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A big data analysis of the gender gap in mobility at the regional scale: Insights from northern Italy☆

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ABSTRACT

Understanding mobility needs and habits has long been essential for shaping sustainable and equitable transportation systems. Traditional approaches, including surveys and census data, have provided valuable insights into how diverse social groups interact with transport systems, with some attention also given to gender disparities in mobility. Recent advances in data collection, such as cell phone big data (CBD), offer new opportunities to analyze travel patterns with greater depth and granularity. Particularly, CBD enables continuous, non-intrusive data collection, allowing researchers to study mobility habits across various user attributes, including gender, and trip characteristics, such as duration and geography.

This study uses CBD to explore gendered mobility patterns in the Friuli Venezia Giulia region in Northern Italy. Employing an entropy-based approach, the research investigates systematic and non-systematic trips, focusing on gender differences in travel habits, particularly in isolated rural areas. The analysis highlights seasonal variations and contrasts between inner and denser locations, offering critical insights into the gender gap in regional mobility. By addressing these unexplored dimensions, this work contributes to the broader understanding of mobility inequities and informs policies aimed at reducing gender disparities in transport access and opportunities.

1. Introduction

Analyzing mobility needs and behaviors has been a focal point of transport research for decades. Gaining insights into the reasons underlying people's mobility choices is essential for building a more sustainable and equitable future (Bruzzone et al., 2023; Steg and Gifford, 2005). Accessibility to opportunities, alongside the availability and use of transport systems, deeply impact on individual and collective quality of life. Those facing poor access to transport and scarce residential self-selection opportunities often experience social disadvantages (Hansen, 1959; Manaugh and Geneidy, 2012; Indelicato et al., 2024). Scholars have extensively studied the intricate relationships between accessibility, transport infrastructure, mobility behaviors, and resulting disparities, highlighting how different social groups interact with mobility systems (Stanley et al., 2011; Bruzzone et al., 2023). Traditional methods -such as qualitative approaches, surveys, and statistical datasets like census records- have been fundamental for categorizing transport users and understanding their challenges, needs, and mobility habits (Indelicato et al., 2024; Nocera, 2010, 2011). Within this context, gender differences in transport have been widely explored, demonstrating distinct mobility behaviors and access to life opportunities between women and men (Gauvin et al., 2020). Alongside studies focusing on the social stratification of communities, attention has also been directed to spatial aspects, examining how people move across different territories, often looking at different patterns in urban and, less frequently, rural areas (Maeder et al., 2023).

Recently, the advent of innovative datasets has opened new research avenues to investigate mobility. GPS data and cell phone big data (CBD) are increasingly accessible, cost-effective, and simpler to analyze compared to traditional survey methods (Xiao et al., 2019; Hadachi et al., 2020). CBD often provides continuous data collection without requiring active user participation, significantly widening data availability compared to conventional samples (Schmücker and Reif, 2022). Over the past decade, the reliability and accuracy of CBD have been validated through extensive research (Nalin et al., 2024), including studies assessing gender gaps in mobility (Gauvin et al., 2020). If gender

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disparities are not fully understood by relevant organizations and policymakers, the possibility of intervening to bridge the gender gap is limited. So far, however, gender differences in mobility patterns have been peripheral focuses within studies with other priorities (Song et al., 2010). Other times, studies focusing on the gender gap are comparatively small-scale, focusing on selected social groups only (Psylla et al., 2017). Thus, despite increasing attention to the potential of CBD to investigate gender issues in mobility, several gaps remain open. Particularly in rural contexts and at regional scales, comprehensive studies explicitly addressing gender mobility gaps remain sparse (Liu et al., 2023).

This study stems from the recognition that CBD offer unprecedented opportunities for studying mobility behavior and patterns, allowing for regional-scale analyses otherwise requiring significant computational and time efforts (Qian et al., 2021; Cheng et al., 2024). It uses CBD to analyze mobility behaviors systematically, with a specific emphasis on gender differences across the Friuli Venezia Giulia (FVG) region in northern Italy. Adopting an entropy-based analytical approach, the study examines systematic (regular commuting) and non-systematic (irregular) trips, comparing gender-specific mobility patterns in both densely populated and isolated rural areas – referred to as "inner areas" at Italian national level (Presidenza del Consiglio dei Ministri, 2014).[1] The study investigates if and to what extent men and women have different mobility habits and how these vary in inner areas compared to denser locations, while also highlighting any seasonality in results. Overall, the paper provides broad insights into regional-scale gender disparities in mobility, contributing to a relatively unexplored area and identifying key factors shaping gendered mobility differences.

The remainder of this paper is structured as follows: Section 2 summarizes relevant literature about the use of CBD in mobility studies, emphasizing gender and spatial dimensions while identifying research gaps. Section 3 presents the data and method, Section 4 applies the methodology and presents relevant results, also offering a discussion of key outcomes; finally, Section 5 concludes the article.

2. Literature review

Cell phone big data (CBD) enables holistic and broad analyses of mobility behaviors with minimal time and financial investments (He et al., 2018). Although this data lacks trip motivation and transport mode information, the frequency and granularity of the dataset facilitate detailed quantitative studies. Compared to conventional datasets, such as survey-based sources, CBD provide unprecedented volume, extensive population and geographic coverage, various collection sources and data types, real-time and sufficiently long periods of data collection, as well as detailed and abundant locational and motional information (Wang et al., 2018). By representing the majority of people's daily movements, using CBD provides detailed and granular information on the travel behavior of various clusters of people, even relative to those micro-movements that a questionnaire, while specific and detailed, may not capture. Scholars have been exploiting different types of CBD, and have applied various models and methods to analyze these data. This section reviews the literature in support of the transition from statistical sources to CBD-based mobility analysis, focusing on three key areas: (1) the use of CBD in mobility studies, (2) gender and spatial disparities in mobility, and (3) the application of Shannon entropy in transportation research.

[1] : "Inner Areas" are areas at some considerable distance from hubs providing essential services (education, health, and mobility), with a wealth of key environmental and cultural resources of many different kinds, which have been subject to anthropization for centuries. Around one-quarter of Italy's population lives in these areas, which cover 60 % of the total national territory and are split into over four thousand municipalities (Presidency of the Council of Ministries of Italy, 2014).

2.1. The application of CBD in mobility studies

Several types of CBD exist, each with unique strengths and limitations. Some studies use call records (Iqbal et al., 2014), or social media and other application logins (Yue et al., 2014), relying on active user engagement. Alternatively, GPS positioning data and Wi-Fi are used in mobility studies (Alessandretti et al., 2020; Geurs et al., 2015), which require activated sensors and user permissions but no proactive input from users. A notably passive method, Cell ID positioning, generates extensive datasets by recording the physical location of devices based on the cellular towers they connect to (Calabrese et al., 2014). This method simply requires the mobile device to be switched on. The spatial resolution Cell ID data varies according to cellular tower density, ranging from coarse approximations in rural areas to finer granularity in urban settings. Combined with telecom-provided or statistical user attributes such as age, gender, or residency, Cell ID data becomes valuable for exploring demographic-specific mobility patterns, including commuting behaviors, leisure trips, and overall mobility access (Cheng et al., 2024).

While Cell ID-based CBD offer valuable analytical opportunities, concerns regarding data quality, reliability, and user privacy persist. Bwambale et al. (2019) discuss travel demand modeling while preserving user privacy and prioritizing correct data management, demonstrating the feasibility of reliable mobility analysis even with limited, anonymized sociodemographic information. Additionally, the veracity of CBD, i.e., the accuracy and trustworthiness of data, is crucial, alongside volume, variety, velocity, and value, all elements of the broader big data paradigm (Nalin et al., 2024). The pertinence of CBD to this paradigm is sometimes questioned over reliance and privacy concerns (Romanillos et al., 2016). Nevertheless, these factors are critical for ensuring robust mobility analysis and addressing ethical considerations (Wang et al., 2018).

2.2. Gender and spatial disparities in CBD mobility studies

The link between gender and mobility studies, intertwined with ethical and philosophical concepts such as mobility justice, equality, and fairness, has been the focus of numerous studies and ongoing debates, which have highlighted persistent research gaps and, at times, conflicting interpretations (Hanson, 2010). Recently, CBD has been extensively utilized to examine mobility patterns across different social groups, including gender-specific dynamics. Mobility, characterized by travel time, frequency, distance, and activity space, facilitates access to services and opportunities, thereby contributing to personal well-being (Vella-Brodrick and Stanley, 2013). However, access to mobility is often shaped by social and spatial factors, leading to disparities (Chen et al., 2023). CBD enables large-scale tracking of mobility patterns, capturing behavioral trends within realistic time and budget constraints (He et al., 2018; Wang et al., 2018).

Xiao et al. (2019) use Cell IDs to study equity in access to public services and green areas in Shanghai, China. Their findings illustrate how CBD can reveal spatially structured inequalities in the provision of opportunities among different social groups. Similarly, Pan and He (2023) apply CBD to investigate the impact of the built environment on mobility disparities among social groups in Shenzhen, China. Their review highlights that lower-income groups exhibit smaller mobility levels compared to higher-income groups, indicating a persistent mobility gap, i.e., a mobility disadvantage for certain groups or individuals, which might hinder their access to opportunities and, thus, their quality of life (Pan and He, 2023; Bruzzone et al., 2023). Their results demonstrate that marginalized groups, particularly those living in suburban areas, face greater mobility constraints. These disparities are exacerbated in outer suburban regions, where access to public transportation and essential services is more limited, contributing to reduced mobility levels (Pan and He, 2023). Overall, scholars have long called for a broad approach to gender disparities in mobility, exploring regional and socioeconomic dynamics rather than limiting the efforts to the transport domain (Cristaldi, 2005). Despite these calls and numerous recent studies employing CBD to explore mobility patterns and behavioral aspects, research focusing on mobility in rural areas, particularly at the regional scale, remains limited (Liu et al., 2023). Masso et al. (2019) investigate generational differences in mobility in Estonia using call and messaging records. They observe decreasing mobility until the age group 60–69, followed by a sudden increase in post-retirement age due to leisure trips and an active lifestyle of older generations. However, this approach may underrepresent younger generations who may rely on alternative communication methods, such as social media, rather than traditional calls and messages. Liu et al. (2023) examine rural travel patterns in China, finding that peripheral populations, including women, older individuals, and low-income groups, perform fewer short-distance trips and experience lower overall mobility rates. Their findings emphasize the mobility disadvantage faced by marginalized groups in rural contexts. Gauvin et al. (2020) focus on gender gaps in mobility at they regional scale around Santiago, Chile. They find that women visit fewer unique locations than men, resulting in more spatially localized movements and lower entropy values. Following their claims, Shannon's entropy, a fundamental measure of the dispersion and diversity of individual mobility, has proven particularly effective in capturing nuanced spatial and temporal mobility behaviors (Song et al., 2010; Gauvin et al., 2020).

2.3. Shannon's entropy in CBD mobility studies

Shannon's entropy offers valuable insights into mobility variability and predictability, although applications in rural and regional contexts remain limited. More in detail, the entropy indicator is a useful variable for measuring the diversity and regularity of people's mobility behavior. It is particularly useful for determining how many different places a person visits and how frequently they return to the same places. High entropy implies that many locations have been visited and that movements are more evenly distributed throughout the region, whereas low entropy signifies predictable, localized mobility. Shannon's entropy is also useful for comparing different mobility profiles (e.g. residents, commuters and tourists) and behaviors (e.g. repetitive trips, returners or explorers, as defined by Pappalardo et al., 2015). Additionally, the entropy measure helps evaluate predictability, which is defined as "the rate at which the value of a character in a sequence can be correctly predicted given all the preceding characters" (Gallotti et al., 2013). The more information a sequence contains, the more difficult it is to predict how it may develop. Thus, low entropy is related to high predictability and vice versa. Finally, the entropy measure captures the richness and variability of movement behavior, and it is a robust method for big data analysis (Popescu et al., 2016).

Studies have widely employed entropy measures to understand mobility patterns. Poliziani et al. (2023), for example, utilize Shannon's entropy to estimate transport demand and trip distribution in the city of Bologna, Italy, demonstrating its potential for assessing travel diversity and urban dynamics. Their work highlights how entropy can identify patterns in high-density areas, which often exhibit complex travel behaviors. In contrast, the use of Shannon's entropy in rural and regional contexts has been limited. The already mentioned study by Gauvin et al. (2020) offers one of the few examples. The study demonstrates that women exhibit lower entropy values than men, reflecting more spatially localized movements. This inequality is linked to broader socio-economic factors, such as household composition, income disparities, and transportation access. Gauvin et al.'s findings underscore the potential of entropy to analyze spatial and demographic inequalities in mobility patterns, even at the regional scale.

Building on these foundational studies, our research seeks to extend the application of Shannon's entropy to the regional scale, with a particular focus on the rural, inner areas of FVG. By adapting this method using high-frequency big data, we aim to investigate gendered mobility patterns and their determinants across more populated and inner areas. The analysis encompasses both systematic and non-systematic trips, i.e., repeated trips between OD pair, typically performed for work or study reasons, and other non-repetitive trips, respectively (Indelicato et al., 2024). This approach offers a comprehensive understanding of mobility disparities in a regional context and addresses existing gaps in the literature and designs a methodological framework for future studies on regional mobility using big data. By using Shannon's entropy, we aim to explore mobility inequality and contribute to the broader discourse on equitable access to mobility.

3. Data and method

The dataset used in this study is sourced from the "Data Analytics WindTre" (DAW) repository, a tool supporting digital transformation initiatives in the Friuli Venezia Giulia region (FVG) by providing and analyzing mobile phone antenna data. FVG, located in Northeastern Italy (Fig. 1), borders Slovenia, Austria, and the Veneto region. It has 1.2 million residents distributed across four provinces - Udine, Trieste, Pordenone, and Gorizia - and 215 municipalities (Regione FVG, 2024). WindTre holds the largest market share (23.9 %; AGICOM, 2025) for active individual SIM cards in Italy, excluding machine-to-machine SIMs (e.g., in vehicles or business devices) to ensure human mobility patterns and demographics are accurately captured. DAW provides high-frequency records (more than one per minute) of data traffic events from both Italian and foreign SIMs across all network frequencies (2G, 3G, 3G LTE, 4G, 4G LTE, 5G), offering detailed insights. As noted by Cavallo et al. (2022), telecom companies can rely on advanced data collection methods from cellular networks. DAW captures frequent SIM location updates leveraging Circuit Switched (CS) and Packet Switched (PS) technologies. Unlike CS-generated Call Detail Records (CDRs) reliant on voice calls or SMS events, PS data captures IP-based activities (internet and app use) and Cell-ID positioning from signaling interactions between devices and antennas. The combination of CS and PS ensures comprehensive data collection without requiring active user participation beyond device activation.

After the CS and PS network logs are collected, they are first elaborated by the telecommunication company. Data is aggregated, extrapolated, and calibrated through a telco proprietary calibration algorithm (Bertocchi et al., 2021), allowing to re-proportionate retrieved data to the entire phone-carrying population, and not only WindTre customers. Data is subsequently anonymized to comply with privacy regulations. To align the mobile phone data spatially, municipalities are mapped to network coverage areas. In some cases, smaller municipalities are grouped due to antenna coverage limitations, while localization in major urban centers (Trieste, Udine, Pordenone, Gorizia, Monfalcone) is refined to Census Areas (ACE), totaling 204 analytical units in FVG.

The dataset used in this study comprises all trips occurring within FVG for the entirety of 2023, explicitly excluding movements beginning or ending outside the region (e.g., neighboring regions or countries). Privacy restrictions necessitate the direct calculation of the origin-destination (OD) matrix by the telecom provider to comply with GDPR requirements (European Parliament, 2016). The authors collaborated with the telecom provider to define unique trips. In this study, a trip is concluded when a change in location is followed by at least a 30-min stay at the destination area. The choice of 2023 reflects a stabilized mobility scenario post-COVID-19 restrictions and normalization of remote working patterns (restricted by Italian regulation from September 2022; Ministero del Lavoro, 2024). Additionally, 2023 sets a solid new benchmark level for future analyses in transportation and traveling, also marking the return of tourism flows to levels comparable to 2019 ISTAT, 2024).

For all OD pairs and each day of the observation period, 3-h time intervals are extracted as follows: 0.01–3.00, 3.01–6.00, 6.01–9.00, 9.01–12.00, 12.01–15.00, 15.01–18.00, 18.01–21.00, 21.01–24.00. Moreover, trip frequency and travel duration are calculated. For each OD pair, the dataset includes: i) Breakdown by time slot; ii)

Fig. 1. Location of Friuli Venezia Giulia (FVG) Region (in the black circle) within Italy. Own elaboration.

Classification of the origin (for both Italian and foreign SIMs). For Italian SIMs, additional demographic data is inferred from contract details. The analyzed sample is representative of the characteristics of the Italian population, with limitations for the youngest age groups (18–24) who may own SIM cards in the name of other members of their household. User behavior and SIM country code allow clustering by:

- Residence location (based on nighttime cell occupancy patterns): within the origin or destination area of a trip, another area in FVG, or another Italian region;
- Gender (based on contract personal details owned by the telecommunication provider): male or female;
- Age range (contract details): 18–24, 25–34, 35–44, 45–54, 55–64, or 65+. This information is not used in the analysis because due to privacy limitations it is not possible to cross-reference it with user gender (e.g., “female under 25”);
- Nationality: Italian or foreigner (SIM country code). Foreign SIMs lack gender information, so their mobility patterns have been excluded from this analysis.

Ultimately, the dataset created for this research represents all trips performed in 2023 within FVG. A total of 439,687,220 trips are made by 86,414,223 unique travelers (SIMs active in at least one OD combination), including both Italian and foreign users. Of these, women constitute 42 % of Italian travelers, decreasing to 36.9 % among foreign nationals using Italian SIMs.

User behaviors were further classified based on trip length and origin/destination. More in detail, five user categories are created based on trips surpassing or not the provincial boundaries and starting/ending at the residential location of the user or elsewhere. Following Cavallo et al. (2022), the residential location is defined as being located within the most frequent nighttime cell occupied in the second half of 2022, i.e., in the semester preceding the period of analysis. The categories are as follows:

- Short-distance commuters (SC): users performing trips which originate or terminate at their residential location and are entirely comprised within the territory of their Province of residence;

- Long-distance commuters (LC): people moving from or to their residential location but performing a trip that surpasses Provincial boundaries within FVG;
- Intra-province travelers (ST): people moving between two municipalities inside their Province of residence, but performing trips that don't originate or terminate at their residential location;
- Intra-region travelers (LT): people moving between two municipalities that are not their residential location and at least one of which is outside their Province of residence;
- Italian travelers (IT): Italian SIM holders with residential location outside FVG, performing any trip in FVG.

This classification is assigned to each individual trip, meaning that a single person could generate different movement patterns and shift categories depending on his/her travel pattern (e.g. commuting behavior on weekday mornings and traveling during the weekend).

To expand the analysis, we introduce a further classification and analyze urban-rural mobility patterns with a focus on gender differences. We thus separate trips originating in inner areas (rural areas defined by the Italian Territorial Cohesion Agency -as described in the introduction- by limited access to essential services like healthcare, education, and mobility) from those originating in urban (i.e., non-inner) areas. In FVG, inner areas encompass 82 (Fig. 2) (Zaccomer and Bertocchi, 2022). Following previous literature, we assume that there are significant differences between mobility patterns of people living in urban and rural areas, both in figure and in distribution, and that these differences are exacerbated when analyzed for men and women separately (Milbourne and Kitchen, 2014; Balarezo et al., 2024).

In order to measure the rate and distribution of mobility generated by each type of traveler, retaining the clusters presented above, we employ an entropy index, conceptually following Section 2.3 and methodologically following Poliziani et al. (2023). In this context, the Shannon's Index assesses mobility dispersion of travelers of a certain gender and group across the 204 areas of FVG. The entropy index H is defined as:

$$H = -\sum_{i=1}^{n} \mathrm{p_i} \cdot \ln(\mathrm{p_i})$$

Where:

- n is the total number of destinations;
- p_i is the proportion of trips directed to each area i relative to total trips;
- ln is the natural logarithm, used to calculate the contribution of each destination to the entropy H.

The normalized entropy index $\overline{H}$ is computed for comparability:

$$\overline{H} = \frac{H}{log(n)}$$

Where $log(n)$ is the maximum possible entropy if movements are evenly distributed across all 204 areas.

A higher normalized entropy index $\overline{H}$ indicates greater regional distribution of movements, where users are more likely to travel to various regional destinations. A lower $\overline{H}$ shows more concentrated mobility, with more concentrated travel patterns and overall fewer unique locations visited.

To examine gender differences in mobility distribution across FVG, the normalized entropy index $\overline{H}$ was calculated separately for men and women and for each user cluster. Overall, this study uses the obtained measures as descriptive indicator of movement diversity in the region.

4. Results

This section presents the main findings, beginning with general mobility indicators (Section 4.1), followed by entropy values (Section 4.2), and concluding with an analysis of mobility in inner versus non-inner areas (Section 4.3).

4.1. Regional mobility: overview and gender gap

The data on travel patterns reveal distinct trends across traveler types created for this research, with variations in volume and timing reflecting both seasonal mobility and regional dynamics (Table 1).

Short-distance commuters (SC) and intra-province travelers (ST) generate the highest trip volumes, totaling 252 and 90 million trips per year, respectively. These trips typically include routine activities such as commuting, shopping, and recreation. Conversely, Italian travelers from outside FVG (IT) record the lowest trip counts, totaling 19 million

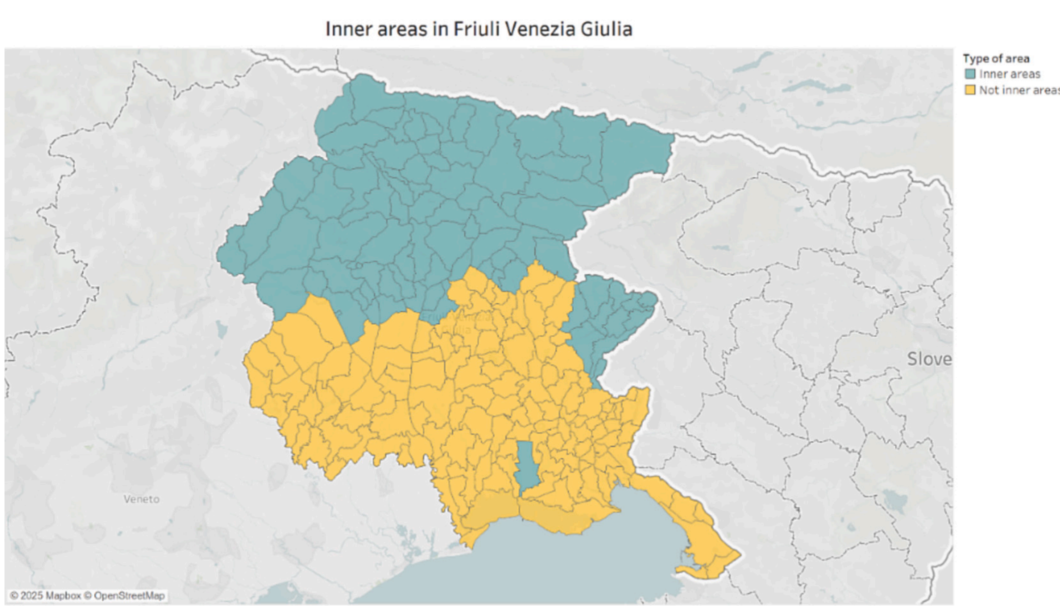

Fig. 2. Inner areas in green (more rural territories) and more urbanized areas (in yellow) in FVG, based on municipal boundaries. Own elaboration on the classification by the Italian Territorial Cohesion Agency (Presidency of the Council of the Ministries, 2014). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Trips by user cluster. Own elaboration.

User cluster	Jan 2023	Feb 2023	Mar 2023	Apr 2023	May 2023	Jun 2023	Jul 2023	Aug 2023	Sep 2023	Oct 2023	Nov 2023	Dec 2023	Total
LT	1,337,439	1,245,657	1,430,314	1,402,416	1,497,321	1,525,018	1,640,258	1,602,442	1,565,548	1,552,302	1,443,144	1,459,744	17,701,603
ST	7,012,123	6,672,631	7,665,208	7168,730	7,847,592	7,623,478	7,687,472	7,100,327	7,778,787	8,114,683	7,726,913	7,723,227	90,121,171
IT	1,346,912	1,167,773	1,347,310	1,588,431	1,662,464	1,584,550	1,873,694	2,459,927	1,642,300	1,586,876	1,412,844	1,611,624	19,284,705
SC	20,016,757	19,220,122	22,107,568	20,250,202	22,231,962	21,290,352	20,952,936	18,755,980	21,785,158	22,801,856	21,688,877	21,221,601	252,323,371
LC	3,585,351	3,413,265	3,996,189	3,840,406	4,148,739	4,177,494	4,288,200	3,948,914	4,197,828	4,170,876	3,846,568	3,792,910	47,406,740
Total	33,298,582	31,719,448	36,546,589	34,250,185	37,388,078	36,200,892	36,442,560	33,867,590	36,969,621	38,226,593	36,118,346	35,809,106	426,837,590

annually, with a notable peak in August (over 2 million trips), driven primarily by tourism, and only 1.16 million trips in February. For a deeper insight into the seasonal specificities, Fig. 3 shows the spatial distribution of destinations of all trips in August 2023. Due to the summer season, the major tourism destinations are favorite destinations (darker shades of red), for all groups, and particularly for LC (long-distance commuters), LT (extra-province travelers), and IT. These destinations include seaside municipalities such as Lignano Sabbiadoro (green dot) and Grado (yellow dot), cultural hotspots like Trieste (grey cross), and mountain destinations like Tarvisio (blue square), stressing the link of these trips with leisure reasons.

Trips of SC and ST users, in addition to seaside destination, stress the role of the regional employment centers, i.e., the urban areas of Udine, Pordenone, and Gorizia, but also major industrial centers like Monfalcone and Tolmezzo.

Expanding the perspective to year-round trends, trips by LT peak in July and August (1,640,258 and 1,602,442 trips, respectively). In contrast, ST exhibit more trips in spring and fall, peaking in October (8,114,683 trips), likely due to the resumption of work-related activities after the summer break. The SC category remains active year-round, peaking in October (22,801,856 trips), and decreasing significantly only in August due to holidays. IT show a strong seasonal trend, with a pronounced peak in August (2,459,927 trips), underscoring FVG's appeal as a tourist destination for both seaside and mountain holidays. LC exhibit similar seasonal patterns, peaking in July (4,288,200 trips) and remaining high through September, suggesting seasonal day-visitors heading to seaside or mountain locations and returning home the same day.

Gender analysis indicates that men consistently perform more trips than women across all clusters (Table 2). Overall, men account for approximately 56 % of trips, with women at 44 %, a distribution that remains stable year-round. Men particularly dominate LC, LT, and IT categories, whereas SC and ST exhibit slightly more balanced gender distributions.

Some more in-depth insights by typology of users are as follows:

- SC: women consistently account for around 45 % of total trips, while men dominate this category at approximately 54–55 %. The monthly variations are minimal;
- LC: men's mobility is noticeably higher, ranging from 56 % to 58 %, compared to women, who account for approximately 42 %–44 %. Men's share peaks in February (58.15 %), while women see a slight increase in August (43.93 %);
- ST: the distribution is slightly closer, with women contributing around 43–44 % and men at 55–56 %. Monthly changes are minor;
- LT: men dominate this category, consistently contributing 58–60 %, while women remain in the range of 39–42 %. The largest disparity appears in February (39.07 % women, 60.93 % men);
- IT: in this category, the gender gap is more noticeable in comparison to other categories; men have the highest share ranging from 56 % to 65 %, and women account for 35–40 %.

4.2. Gender mobility and distribution: regional overview

The study proceeds with understanding the distribution of users in the territories and the mobility rate per gender. Entropy indices, particularly Shannon's entropy, are established measures of mobility distribution, able to describe the heterogeneity in the distribution for different clusters as, in this research, gender and type of mobility. Following section 3, both the Shannon's index H and its normalized entropy index $\overline{H}$ has been calculated on the OD matrix per user cluster and gender. A seasonal in-depth analysis on every single month and by every single group of travelers has been developed with the scope to underline gender differences in regional mobility in terms of distribution (number of destinations reached).

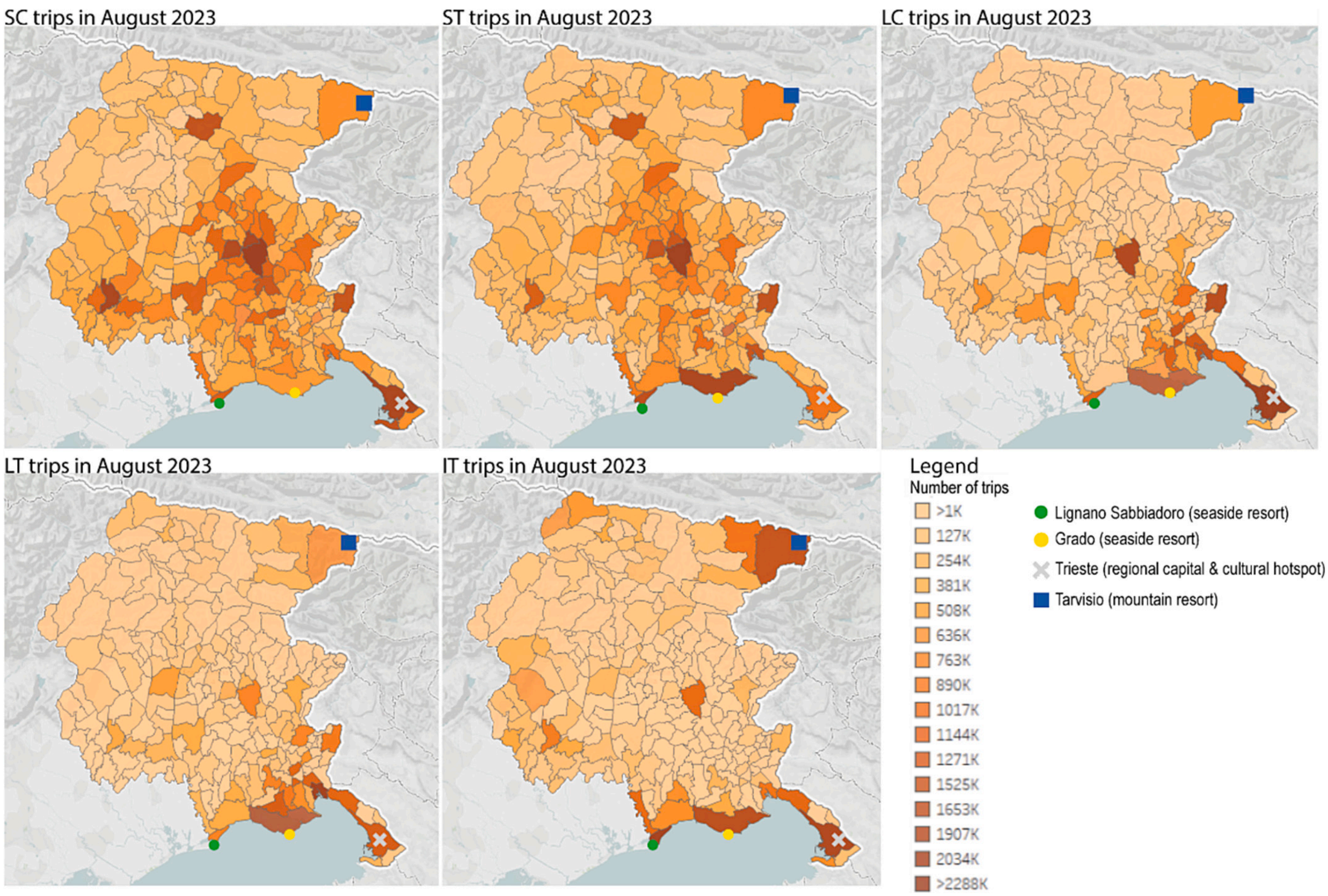

Fig. 3. Trips by user cluster and destination in August 2023. Own elaboration.

Table 3 presents the results of the entropy analysis, disaggregated by gender and traveler type. The table reports the Shannon's index (calculated using the *entropyetc* function in STATA) alongside standard errors and bootstrap-derived 95 % confidence intervals. Overall, the analysis reveals minimal gender-based differences in mobility dispersion across all traveler categories. In every case, the confidence intervals for male and female travelers substantially overlap, indicating that the observed differences in entropy values are not statistically meaningful. The highest entropy values are recorded among intra-province travelers (ST) for both genders, reflecting a high degree of variability in destination choices within the same province. In contrast, long-distance commuters (LC) show the lowest entropy scores, suggesting more spatially concentrated movement patterns. The consistent overlap in confidence intervals across all traveler types reinforces the interpretation that gender is not a determining factor in the degree of spatial dispersion in this dataset. For this reason, the analysis was extended by calculating the entropy index on a monthly basis, in order to explore potential temporal variations in mobility behavior more accurately.

Monthly entropy analysis (Fig. 4) shows slight but consistent differences between genders, with men generally displaying higher spatial dispersion. Entropy values peak in August, indicating greater travel diversity during summer holidays, particularly notable among ST, LT and IT groups. In LC, both genders show the lowest entropy values, indicating limited territorial distribution compared to other mobility types. However, women's entropy values are slightly higher during the first two months of the year, exacerbating a trend that show men and women values much closer together in the winter for all groups. Cluster-specific entropy values (Table 4) reinforce these observations. In the SC cluster, the entropy values are nearly identical for both genders, suggesting similar degrees of territorial distribution for short-distance travel. Women's entropy values range from 0.0222 in November to 0.0228 in August, with a slight increase during the summer months. Men's entropy follows a similar pattern, ranging from 0.0223 in November to 0.0229 in August. In LC, both genders show the lowest entropy, with women's values ranging from 0.0198 (October) to 0.0203 (January and August) and men's values slightly higher, ranging from 0.0199 (October) to 0.0204 (August). In ST, entropy values are higher, with women's values ranging from 0.0230 to 0.0238, peaking in August, while men's values range from 0.0233 to 0.0239. In LT, women's entropy values range from 0.0212 (June) to 0.0232 (August), with a dip in summer followed by an increase toward the end of the year, while men show a slightly broader territorial distribution, ranging from 0.0215 in June to 0.0233 in August. In IT, women's entropy values range from 0.0219 in May to 0.0232 in August, with a noticeable increase in the summer months due to holiday travel, mirroring the trend in men's entropy values (0.0221–0.0233).

4.3. *Insights on inner and non-inner areas*

Mobility analyses from inner (rural) versus non-inner (urban) areas reveal distinct patterns. Men perform approximately 55 % of trips from both inner and non-inner areas (Table 5), consistently outnumbering women's trips across most OD pairs.

Figure 5 graphically illustrates the difference between the total trips made by women and those made by men, originating from internal or non-internal areas and directed toward any FVG destination, indicated by dots. This representation provides a measure of the prevalence of trips made by women (dark yellow shade) or by men (dark blue). Both maps use the full color scale, but it is important to note that the prevalence ratio is different. For trips starting from inner areas (right side),

Table 2
Gender distribution of number of trips (OD) in FVG (percentage; clustered by user groups). Own elaboration.

User type	Jan		Feb		Mar		Apr		May		Jun	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
SC	45.46	54.54	45.16	54.84	45.34	54.66	45.39	54.61	45.33	54.67	45.29	54.71
LC	42.48	57.52	41.85	58.15	41.95	58.05	43.09	56.91	42.30	57.70	42.82	57.18
ST	44.00	56.00	43.59	56.41	43.89	56.11	44.30	55.70	44.07	55.93	44.05	55.95
LT	39.97	60.03	39.07	60.93	39.34	60.66	41.09	58.91	39.67	60.33	40.60	59.40
IT	38.10	61.90	36.37	63.63	35.90	64.10	40.26	59.74	35.39	64.61	38.23	61.77
Total	44.36	55.64	43.97	56.03	44.15	55.85	44.51	55.49	44.13	55.87	44.29	55.71

User type	Jul		Aug		Sep		Oct		Nov		Dec	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
SC	45.01	54.99	45.38	54.62	45.32	54.68	45.40	54.60	45.18	54.82	45.59	54.41
LC	43.27	56.73	43.93	56.07	42.89	57.11	42.21	57.79	41.80	58.20	42.62	57.38
ST	43.66	56.34	44.16	55.84	43.96	56.04	44.14	55.86	44.02	55.98	44.48	55.52
LT	41.49	58.51	42.55	57.45	40.59	59.41	39.93	60.07	39.56	60.44	41.18	58.82
IT	40.40	59.60	43.82	56.18	38.22	61.78	35.89	64.11	35.01	64.99	38.66	61.34
Total	44.15	55.85	44.71	55.29	44.29	55.71	44.21	55.79	44.00	56.00	44.57	55.43

the extremes of the color scale are [−9.032;121.387]. An even more disproportionate situation is observed for trips around FVG from non-inner areas: in this case, the extremes of the color scale are [−51.100;703.561].

Entropy values (index $\overline{H}$) further highlight territorial disparities, non-inner areas consistently exhibit higher entropy, indicating broader territorial dispersion (Fig. 6). In inner areas, women's entropy values range from 0.0204 in November to 0.0215 in August, while men's range from 0.0211 to 0.0220. In contrast, non-inner areas show higher values for both genders and a smaller gender gap, with women's values peaking at 0.0220 and men's at 0.0225 during the summer months. Thus, the differences between inner and non-inner areas are more consistent for women especially in the first (January, February and March) and last months (October and November) of the year, while men's mobility is less penalized by residency in inner areas.

Besides the spatial dispersion of destinations in inner and non-inner areas, Table 6 reveals overlapping confidence intervals, implying that the gender differences are statistically indistinguishable. However, the most pronounced contrast is observed between area types, where non-overlapping confidence intervals suggest a statistically significant difference in mobility dispersion between inner and non-inner areas, regardless of gender.

4.4. Discussion of results

Overall, our main findings show that men consistently exhibit higher entropy values than women, reflecting a broader range of daily activities and travels. In contrast, women tend to visit fewer, more predictable locations. These results align with prior studies (Gauvin et al., 2020; Liu et al., 2023; Polizиani et al., 2023), and hold true across all user categories analyzed, reinforcing that the gender gap in mobility is a structural feature of the system, independent of geographical context or scale. Specifically, SC and ST show the highest entropy values, with men's and women's scores ranging from 0.0223 to 0.0234, and from 0.0222 to 0.023, respectively, peaking at 0.0229–0.0239 for men and 0.0228–0.0238 for women. Notably, this gender divide narrows slightly during the summer months, especially in August, when entropy peaks (Fig. 5, above).

Short-distance travelers within their province (ST) are the most dynamic, visiting a wide range of locations. In the summer, this expands further as people take advantage of outdoor opportunities, particularly in regions like FVG, where three out of four provinces feature seaside destinations and two offer mountain resorts. On the other hand, LC users, who travel outside their province but return the same day, exhibit the lowest entropy levels (0.0198 for women and 0.0204 for men). For LC, contrary to ST, the gender gap is most prominent in the summer, with men showing more diverse travel patterns, while in fall, the gap diminishes, and by winter, women's entropy slightly surpasses men's. This could be due to seasonal shifts that encourage more localized mobility, with women possibly engaging in more trips within familiar areas during colder months.

Entropy in the summertime is overall higher for both genders, reaching 0.0233 for men and 0.0232 for women, compared to October values as low as 0.0199 and 0.0198 respectively. Men and women Moreover, for SC and IT, the gender gap in entropy drops during the summer, with almost equal values, contrasting with the fall and spring, when the gap is exacerbated (Fig. 3 and Table 3). This trend also holds for ST — those traveling outside their province but not to/from home — the category with the widest entropy gap, where women show a more localized travel pattern, particularly in peak tourist months. The narrowing of the gender gap in the winter months further supports the idea that both genders engage in similar local travel behaviors during colder periods, when travel is less reliant on long-distance or leisure trips.

The main getaway when looking at gender entropy in inner areas versus more accessible municipalities (Figs. 4 and 5) is that despite

Table 3
Entropy levels per gender and type of traveler for 2023. Own elaboration.

User type	Shannon (Female)	Standard Error (Female)	CI 95 % lower (Female)	CI 95 % Upper (Female)	Shannon (Male)	Standard Error (Male)	CI 95 % lower (Male)	CI 95 % Upper (Male)
ST	4.751	0.1026	4.537	4.92	4.788	0.0957	4.586	4.944
LT	4.615	0.0664	4.478	4.75	4.644	0.0728	4.499	4.785
IT	4.63	0.0991	4.446	4.835	4.654	0.0929	4.479	4.841
LC	4.1	0.1304	3.844	4.355	4.125	0.1497	3.838	4.426
SC	4.57	0.1307	4.319	4.804	4.584	0.1239	4.343	4.807

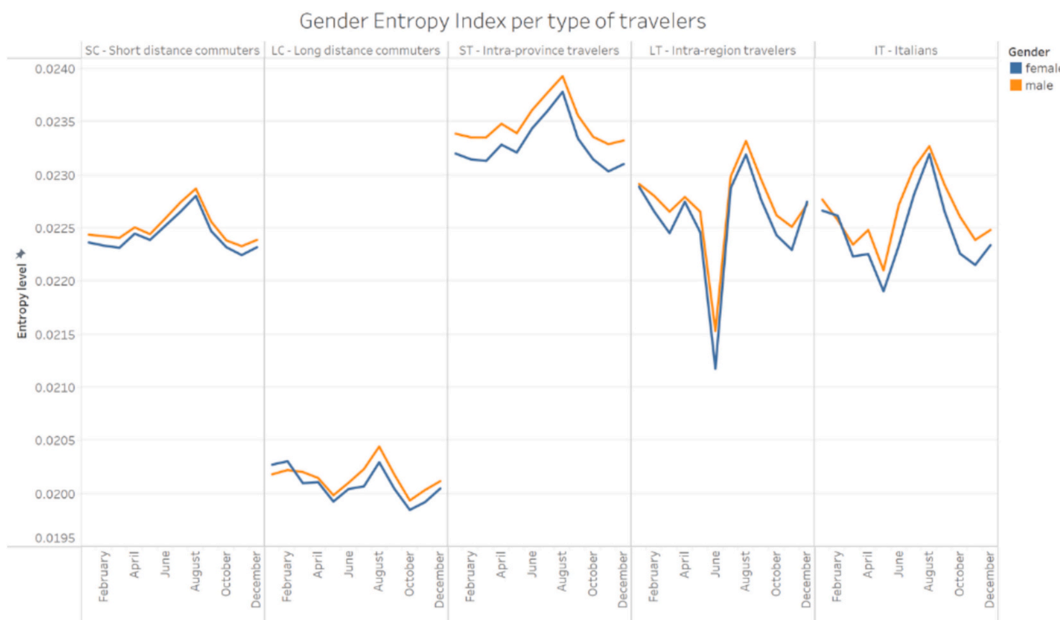

Fig. 4. Gender levels of mobility distribution (normalized entropy index $\overline{H}$) between types of travelers at the monthly level. CDB for the Year 2023. Own elaboration.

Table 4
Normalized entropy index $\overline{H}$ by gender and cluster. Own elaboration.

Gender	User type	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	ST	0.0232	0.0231	0.0231	0.0233	0.0232	0.0234	0.0236	0.0238	0.0233	0.0231	0.0230	0.0231
	LT	0.0229	0.0227	0.0225	0.0227	0.0225	0.0212	0.0229	0.0232	0.0228	0.0224	0.0223	0.0227
Female	IT	0.0227	0.0226	0.0222	0.0223	0.0219	0.0223	0.0228	0.0232	0.0227	0.0223	0.0222	0.0223
	LC	0.0203	0.0203	0.0201	0.0201	0.0199	0.0200	0.0201	0.0203	0.0200	0.0198	0.0199	0.0200
	SC	0.0224	0.0223	0.0223	0.0224	0.0224	0.0225	0.0227	0.0228	0.0225	0.0223	0.0222	0.0223
	ST	0.0234	0.0234	0.0234	0.0235	0.0234	0.0236	0.0238	0.0239	0.0236	0.0234	0.0233	0.0233
	LT	0.0229	0.0228	0.0227	0.0228	0.0227	0.0215	0.023	0.0233	0.0230	0.0226	0.0225	0.0227
Male	IT	0.0228	0.0226	0.0223	0.0225	0.0221	0.0227	0.0231	0.0233	0.0229	0.0226	0.0224	0.0225
	LC	0.0202	0.0202	0.0202	0.0201	0.0200	0.0201	0.0202	0.0204	0.0202	0.0199	0.0200	0.0201
	SC	0.0224	0.0224	0.0224	0.0225	0.0224	0.0226	0.0227	0.0229	0.0226	0.0224	0.0223	0.0224

Table 5
Trips originating from people living in inner and non-inner areas. Own elaboration.

From	Women	(%)	Men	(%)
Inner areas	6,168,100	44.6	7,660,457	55.4
Non-inner areas	47,958,859	44.9	58,757,365	55.0
Total	54,126,959	44.9	66,417,822	55.1

similar entropy levels and distribution throughout the year, the gap between men and women in inner areas is significantly wider, with women again showing lower values. This suggests that it is women that pay the most the toll of isolation and poor connection to services, by drastically reducing -compared to men individuals- the number of visited locations throughout the year, particularly in the winter months.

5. Conclusions

This study provides a comprehensive analysis of gender disparities in mobility patterns at the regional scale in Northern Italy, using cell phone big data (CBD) to examine systemic differences in travel behaviors between men and women. The findings reveal that men consistently exhibit higher entropy values, reflecting a broader range of daily activities and more diverse travel destinations. In contrast, women exhibit more localized and predictable mobility patterns. These disparities persist across all user categories, highlighting the structural nature of the gender gap in mobility, regardless of geographic or temporal context.

Among the categories analyzed, short-distance travelers (ST) emerge

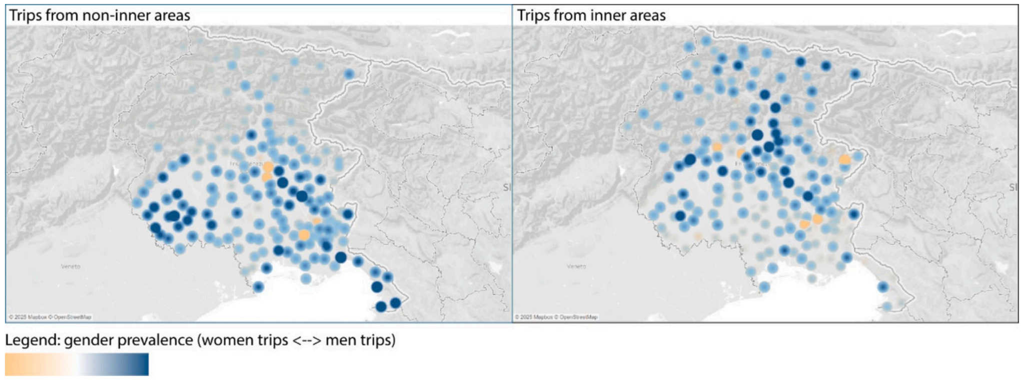

Fig. 5. Gender prevalence in trips from inner and non-inner areas. Own elaboration on DAW 2023 data.

Fig. 6. Gender levels of monthly mobility distribution (normalized entropy index $\overline{H}$) between users living in inner or non-inner areas. Year 2023. Own elaboration.

Table 6
Shannon index values and intervals of confidence by gender and inner or non-inner area. Own elaboration.

Gender	Area type	Shannon	CI 95 % lower	CI 95 % Upper
Female	Non-inner areas	73,474	71,687	75,134
	Inner areas	64,608	63,148	65,987
Male	Non-inner areas	74,525	72,714	76,214
	Inner areas	66,371	64,980	67,649

as the most dynamic group, particularly in summer, influenced by increased outdoor recreational opportunities in regions like Friuli Venezia Giulia. Conversely, long-distance commuters (LC) showed the lowest entropy levels, reflecting more spatially concentrated travel patterns. Seasonal influences significantly affect these patterns, narrowing the gender gap during winter months when travel behaviors become more localized and homogeneous across genders.

A notable finding is the pronounced gender mobility gap in inner areas, where women's mobility is disproportionately affected by isolation and limited access to services. This disparity highlights the challenges faced by women in these areas, who tend to visit fewer locations compared to men, especially during winter months. These patterns underscore the structural challenges women face in maintaining diverse mobility in contexts of limited connectivity and accessibility.

The results can inform policymaking and lead to important policy implications. Addressing the gender gap in mobility requires a holistic approach that integrates structural and seasonal factors. This would facilitate a deeper understanding of how societal norms and spatial elements shape mobility access and disparities, ultimately contributing to the nuanced discussion about transport equity and positively impacting policymaking. Although deeper analyses on trip purpose and mode choice would be needed to complement our results, monitoring gender disparities in regional mobility using data-driven approaches – one of the key goals of this research- can help assess the effectiveness of interventions and guide future policies. Future research could integrate CBD mobility analyses with mode-specific studies, as well as with territorial analyses exploring the interrelations between built environment, social structure, and mobility systems. This would allow to expand the qualitative framework understanding whether performing "more" mobility, measured through Shannon's entropy, corresponds to more, better life opportunities or rather reflects the need to support one's needs with significant efforts, thus enhancing policymaking and mobility-related interventions to foster people's well-being. Enhancing the viability of collective transport as a way to reach daily needs and improve social inclusion could be an effective first step to reduce the gender gap, particularly in inner areas where options and opportunities are limited (Bruzzone et al., 2025).

The study acknowledges certain limitations, notably the exclusion of trips with origin or destination outside FVG due to data constraints. Additionally, user and trip classification were limited in granularity to protect user privacy, potentially overlooking nuances such as exact trip purposes and home locations. Despite these limitations, the approach ensures robust insights as well as extreme consciousness of user privacy and data management issues affecting CBD. The coarse classification and the use of Shannon's entropy index help, in this sense, in limiting the rise of privacy concerns due to the intrinsic nature of CBD.

Future research paths can improve the granularity of the analysis by focusing on trip distance, systematic movements, and sub-area trips (e.g., mobility to/from mountain areas or large attractors, such as shopping districts). Moreover, future research could refine trip classification methods, integrating additional socio-demographic variables (e.g., age, nationality) to better capture the complexity of mobility patterns. Finally, better territorial and mobility analyses could support the discussion of any phenomenon of forced mobility, challenging the idea that more mobility equals more freedom of choice and better opportunities, as well as gaining behavioral insights into the gender gap in modal choice, a key topic for informed and gender-equal planning and policymaking (Bruzzone et al., 2021).

Starting from the findings presented here, local authorities and policymakers can develop targeted interventions to optimize transport modes, infrastructure, and regulatory frameworks. These efforts should aim to deliver a more inclusive and equitable mobility environment, effectively addressing gender-specific mobility needs and promoting broader social inclusion.

CRediT authorship contribution statement

Dario Bertocchi: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Francesco Bruzzone:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Silvio Nocera:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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