size of the household negatively influences e-commerce deliveries (Sousa, Oliveira, Oliveira et al., 2023). On the other hand, Weltevreden (2008) showed that access to shopping opportunities reduces online shopping, while retail shops have a positive effect on e-commerce deliveries (Sousa, Oliveira, Oliveira et al., 2023). Recent research supports the widespread adoption of online shopping. Cárdenas et al. (2017) identified that parcel deliveries are higher in rural areas. (Sousa, Oliveira, Santos Junior et al., 2023) identified a positive effect of retail stores on parcel delivery before and during the COVID-19 pandemic. Beckers et al. (2018) suggested that the profile of online shoppers is now independent of the level of urbanization.

Table 1 summarizes the effects of the variables on the parcel deliveries identified in the literature. It should be mentioned that only a few of these studies used delivery data to determine the analyzed effects. The majority uses data obtained through surveys. Some exceptions using delivery data to perform spatial analysis and implement regression models can be found in (Beckers et al., 2018; Shin et al., 2023; Sousa, Oliveira, Oliveira et al., 2023; Sousa, Oliveira, Santos Junior et al., 2023). Furthermore, research has focused more on the impact of individual socioeconomic characteristics on parcel delivery than on the effect of land use variables. The exception is the work of Shin et al. (2023), which showed a positive effect of residential and commercial areas on the demand for parcel delivery.

Despite the extensive body of research that examines the socioeconomic determinants of online shopping and parcel delivery demand, a notable gap persists in the spatial analysis of these relationships within urban contexts. Most prior studies relied mainly on survey data or aggregate socioeconomic indicators, with limited use of actual delivery data coupled with advanced spatial modeling techniques. In addition, the literature has largely concentrated on individual socioeconomic characteristics, while the influence of land use variables and spatial dependencies remains underexplored.

Furthermore, much of the existing research is situated within developed countries, leaving a considerable gap in understanding how these dynamics manifest in Latin

American urban environments characterized by significant socio-economic disparities and infrastructural heterogeneity. In this context, studies are needed to integrate detailed spatial data, land use variables, and multivariate spatial analysis to elucidate the complex interactions that influence parcel delivery patterns.

Table 1. Summary of the effects of socioeconomic and land use variables on parcel delivery

| Variable | Positive effect | Negative effect | Non-significant effect |
|--|---|--|--------------------------|
| Socioeconomic and Demographic Characteristics | | | |
| Income | (Beckers et al., 2018; Colaço & de Abreu e Silva, 2022; Gong et al., 2013; Pérez-Amaral et al., 2020; Reiffer et al., 2023; Sousa, Oliveira, Oliveira et al., 2023; Sousa, Oliveria, Santos Junior et al. 2023) | (Shin et al., 2023) | (Hernández et al., 2011) |
| Gender (Male) | (Beckers et al., 2018; Pérez-Amaral et al., 2020; Reiffer et al., 2023) | | (Hernández et al., 2011) |
| Age | | (Cárdenas et al., 2017; Colaço & de Abreu e Silva, 2022; Gong et al., 2013; Pérez-Amaral et al., 2020; Reiffer et al., 2023; Shin et al., 2023; Sousa, Oliveira, Oliveria et al., 2023; Sousa, Oliveria, Santos Junior et al., 2023) | (Hernández et al., 2011) |
| Household Size | (Cheng et al., 2021; Pérez-Amaral et al., 2020) | (Sousa, Oliveira, Oliveira et al., 2023) | |
| Household Composition | (Gong et al., 2013) | (Sousa, Oliveira, Oliveira et al., 2023; Sousa, Oliveira, Santos Junior et al., 2023) | |
| Vehicle Ownership | (Cheng et al., 2021) | | |
| Education Level | (Beckers et al., 2018; Colaço & de Abreu e Silva, 2022; Pérez-Amaral et al., 2020) | (Gong et al., 2013) | |
| Digital Skills | (Pérez-Amaral et al., 2020) | | |
| Employment Situation | (Pérez-Amaral et al., 2020; Reiffer et al., 2023) | | |
| Land Use | | | |
| Population Density | (Cheng et al., 2021) | | |
| Retail | (Shin et al., 2023; Sousa, Oliveira, Oliveira et al., 2023; Sousa, Oliveira, Santos Junior et al., 2023) | | |
| Shopping Mall | | (Cheng et al., 2021) | |
| Public Transit | (Loo & Wang, 2018) | (Cheng et al., 2021) | |

The present study aims to close this gap by employing detailed delivery data within a spatial regression framework to analyze the effects of socioeconomic and land use variables on parcel delivery patterns in Belo Horizonte. By doing so, it advances the understanding of urban logistics in emerging cities and provides a valuable evidence base for policymakers and urban planners seeking to develop sustainable, equitable, and efficient delivery systems in complex urban environments.

3 Case study, data and method

3.1 Case study

Belo Horizonte is a municipality in southeastern Brazil with 99% of the population living within its urban perimeter (IBGE, 2023b). Belo Horizonte has 2.3 million inhabitants, and 80% of its population lives in 37% of its 487 neighborhoods (Oliveira et al., 2023). High-street retail is concentrated in the city center, around Sete de Setembro Square, with some lower-order commercial centers located in the southwest and to the north and, generally, along high accessibility roads along the city. Figure 1 (a) presents the commercial density of Belo Horizonte (stores/km²), thus giving a general idea of the commercial structure of the city. Some areas that do not have commercial activity are the Campus of the Federal University of Minas Gerais (UFMG) campus, and the Pampulha–Carlos Drummond de Andrade Airport.

Informal settlements are an unregulated form of occupation of land owned by absentee landowners or of public property and are built essentially for housing purposes in urban areas. The criteria for classifying an area as informal settlements consider the absence of a property title for the houses and at least one of the following characteristics: (a) the unregulated nature of the land occupation, namely the absence of any instruments of formal planning; (b) the existence of land occupation restrictions (e.g., environmental restrictions) not being abided; (c) the lack or the inadequacy of one or more public utilities, namely water supply, sewage, electricity supply, and waste collection (IBGE, 2023a). Currently, there are 336 informal settlements in Belo Horizonte, housing 480,000 people in 120,000 households (Belo Horizonte, 2021). Figure 1 (b) shows the location of the areas classified as informal settlements in Belo Horizonte.

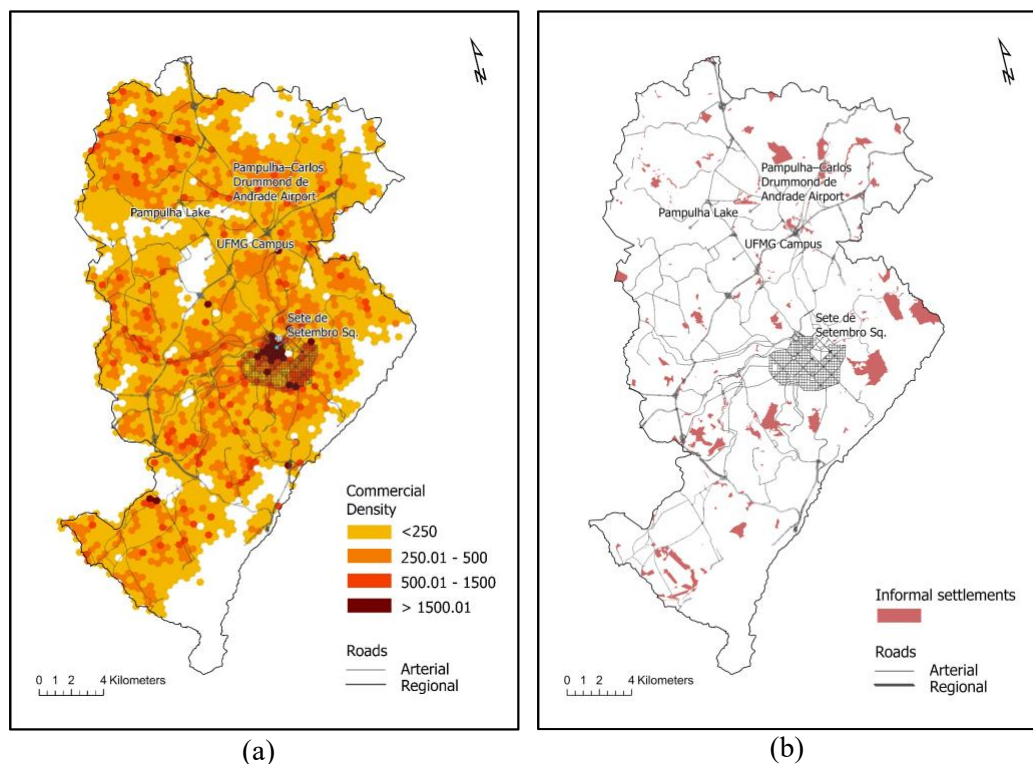


Figure 1. Belo Horizonte: (a) Commercial density (stores per km²) and (b) location of informal settlements in Belo Horizonte

Sources: Based on Belo Horizonte, 2023; Belo Horizonte, 2025

Food deserts refer to regions with limited or no access to fresh, nutritious foods, which is often associated with low-income communities and marginalized populations (Shaw, 2006; Ver Ploeg et al., 2009). These areas face significant barriers to obtaining healthy food options, exacerbating health disparities and nutritional deficiencies. In contrast, a food swamp describes areas flooded with ultra-processed foods, fast food outlets, and unhealthy options, typically found in economically vulnerable neighborhoods where access to healthy, affordable food is scarce (Ver Ploeg et al., 2009). Both phenomena highlight systemic inequalities in resource distribution, infrastructure, and access to healthy foods, reflecting broader social and economic disparities that persist within urban environments.

To classify food deserts and food swamps, we adopted the methodology devised by Honório et al. (2021), which analyzed the social inequalities surrounding food deserts and swamps in Belo Horizonte. The first step involves classifying food retailers into three categories: (A) establishments that mostly sell fresh or minimally processed foods (e.g., public establishments for food security, fresh product stores, butcher shops, and fish markets); (B) mixed establishments (e.g., restaurants, bakeries, minimarkets, grocery stores, supermarkets, dairy shops); and (C) establishments that primarily sell ultra-processed foods (e.g., pubs, snack bars, candy shops). In the second step, the density of establishments classified as selling fresh or minimally processed foods and mixed stores per 10,000 inhabitants is calculated. Census tracts with a density below the 25th percentile are identified as food deserts, following the criteria outlined by (CAISAN, 2018) and Honório et al. (2021).

3.2 Description of variables

This article combines three databases: (i) socioeconomic and demographic data, (ii) land use data, and (iii) parcel delivery records. To facilitate this analysis, we organized the variables into distinct thematic categories: social inequalities, urban structure-related variables, economic and demographic factors, and economic vitality. Table 2 provides a summary of the variables considered in this study, which are detailed below. The choice of variables was based on the literature. All of these variables are spatialized using a zoning system composed of a hexagonal spatial grid developed by Pereira et al. (2022). Each hexagonal cell covers an area of 0.11 km².

Table 2. Description of variables

| Category | Name | Description | Source |
|--------------------------|---------------------|--|-------------------------------------|
| Parcel delivery | | Number of parcel deliveries performed per hexagon | Logistic operator |
| Social inequality | Food deserts | Dummy variable representing whether the hexagon is limited or has no access to fresh food | Computed |
| | Food swamps | Dummy variable representing whether it is scarce affordable food in the hexagon | Computed |
| | Informal settlement | Dummy variable representing whether the hexagon is an informal settlement. | Belo Horizonte (2025) |
| Urban structure | CDB distance | Network distance between the centroid of each hexagon and the Sete de Setembro Square, in km | Computed |
| | CDB distance | Network distance between the centroid of each hexagon and the Sete de Setembro Square, in km | Computed |
| Economic and demographic | Income | Average income per capita in the hexagon (in BRL) | Pereira et al. (2022) |
| | Job | The number of job opportunities in all sectors in the hexagon | Pereira et al. (2022) |
| | %19-24yo | Proportion of 19- to 24-year-old individuals in the hexagon | Computed from Pereira et al. (2022) |
| | %25-39yo | Proportion of individuals aged 25- to 39-year-old in the hexagon | Computed from Pereira et al. (2022) |
| | %40-69yo | Proportion of individuals aged 40- to 69-year-old in the hexagon | Computed from Pereira et al. (2022) |
| | Retail density | Number of stores in the hexagon | Belo Horizonte (2025) |
| Economic vitality | RDV | Retail Diversity-Variety in the hexagon | Computed |
| | RDC | Retail Diversity-Concentration in the hexagon | Computed |

The number of parcel deliveries per hexagon was obtained from records of one of the largest delivery companies operating in Belo Horizonte, whose identity remains anonymous for privacy reasons. This variable reflects the spatial distribution and intensity of parcel delivery activity across the city. The company, which handles products from some of the leading Brazilian online marketplaces and is one of the top ten Brazilian logistics firms, completed a total of 23,437 deliveries in Belo Horizonte between May 2 and May 8, 2022. These were spatially distributed as shown in Figure 2. This data set provides a direct measure of how different areas, particularly those with varying sociodemographic and economic vitality, engage with parcel delivery services.

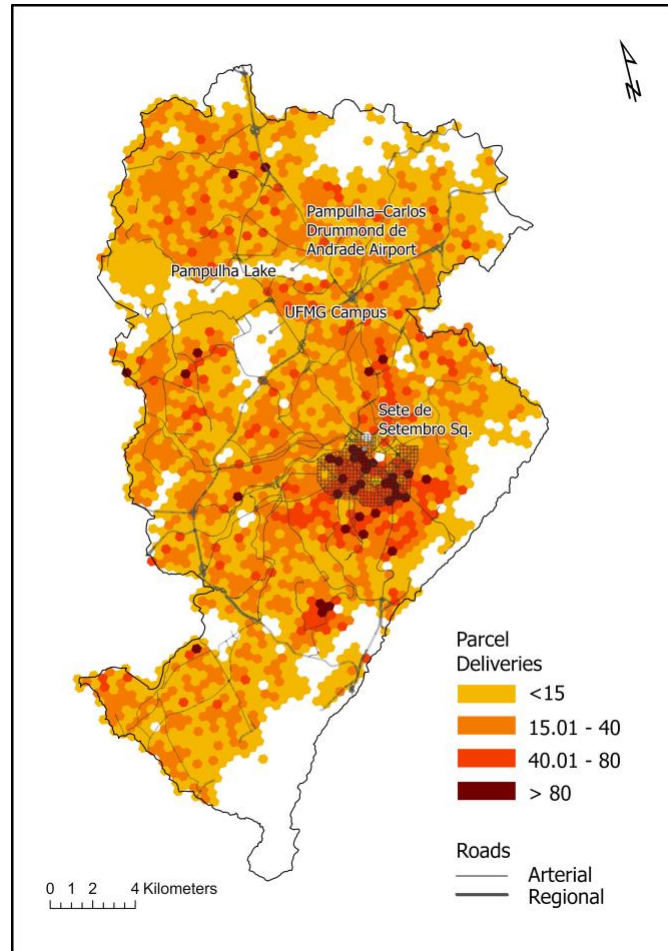


Figure 2. Spatial pattern of parcel deliveries between May 2 and 8, 2022, in Belo Horizonte

For our analysis, we use data on commercial establishments from the Belo Horizonte Municipality Open Data Portal called BHGEO (Belo Horizonte, 2025) to calculate density and diversity, but at a finer spatial level. We use the CNAE classification (the acronym for Classificação Nacional de Atividades Econômicas in Portuguese, similar to the North American Industry Classification System) to identify stores that offer fresh products, such as butcher shops and fish markets. Data on public food security establishments came from the Food and Nutrition Security Program (Belo Horizonte, 2023). We calculate the density of stores that mainly sell fresh or minimally processed foods and mixed establishments per 10,000 inhabitants. Hexagons with a density below the 25th percentile are classified as Food Deserts. In the same way, each hexagon is classified as being, or not, a food swamp. In the case of informal settlements, the hexagon with 75% of its territory occupied as informal settlement is considered an informal settlement and assigned value 1.

The category of urban structure is a function of the distance to the Central Business District (as a proxy for centrality). This distance is calculated by considering the network distance between the centroid of each hexagon and Sete de Setembro Square, which serves as Belo Horizonte’s “central” CBD point. Data for variables in the economic and demographic categories are derived from Pereira et al. (2022), where we retrieved the total number of residents, the number of residents aged 19–24 years, 25–30 years and 40–

69 years (to calculate the respective percentage), the number of job opportunities, and the income per capita in BRL (Brazilian reais). As of February 20, 2024, 1 BRL is approximately equivalent to €0.18 or \$0.21, which provides context for interpreting income data within the study. We also consider this grid as the spatial unit of our work. As mentioned above, the retail density is retrieved from Belo Horizonte (2025), which provides information about location and type, disaggregated by address.

Lastly, variables related to the diversity and concentration of retail activity provide perspectives on economic vitality and competition within different areas. The retail data were grouped into eight categories based on the method used by Colaço and de Abreu e Silva (2021) in Lisbon, which is itself an adaptation of the classification used by Lisbon's city council (Câmara Municipal de Lisboa, 2009). This classification was done considering that similar establishments tend to agglomerate and may generate similar traffic patterns, while the cargo itself may be similar (e.g., size, weight). In Belo Horizonte, these eight categories correspond to: (1) Foodstuffs (supermarkets, bakeries, groceries, and similar establishments), (2) Personal Use items (mainly clothing, clothing accessories, and shoes), (3) Household items (primarily furniture, home appliances, and home decoration items), (4) Leisure items (e.g., bookstores, music stores, sporting goods), (5) Health and Hygiene (pharmacies and optical stores, perfumes, and cosmetics), (6) Hardware and similar items (Home improvement stores and others selling specific tools or products, such as paint stores), (7) Miscellaneous (all items not included in the remaining categories), and (8) Restaurants and pubs.

Retail density alone cannot fully capture the complexity of Belo Horizonte's retail landscape in terms of supply characteristics. For instance, a single block may contain numerous stores, all selling the same type of products, thus providing consumers with very limited shopping options. Conversely, a block might feature a variety of different product categories, although only one or two stores may dominate in size or number, which, while offering greater diversity, still constrains overall supply diversity. To address these nuances, we devise two additional variables, variety and concentration, that serve to better characterize the level of commercial diversity within the area.

The variety measure used in this study is a straightforward metric that counts the number of distinct categories of retail establishments present in a given location, as suggested by Batty et al. (2004). This variable, referred to as RDV, is calculated by summing the presence of different retail categories within hexagon i , as expressed by Equation 1, where $b(i, k)$ is a binary variable that takes the value of 1 if category k is present in hexagon i , and 0 otherwise. Consequently, RDV ranges from 0, indicating that there is no retail activity in the area, to K , the total number of categories considered, when all types of activity are present. This approach provides a simple and intuitive measure of retail diversity, reflecting the extent of a region's offering of different activity categories, and contributing to the understanding of how retail variety may influence the adoption of e-shopping services.

$$RDV_i = \sum_k b(i, k) \quad (1)$$

We used the Simpson index to evaluate the concentration of retail activities (Simpson, 1949). This index quantifies the degree of dominance of retail establishments across different categories for each hexagon, calculated by Equation 2 (referred to here as RDC, for "Retail Diversity-Concentration"), where k represents the total number of retail establishments of a particular category, and K is the total number of retail establishments of all categories. The index reaches a value of 1 when only one type of establishment is

present in the hexagon, indicating complete concentration. In contrast, values closer to 0 suggest a more balanced, competitive utilization of stores across all K categories.

$$RDC_i = 1 - \left(\frac{\sum k(k-1)}{\sum K(K-1)} \right) \quad (2)$$

Table 3 shows the descriptive statistics of the data, which reveal considerable variability among the continuous variables. The mean number of parcel deliveries per area is approximately 14.9, with a median of 10, indicating a distorted distribution to the right. The average population per area is roughly 791 residents, with a median of 695, reflecting some degree of heterogeneity in population density. Binary variables convey notable information: approximately 49% of the areas experience food desert conditions, indicating widespread food insecurity, while around 12.5% are characterized by swamp-like environments that pose environmental challenges. The prevalence of informal settlements accounts for approximately 5%, emphasizing persistent social inequalities.

Table 3. Descriptive statistics of data

| Category | Name | Mean | Median | Standard deviation |
|--------------------------|---------------------|------------------------|--------|--------------------|
| Parcel delivery | Parcel delivery | 14.91 | 10.00 | 18.466 |
| Urban structure | CDB distance | 8.061 | 7.956 | 3.762 |
| Economic and demographic | % male | 0.4395 | 0.5213 | 0.196 |
| | %19-24yo | 0.0882 | 0.1022 | 0.043 |
| | %25-39yo | 0.2209 | 0.2531 | 0.106 |
| | %40-69yo | 0.3222 | 0.3217 | 0.059 |
| | Income | 966.2 | 621.9 | 1135.659 |
| Economic vitality | Job | 236.0 | 59.5 | 606.715 |
| | Retail density | 27.15 | 21.00 | 43.952 |
| | RDV | 4.831 | 6.000 | 3.092 |
| | RDC | 0.2194 | 0.1983 | 0.199 |
| | | | | |
| Category | Name | Number of hexagons = 1 | | Proportion |
| Social inequality | Food deserts | 1494 | | 49.04% |
| | Food swamps | 380 | | 12.47% |
| | Informal settlement | 155 | | 5.08% |
| Total | | 3046 | | 100% |

3.3 Research approach

To investigate the complex spatial dynamics of parcel delivery demand in Belo Horizonte, particularly within the context of the Global South, our research approach extends beyond conventional modeling. We adopt an adaptive analytical framework that prioritizes the diagnostic assessment of data characteristics to ensure the selection of the most appropriate statistical models. This approach is crucial for accurately capturing the spatial interdependencies and heterogeneities inherent in urban systems, especially in cities marked by significant socio-spatial inequalities.

Our analytical procedure began with an initial estimation using an Ordinary Least Squares (OLS) linear regression model. This served as a foundational diagnostic step rather than the sole analytical framework. Multicollinearity among predictors was assessed using the Variance Inflation Factor (VIF). All variables demonstrated VIF values below 3, indicating an acceptable level of collinearity and suggesting that the

independent variables are not highly collinear. As a result, the estimated model retains all variables, regardless of their statistical significance.

The Breusch-Pagan test revealed the presence of heteroscedasticity, a violation of OLS assumptions that would compromise the validity of statistical inferences. This finding further underscored the need for a more robust modeling strategy. The test yields a substantially high BP statistic of 431.79 with 13 degrees of freedom, accompanied by a p-value of less than 0.05. These results strongly indicate the presence of heteroscedasticity, suggesting that the variance of the residuals is not constant across the range of predicted values. In practical terms, this violation of homoscedasticity may undermine the validity of the statistical inferences derived from the model. Therefore, it is advisable to consider alternative modeling approaches that do not assume constant variance of the residuals.

Even more critically, the global Moran's I for the OLS residuals indicated a strong and significant presence of spatial autocorrelation. The result of the global Moran's I for the linear regression model indicates a Moran I statistic of approximately 0.132, with a significant p-value (< 0.05). This positive and highly significant value suggests the presence of spatial autocorrelation in the regression residuals, meaning that geographically adjacent observations tend to exhibit similar residuals. The expected value and variance of Moran's I further support this evidence of spatial dependence. This unambiguous evidence of spatial dependence demonstrates that the simple OLS framework is inherently limited in its capacity to model the interconnected nature of urban phenomena in Belo Horizonte.

The diagnostic results from the Lagrange Multiplier tests of a fitted linear model for spatial autocorrelation solidify these findings and guide us towards specialized spatial models capable of adequately capturing these complex relationships. The tests for spatial error dependence ($RSerr = 118.85$, $p < 0.05$) and spatial lag dependence ($RSlag = 171.44$, $p < 0.05$) both indicate significant spatial autocorrelation. Robust tests further support this, with $adjRSlag (54.023, p < 0.05)$ remaining significant, while $adjRSerr (1.431, p = 0.2316)$ suggests no strong evidence of spatial error dependence when adjusting for potential heteroskedasticity. Additionally, the Spatial Autoregressive Moving Average (SARMA) model test ($SARMA = 172.87$, $p < 0.05$) strongly indicates that a spatial autoregressive moving average model is the most appropriate specification. These results confirm that there is significant spatial dependence in the data, with the effects properly captured by separate spatial lag and error models. Consequently, recognizing the inherent spatial structure of our data and the limitations of non-spatial models, we proceeded to fit both the Spatial Autoregressive (SAR) and Spatial Moving Average (SMA) models. These spatial regression models represent a significant methodological advancement over traditional OLS in contexts where spatial dependence is prevalent, allowing for more reliable estimates and interpretations of the true effects of covariates while accounting for neighborhood interactions.

The SAR model assumes that the value of a variable in a given location is influenced by the values of the same variable in neighboring locations, incorporating a spatial lag effect through a parameter (ρ). This model is particularly useful when hypothesizing that observations are directly affected by those of their neighbors, reflecting the presence of spillover effects or direct spatial influence between adjacent units. The SMA assumes that autocorrelation exists in error terms, which means that the unexplained variability exhibits spatial dependence, characterized by an autocorrelation parameter (λ). This specification is appropriate when the dependence is believed to originate from unobserved factors or random effects that are spatially correlated, rather than from the response variable itself. Both models are essential for adjusting spatial data, mitigating

residual autocorrelation issues, and providing more reliable estimates and interpretations of spatial effects on the variable of interest (LeSage & Pace, 2009).

4 Results and discussion

Table 4 presents the results of the SAR and SMA models. The results of the SAR model indicate a significant spatial autocorrelation in the data, as evidenced by the estimated lag coefficient, which is positive and statistically significant. This suggests that the number of parcel deliveries in a given hexagon is not independent but is strongly influenced by the delivery activity in neighboring hexagons, consistent with the hypothesis that logistics and urban mobility in the city are interconnected through local spatial networks. The model's residuals show no remaining autocorrelation, confirming that the SAR specification effectively captures the spatial dependence structure.

Table 4. Estimated coefficients

| Variables | SAR Model | SMA |
|--------------------------------------|------------------------|------------------------|
| Intercept | -14.284** | -15.881** |
| Food desert | 2.126*** | 2.215*** |
| Food swamp | -0.833 | -0.732 |
| Informal settlement | 1.392 | 1.507 |
| CBD distance | -0.136* | -0.369*** |
| Income | 3.589*** | 4.138*** |
| Job | 0.0001 | 0.0001 |
| % Male | 24.528*** | 26.162*** |
| % 25-39yo | 5.277 | 10.289 |
| % 49-69yo | -15.210* | -5.719 |
| Retail | 0.118*** | 0.139*** |
| Retail Diversity-Variety | 1.849*** | 2.040*** |
| Retail Diversity-Concentration | -1.400 | -0.641 |
| Rho | 0.3118 | 0.316 |
| LR test value | 151.02*** | 112.09*** |
| Asymptotic standard error | 0.024*** | 0.0275*** |
| Wald statistic | 161.06*** | 132.21*** |
| AIC | 20708 | 20747 |
| ML residual variance | 193.13 (sigma: 13.897) | 195.98 (sigma: 13.999) |
| LM test for residual autocorrelation | 7.005*** | - |

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

The results of the SMA model indicate that significant spatial autocorrelation is present in the residuals, as evidenced by the estimated spatial error parameter, which is positive and statistically significant. This suggests that the unobserved factors influencing the dependent variable are spatially correlated, and the model effectively captures this dependence by modeling the autocorrelation within the error terms. The residual analysis shows a substantial reduction in spatial autocorrelation, confirming the suitability of the SMA specification to address unobserved spatial effects. Both models exhibit a good fit, as indicated by the log-likelihood and AIC values, and provide consistent estimates of covariate effects after accounting for spatially correlated errors.

The SAR intercept is approximately -14.284, statistically significant at $p < 0.05$, indicating a baseline negative effect in the absence of predictors. Conversely, in the SMA, the intercept is -15.881, which is also significant ($p < 0.05$), reflecting a negative baseline level of parcel deliveries when predictors are at zero. These findings emphasize the crucial role of the unmeasured factors captured by the intercepts and demonstrate the ability of the model to accurately reflect the foundational negative effects within the data, reinforcing the reliability and importance of our results.

The food desert variable is significantly positive in both models (2.126 in SAR; 2.215 in SMA), implying that regions characterized as food deserts tend to have higher delivery volumes, possibly due to limited access to physical stores and increased dependence on delivery services. The coefficients of the food swamp are negative but not statistically significant in either model (-0.833 in SAR, -0.732 in SMA), suggesting limited evidence of the effect of the food swamps on parcel delivery patterns.

The informal settlement variable has an estimated coefficient of approximately 1.392, with a p-value of 0.264 in the SAR model, indicating that its relationship with delivery volume is not statistically significant at 5% level. Despite the positive direction of the coefficient, this lack of significance suggests that, after controlling for spatial dependence, the presence of informal settlements does not exert a direct and consistent effect on delivery volume in the study area. On the other hand, the informal settlement coefficient is approximately 1.507 in the SMA model, also without statistical significance ($p \approx 0.273$). As with the SAR, the variable does not have a statistically reliable effect on delivery volume when autocorrelation in the residuals is considered.

Regarding the variable related to urban structure, the CBD distance has a significantly negative coefficient in both models (-0.136 in SAR and -0.369 in SMA), indicating that proximity to the city center is associated with lower delivery volumes, aligning with urban accessibility. Regarding the economic and demographic characteristics, both models show a positive and highly significant coefficient for Income (3.589 in SAR and 4.138 in SMA), indicating that higher income levels are consistently associated with increased parcel delivery volumes. The statistical significance ($p < 0.001$) of the coefficients underscores the influence of income on the parcel delivery pattern. The near-zero coefficient indicates that the number of jobs (employment levels) has a negligible impact on parcel deliveries within the models. The lack of statistical significance further confirms that there is no evidence of a meaningful relationship between employment levels and parcel delivery activity in this context.

The percentage of male individuals shows a significant positive effect in both models (24.528 in SAR, 26.162 in SMA, $p < 0.05$), indicating that hexagons with higher male proportions tend to have more deliveries. The positive coefficients for the 25-39 age group suggest that middle-aged adults may be an active segment for parcel deliveries, possibly due to work or lifestyle factors. Meanwhile, the 49-69 age group exhibits a negative coefficient in both models (statistically significant in the SAR), which is consistent with the literature, as older individuals tend to be less prone to adopting e-commerce (Beckers et al., 2018; Colaço & de Abreu e Silva, 2022; Gong et al., 2013; Pérez-Amaral et al., 2020; Shin et al., 2023; Sousa, Oliveira, Oliveira et al., 2023; Sousa, Oliveira, Santos Junior et al., 2023).

Finally, the variables related to economic vitality offer valuable insights into how the structure of retail activity influences parcel delivery patterns. The significant positive coefficients of Retail Diversity-Variety (RDV) (1.849 in SAR and 2.040 in SMA) indicate that areas with a broader mix of retail options tend to have higher parcel delivery volumes. This suggests that a diverse retail environment stimulates consumer activity, shopping behavior, and online orders, leading to an increased demand for parcel services. The retail variety is likely to attract a wider customer base and facilitate more frequent deliveries. On the other hand, the negative and non-significant coefficients of Retail Diversity-Concentration (RDC) (1.400 in SAR and -0.641 in SMA) imply that higher retail concentration (meaning fewer retail types or dominance of certain retail categories) may hinder parcel delivery volume. This could be due to limited shopping options, reduced consumer engagement, or accessibility challenges in concentrated retail areas, which might decrease parcel delivery. These results underscore that a diverse retail

ecosystem positively influences parcel delivery activity by fostering increased consumer engagement and logistic demand, while retail concentration may restrict delivery volume.

4.1 Discussion

Our analysis of parcel delivery patterns in Belo Horizonte reveals several key insights, many of which offer distinctive contributions to the understanding of e-commerce logistics in the Global South, moving beyond established expectations from developed country contexts. These findings underscore the critical role of spatial inequalities and urban structure in shaping delivery demand, with significant implications for urban planning and policy.

A particularly interesting finding is the significantly positive coefficient for the “food desert” variable in both SAR and SMA models. This suggests that regions characterized by limited access to physical food stores tend to experience higher delivery volumes. This result indicates a vital compensatory role for e-commerce and parcel delivery services, acting as a critical alternative addressing retail scarcity in underserved areas. This phenomenon highlights how parcel delivery can serve as a tool for social inclusion, potentially mitigating existing spatial inequalities in access to essential goods. For municipal planners and policymakers, this insight suggests that interventions in logistics should not only target efficiency but also equity. They should recognize areas with a high prevalence of food deserts as priority zones for enhanced delivery services or localized delivery hubs, potentially through policy levers like zoning adjustments or public-private partnerships. This can support vulnerable populations, leading to measurable improvements in food security and access to essential goods. Logistics providers can leverage this finding to design more equitable and socially responsible service routes, identifying new market segments while fulfilling corporate social responsibility objectives. Furthermore, community organizations in food desert areas can advocate for improved delivery access and partner with local governments and logistics firms to facilitate the establishment of community-led delivery solutions, thereby directly contributing to the enhancement of residents’ quality of life.

Conversely, while one might a priori expect informal settlements to exert a direct and significant influence on parcel delivery volumes due to inherent infrastructure challenges or lower socioeconomic status, our analysis reveals a more nuanced and less direct relationship. The “informal settlement” variable does not show a statistically significant effect on delivery volume after controlling for spatial dependence. This nuanced finding has significant implications for municipal planners and policymakers, advising against broad policies based solely on the “informal settlement” label. Instead, it calls for more granular assessments of specific needs and underlying socio-spatial factors (such as the pervasive presence of food deserts or specific retail structures) that may be more influential in shaping delivery demand within these areas. This tailored approach can lead to more effective resource allocation and the prevention of misdirected policy interventions. Logistics providers should, therefore, conduct detailed local assessments rather than relying on generalized assumptions, optimizing service design based on actual local access challenges and existing informal networks. Community organizations can play a crucial role by providing local knowledge to inform these granular assessments, ensuring that solutions are context-sensitive and effectively address local accessibility barriers, leading to services that truly meet the community’s specific demands.

The detection of significant spatial autocorrelation further reinforces the complex, interconnected nature of parcel delivery activity across neighborhoods. This result suggests that delivery dynamics in one area are influenced by neighboring areas, likely due to social networks, mobility patterns, and public policies (LeSage & Pace, 2009).

Neglecting this spatial dependence would lead to erroneous conclusions and biased interpretations of the effects of socioeconomic and infrastructure variables. By explicitly considering spatial autocorrelation through SAR and SMA models, our study provides a more precise understanding of these relationships, capturing nuances not evident in traditional regression models. This methodological advancement provides a robust framework for analyzing spatially dependent phenomena in urban studies and directly informs policy by advocating for regionally coordinated approaches to logistics optimization. For municipal planners and policymakers, this implies the need for inter-municipal cooperation and integrated urban planning strategies that consider logistics networks as regional systems rather than isolated local components, aiming for measurable improvements in overall urban mobility and service efficiency. Logistics providers can use this understanding to optimize network design, route planning, and facility location at a regional scale, potentially reducing vehicle kilometers traveled, improving efficiency, and achieving reductions in environmental impacts. Community organizations can benefit from understanding how their local delivery environment is influenced by broader regional patterns, empowering them to advocate for changes on a larger scale that benefit their members and the wider community.

Beyond these novel spatial insights, our study also reinforces the importance of other socioeconomic characteristics. Income levels show a positive and highly significant association with increased parcel delivery volumes, consistent with the literature (Beckers et al., 2018; Sousa, Oliveira, Oliveira et al., 2023; Sousa, Oliveira, Santos Junior et al., 2023). Similarly, the positive coefficients for the 25-39 age group suggest an active segment for online shopping, while the negative association for the 49-69 age group aligns with trends in e-commerce adoption among older individuals. The negative effect of distance from the CBD suggests that areas further from commercial centers face logistical barriers, highlighting the importance of urban accessibility. Regarding retail characteristics, a higher Retail Diversity-Variety positively influences parcel delivery, suggesting that diverse retail environments stimulate consumer activity. Conversely, a higher Retail Diversity-Concentration shows a negative (though not always significant) association, indicating that an over-concentration of specific retail types might hinder overall delivery volumes. These findings collectively emphasize that effective urban logistics strategies must integrate socioeconomic factors with a deep understanding of urban structure and spatial dynamics.

5 Conclusions

This research offers a distinctive and nuanced empirical analysis of parcel delivery patterns in Belo Horizonte, Brazil, significantly advancing the understanding of last-mile logistics within the rapid urbanization and persistent social inequalities characteristic of the Global South. Moving beyond conventional models of e-commerce adoption prevalent in developed contexts, our study demonstrates that economic drivers, urban structure, and particularly complex spatial dynamics fundamentally shape delivery landscapes throughout the city.

A key and novel insight is the identification of “food deserts” as a strong predictor of parcel delivery. This result challenges common assumptions and underscores a compensatory role for e-commerce and delivery services in areas lacking physical retail access, establishing parcel delivery as a vital lifeline for underserved communities and a potent tool for promoting social inclusion. Furthermore, our analysis reveals a more nuanced reality regarding informal settlements, demonstrating that their mere presence does not, in itself, directly predict delivery patterns once spatial dependencies are accounted for. This suggests that urban interventions must go beyond broad

classifications, focusing instead on underlying spatial inequalities and retail accessibility. The explicit incorporation of a spatial lens, using advanced spatial regression models (SAR and SMA), proved critical in unveiling these intricate interdependencies and providing a robust methodological framework for analyzing spatially correlated phenomena, thereby ensuring more reliable estimates and actionable insights.

These distinctive findings offer concrete and actionable lessons for a wide range of stakeholders, including planners, logistics providers, and community organizations. Firstly, for planners and policymakers, our research underscores the paramount importance of integrating granular spatial indicators into e-commerce and parcel delivery analyses to inform data-driven urban planning. This involves developing policy levers that promote equitable access to delivery services, particularly in spatially vulnerable areas, and fostering inter-municipal cooperation for regional logistics planning, with the ultimate goal of reducing spatial disparities in access to essential goods and services. Secondly, for logistics providers, the compensatory role of parcel delivery in “food deserts” suggests a clear opportunity for targeted interventions. This includes optimizing delivery routes, establishing community pick-up points, or exploring innovative delivery models in these underserved areas, which can both address social needs and potentially open new market segments, leading to measurable improvements in delivery efficiency and customer satisfaction within these communities. Thirdly, community organizations can leverage these findings to advocate for improved access to delivery services, partner with local authorities and logistics companies to co-create solutions tailored to local needs and empower residents by facilitating access to the digital economy. These applications aim to achieve measurable improvements such as a reduction in spatial inequalities in access to goods, enhanced quality of life for vulnerable populations, increased efficiency in logistics operations, and a decrease in environmental impacts from optimized delivery networks. Ultimately, the emphasis on the interplay between economic, social, and spatial factors necessitates holistic, multi-sectoral approaches for sustainable and equitable urban development, prompting all stakeholders to integrate logistics planning into broader strategies for addressing social inequality and fostering more inclusive urban environments.

As for limitations, since this study relies on data from a single delivery company (albeit a major one), it may not fully capture the entire spectrum of delivery services operating within the city. Moreover, while spatial regression models address spatial autocorrelation, they may not fully account for all potential confounding factors that influence parcel delivery demand. Despite these limitations, the study also opens several avenues for future research. Firstly, enhancing the robustness and granularity of the analysis could be achieved through the integration of additional data layers, such as detailed transportation network data (including road infrastructure quality and traffic congestion metrics) and more refined measures of digital connectivity and Internet access. Secondly, given the inherently dynamic nature of urban systems, future studies could benefit from longitudinal analysis to explore the temporal dynamics of parcel delivery demand. Third, to complement the quantitative findings, qualitative research methods, such as semi-structured interviews with residents, planners, logistics providers, and community leaders, could provide valuable insights into the behavioral and experiential dimensions of parcel delivery. Finally, comparative studies in diverse urban contexts, particularly within Latin America or other regions characterized by significant socio-economic disparities and infrastructure challenges, would allow for a more nuanced understanding of the contextual factors shaping parcel delivery patterns and inform the development of context-specific policy recommendations.

By following these future research directions, we can move toward a more comprehensive and theoretically robust understanding of urban logistics in the context of

e-commerce adoption, spatial inequalities, and sustainable urban development. This knowledge base is essential for policymakers, urban planners, and logistics providers looking to create more equitable, efficient, and environmentally responsible delivery systems in rapidly growing and increasingly complex urban environments.

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Author contribution

All authors contributed to the design and implementation of the research, the analysis of the results, and the writing of the manuscript.

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