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ORIGINAL RESEARCH

Analyzing Census data for patterns of mobility inequity: gender, geography, and public policy in India

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Abstract
We study gender- and residence-based inequities in travel mobility across India using the 2011 Census—the country's largest household travel dataset, covering over 200 million person-trips across 35 states and union territories. For each state and for four Census-defined groups (rural male, urban male, rural female, urban female), we estimate empirical survival functions for trip distance (probability of traveling at least x kilometers) via non-linear least squares and summarize expected trip lengths via the conditional mean up to a 50 kilometer cutoff. Nationally, rural males consistently travel farther than urban males, whereas urban females travel farther than rural females; these orderings persist across policy-relevant thresholds (5, 10, 20 kms). Inter-state variation is marked, e.g., short-distance mobility for rural males is much lower in Punjab than in Nagaland suggesting state-tailored transportation policies. Our results also indicate substantial constraints on rural female mobility. We translate these findings into data-informed guidance for facility siting and transport improvements, emphasizing state-specific targeting and near-access enhancements. The framework provides a scalable basis for macroscopic mobility analysis in India and supports progress towards Sustainable Development Goals 5 (Gender Equality) and 11 (Sustainable Cities and Communities).

Keywords Indian Census · Travel mobility inequity · Gender disparity · Rural–urban mobility · Public policy · Sustainable development goals

1 Introduction

The 2011 Census of India introduced a groundbreaking dataset on household travel patterns, collecting modes and distances traveled by gender and geographic location (Office of the Registrar General & Census Commissioner, 2024). Despite its unprecedented scale and public availability, this dataset remains underutilized. Most existing studies on Indian

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mobility focus on urban settings or rely on qualitative data leaving a major gap in large-scale quantitative analyses that is essential for evidence-based transport policy. We address this gap by modeling macroscopic mobility patterns and quantifying travel disparities across India's administrative regions. Our work's relevance extends to broader global challenges, such as achieving equitable access to infrastructure under the United Nations Sustainable Development Goals (SDGs). Specifically, improved accessibility is reflected in SDG 2 via increased access to food and in SDG 3 via increased access to sexual healthcare.

The Census data includes a total of 200, 408, 230 person-trips nationwide, split across the then 28 states and seven union territories of India. This number represents almost 16% of the total population of India in 2011, and is likely the largest household survey data available in India till date. For global comparison, the US National Household Travel Survey data of 2009 included only 330, 000 person-trips U.S. Department of Transportation (2009); i.e., less than 0.2% of the person-trips in the Census. The Census data also introduced two critical demographic dimensions: (a) gender, and (b) rural/urban classification of residence. Despite the public availability of these components, systematic analysis of gendered and geographic mobility patterns remains scarce, see, e.g., Goel (2018); Singh (2017). Existing research on disparity and inequity in travel patterns in India is largely restricted at the micro-geographic or city-level studies, see, e.g., Goswami et al. (2015); Mahadevia and Advani (2016); Page (2015); Srinivasan (2004). Thus, travel patterns of the general population (i.e., at the macroscopic level) of India or its different states—that are vital for reforming and updating socioeconomic transportation policy—remain poorly understood (Singh, 2017).

We fill this gap via empirical modeling that answers a simple but fundamental question: how likely is a population group in India to travel a particular distance away from home? We analyze four population groups defined in the Census: (i) rural males, (ii) urban males, (iii) rural females, and (iv) urban females. Although past studies have revealed disparity in travel patterns of these population groups (Mahadevia & Advani, 2016; Page, 2015; Srinivasan, 2004), such disparity is not quantified.

However, quantifying such disparities is critical for policy design. Excessive travel distance directly constrains access to essential services (e.g., healthcare, education, and employment) for particular target groups. Even in developed countries, inequity in accessibility remains, e.g., a previous study finds almost 24% of American Indian women were without access to a physician within 100 miles (Desjardins et al., 2020). In India, these disparities are far more acute. The World Health Organization (WHO) has long focused on providing increased access to rural healthcare facilities in India (World Health Organization, 2024). In 2022, the under-5 mortality in India was 29 per 1, 000 live births (World Bank Group, 2024); although this number has improved since 2015, there are strong inequities between rural and urban regions (Ministry of Health and Family Welfare, 2022). It is even predicted that although India might achieve the overall 2030 UN maternal mortality ratio goals, it is unlikely that the poorer states would also do so unless "further intervention" is sought (Meh et al., 2021). A key reason for such marked inequity is the unbalanced access to healthcare facilities in India: rural and semi-urban populations are forced to travel to hospitals in urban areas even for routine checkups (Potnuru, 2019). Yet, the extent of such travel inequities has not been measured empirically leaving policymakers to act on speculative judgment rather than evidence.

Transport accessibility is particularly consequential in the context of female reproductive health. In a landmark ruling in late 2022, the Indian Supreme Court defined access to abortion services as an individual's fundamental right (Jain, 2023). Although "easy" access to abortion facilities is mandated in almost all Indian states since 1972 via the Medical Termination of Pregnancy Act (Khan et al., 2001), accessibility for women to maternity hospitals continues to remain low (Adamson et al., 2012; Kumar & Dansereau, 2014). This mismatch between governmental initiatives and successful deployment has tragic consequences, e.g., nearly eight women die daily in India due to unsafe abortion practices (Malik et al., 2023) with disproportionately higher risk of engaging in unsafe practices in rural areas (Yokoe et al., 2019). Over 60% of India's population lives in rural areas; thus, improved transportation infrastructure is not simply a socioeconomic concern but also a determinant of survival.

Comparable international contexts show that evidence-backed preferential infrastructure policies can indeed reduce inequities. For example, a retrospective study of antiviral dispensing locations in Texas, US for the 2009 H1N1 pandemic prioritizes a policy of maximizing coverage in smaller ZIP codes before proceeding to larger ones (Schmidt & Singh, 2024). A similar policy is proposed in Bavaria, Germany for closures of recycling centers, with a preferential priority to keep centers open in rural areas (Singh et al., 2015). Both these studies include models to measure the population's mobility patterns. Such preferential measures, although discussed, have not been implemented in India (Potnuru, 2019). Our work provides such data-driven evidence, offering empirical guidance to support equitable infrastructure and healthcare planning.

The structure of the rest of this article is as follows. Section 2 presents our mathematical models for the four population groups. In Section 3, we analyze these and discuss their implications for public policy in India. We summarize and provide concluding remarks in Sect. 4. We provide additional figures in the Online Appendix.

2 Mathematical methods

We employ an empirical travel model by fitting a continuous function to the discrete data obtained from the Census. This approach draws inspiration from a previously established willingness-to-travel model, which estimated the probability of individuals traveling a minimum distance to access antiviral medications during an influenza pandemic (Singh et al., 2015). Originally developed for underserved populations in Texas, this model provides valuable insights into accessibility challenges. Subsequent adaptations extend its application to analyze travel patterns for accessing postal services in the United States (Singh et al., 2021). By leveraging this established methodology, we aim to address similar challenges in understanding mobility patterns within the Indian context, ensuring that the model aligns with the characteristics of the Census data.

The Census data was collected for the following one-way trip lengths between home and place of work: (i) 0–1 km, (ii) 2–5 km, (iii) 6–10 km, (iv) 11–20 km, (v) 21–30 km, (vi) 31–50, (vii) 51+ km, (viii) no travel, (ix) distance not stated. The "no travel" category includes person-trips where a person works from home. Since the Census was conducted prior to the COVID-19 pandemic, the number of such person-trips is small. For the purposes of our analysis, we remove the two categories of "no travel" and "distance not stated"; i.e., we effectively remove 0.65% and 1.74% of the total person-trips, respectively.

India defines urban areas comprising of either (i) statutory towns, which are administrative units designated as urban (e.g., Municipal Corporation, Municipality, Cantonment

Board, Notified Town Area Committee, Town Panchayat, and Nagar Palika), or (ii) Census Towns, which simultaneously meet three criteria: (a) minimum population of 5,000, (b) at least 75% of the male main working population engaged in non-agricultural pursuits, and (c) population density exceeding 400 persons per square km. Rural areas are any administrative areas not classified as urban. For a discussion on the problems with this classification, see (Ravi, 2023).

Further, the Census data is not representative of the entire population of India as it includes trips solely for the means of employment; i.e., between the respondent's place of residence and place of work. The Census classified travel based on the following ten modes: (i) foot, (ii) bicycle, (iii) moped/scooter/motorcycle, (iv) car/jeep/van, (v) tempo/ autorickshaw/ taxi, (vi) bus, (vii) train, (viii) water transport, (ix) any other, and (x) no travel. The Census collected this data from a population group it calls as "Other Workers"; this includes people working in jobs other than cultivation, agriculture labor, or a household-based industry. For details on this classification, see (Goel, 2018; Office of the Registrar General & Census Commissioner, 2024). Although the Census data is collected for travel to work rather than travel for any purpose, commuting for work is the most consistent and regular form of population mobility (Rosenbloom, 2006). Since the same transport networks (e.g., roads) support access to healthcare and education, the disparities revealed in worker travel patterns provide credible conservative estimates of broader accessibility inequities that affect non-workers as well. Next, we describe our modeling framework.

Indices/ Sets

$i \in I$ Index set for distance bins

Parameters

d_i Left endpoint of bin *i* [km]

p_i Number of person-trips in bin *i* [integer]

P(*x*) Fraction of target population traveling at least *x* km [$0 \leq P \leq 1$].

We let $I = \{1, 2, 3, 4, 5, 6, 7\}$ denote the seven bins available in the Census data. These denote the following distances: (i) 0–1 km, (ii) 2–5 km, (iii) 6–10 km, (iv) 11–20 km, (v) 21–30 km, (vi) 31–50 km, and (vii) 51+ km, respectively. Let d_i be the left endpoint of bin *i* (i.e., $d_1 = 0$, $d_2 = 2$, ..., $d_7 = 51$), and let p_i be the number of trips in bin *i*. Then, an empirical tail estimate of the fraction of the target population traveling a distance of at least d_i km is:

$$\hat{P}(d_i) = \frac{\sum_{j \geq i} p_j}{\sum_{j \in I} p_j}, \quad \forall i \in I. \tag{1}$$

The denominator in Eq. (1) is the total number of person-trips of the target population. To evaluate mobility for any distance $x \geq 0$ (i.e., not just restricted to the bin cut-points), consider the following spatial mobility model of traveling at least *x* km:

$$P(x) = 1 - A\Big(1 - \exp(-\alpha x^{\beta})\Big), \quad \forall x \geq 0, \tag{2}$$

where parameters, $A \in (0, 1), \alpha > 0, \beta > 0$. In model (2), $P(0) = 1$ and *P*(*x*) is decreasing in *x*. Setting $A = 1$ provides a standard Weibull distribution. The tail model *P*(*x*) is analogous to the empirical quantity in Eq. (1); both represent $\Pr\{X \geq x\}$ (i.e., the probability of traveling at least x km), both decrease with x, and satisfy $P(0) = \hat{P}(0) = 1$. Such decaying exponential functions, inspired by statistical mechanics, are standard for modeling human mobility, see, e.g., Kölbl and Helbing (2003); Riccardo et al. (2012).

We determine the three parameters of Eq. (2) by a nonlinear least-squares fit using the seven points $d_i, i \in I$. Then, we obtain the following fitted tails for the four Census groups.

$$P(x) = \begin{cases} 0.921 \exp(-0.134x^{0.958}) + 0.079; & \text{rural male} \\ 0.967 \exp(-0.283x^{0.856}) + 0.033; & \text{rural female} \\ 0.946 \exp(-0.146x^{1.046}) + 0.054; & \text{urban male} \\ 0.963 \exp(-0.191x^{0.961}) + 0.037; & \text{urban female} \end{cases} \tag{3}$$

For all the four models in equation (3), the degrees-of-freedom adjusted R^2 values exceed 0.997 and the sum of squares due to error is smaller than 0.2% suggesting suitable fits. Both rural models perform slightly better than their urban counterparts, with a lower root mean squared error (RMSE), mean absolute error (MAE), and and Theil's U-statistic, suggesting a better accuracy in capturing rural travel behavior; here, we compute the errors as the difference of the empirical and fit probabilities. Similarly, model selection criteria (AIC and BIC) further confirm a marginally superior fit for rural models, with lower values compared to urban counterparts. All errors are small; e.g., for females, rural models exhibit an RMSE of 0.0095 and MAE of 0.0073 compared to 0.0115 and 0.0088 for urban models.

Figure 1 provides a plot of the four models in Eq. (3) that we analyze in Sect. 3. Since the exponential terms decay rapidly, for distances beyond 51 km (i.e., the left endpoint of the last bin) $P(x)$ approaches its asymptote $1 - A$. This quantity equals: 7.9% (rural male), 3.3% (rural female), 5.4% (urban male), and 3.7% (urban female). Thus, beyond ≈ 50 km the model differentiates groups primarily through their asymptotes. The truncated expected travel distance over $(0, \bar{x})$ follows by integrating Eq. (2).

$$\mathbb{E}[X \mid X \leq \bar{x}] = \frac{\displaystyle\int_0^{\bar{x}} P(x)\, dx \;-\; \bar{x}\, P(\bar{x})}{1 - P(\bar{x})} \tag{4a}$$

$$= \frac{\dfrac{1}{\beta}\, \alpha^{-1/\beta}\, \gamma\!\left(\dfrac{1}{\beta},\, \alpha\, \bar{x}^{\beta}\right) \;-\; \bar{x}\, e^{-\alpha\, \bar{x}^{\beta}}}{1 - e^{-\alpha\, \bar{x}^{\beta}}}. \tag{4b}$$

Equation (4) provides the average trip length among trips not exceeding $\bar{x}$ km, and is independent of A. Here, $\gamma(s, z) = \int_0^z t^{s-1} e^{-t} dt$ denotes the lower incomplete gamma function.

We also separately fit analogous models for the 35 states and union territories reported in the 2011 Census. At the time of publication of this article, there are 28 states and eight union territories in India; the next Census is planned for 2027. For the corresponding plots and tables of (i) $P(x)$ values by sex and (ii) estimated coefficients of (2), see the Appendix.

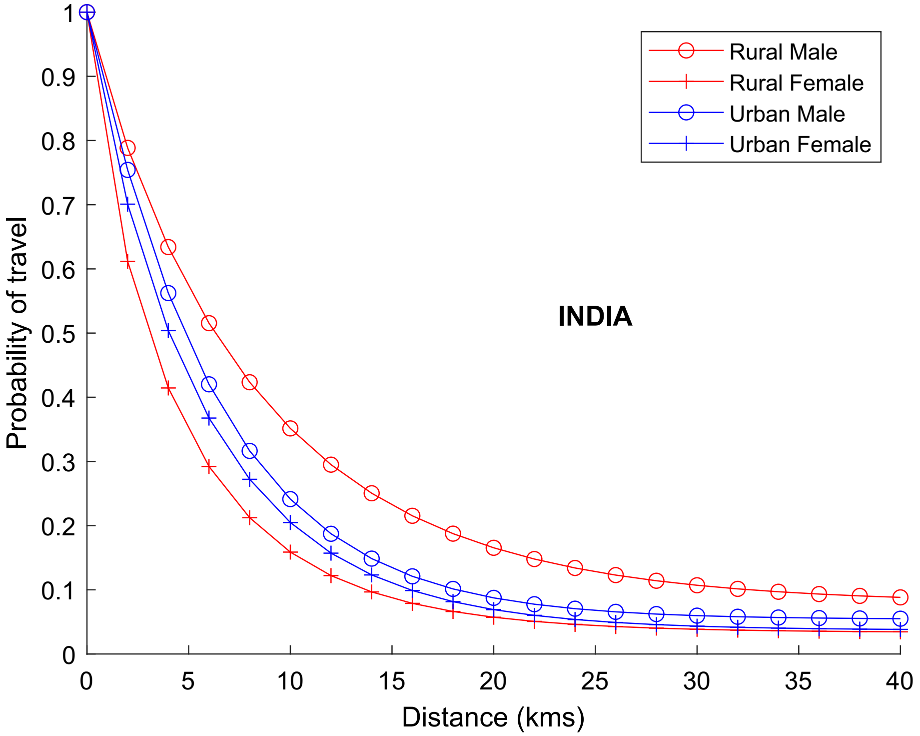


Fig. 1 Mobility models for the four population groups in the 2011 Census of India. The plots indicate the probability of traveling (y-axis) at least some distance (x-axis) away from home. See Eq. (3) for details

3 Impact on public policy

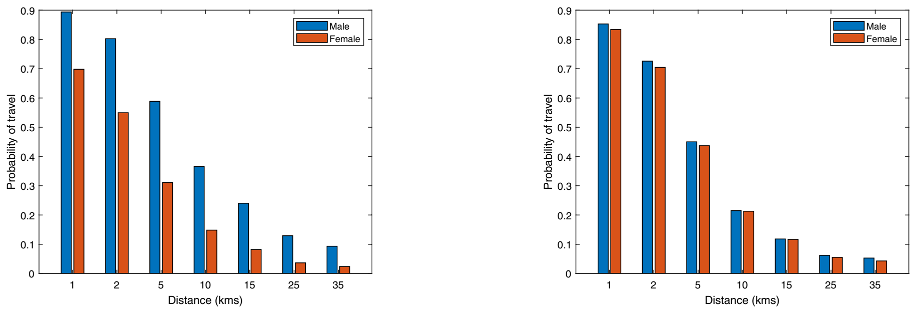
Figure 1 quantifies disparities in travel patterns across population groups by comparing the fraction (on the y-axis) traveling at least a given distance (on the x-axis). Two trends emerge: (a) rural males have the highest likelihood of traveling any given distance, while rural females have the lowest; and (b) gender disparities are more pronounced in rural than in urban populations. The second trend corroborates prior qualitative findings (e.g., survey and interview studies), while our analysis provides a quantitative basis for policy-relevant comparisons.

At the all-India level, short-distance mobility is similar by place of residence; specifically, approximately 87% of males in both rural and urban areas travel at least 1 km. However, geographic disparities widen with distance. For example, 57% of rural males versus 49% of urban males travel at least 5 km; this gap increases to 11 percentage points at 10 km. Gender gaps are most striking in rural areas: 88% of rural males travel at least 1 km compared with 76% of rural females, and the gap reaches 23 percentage points at 5 km. These differences signal persistent inequities in access to essential services despite the National Rural Health Mission (NRHM), launched in 2005 to improve rural healthcare accessibility (Ministry of Health & Family Welfare, 2024). While the NRHM has achieved notable gains in its mission "to provide accessible, affordable and quality health care to the rural population, especially the vulnerable groups", accessibility remains limited in many rural settings (Potnuru, 2019; Singh & Sarkar, 2022). Quantitative insights of this kind are critical for closing mobility and access gaps.

The tail model in Eq. (2) highlights that rural populations—and, men in particular—tend to travel farther for work, whether due to necessity or a higher willingness to travel. These possibilities imply different policies. If the "country-mile" phenomenon (Royce, 2006) (greater willingness to travel longer distances in rural areas) dominates, siting new facilities slightly farther from rural settlements may not materially reduce accessibility. Conversely, if longer trips reflect scarcity of nearby opportunities, facilities should be prioritized closer to rural populations to reduce travel burden and also to improve equity. While our analysis does not identify the causal mechanism behind longer trips, previous evidence indicates that necessity rather than a greater willingness to travel explains the observed patterns (Page, 2015; Sabapathy et al., 2012) (see also Sect. 1).

We illustrate with Uttar Pradesh which is India's most populous state (nearly 200 million people at the time of the 2011 Census). Figure 2 plots rural and urban travel patterns, with numerical values reported in Tables 1 and 2. In urban Uttar Pradesh (Fig. 2b), gender differences are small: about 72% of urban males and 70% of urban females travel at least 1 km, similar to the national urban pattern (75% vs. 70%). This small gap persists at longer distances, e.g., approximately 21% of both urban males and females travel at least 10 km. By contrast, rural Uttar Pradesh shows pronounced divergence (Fig. 2a): 80% of rural males travel at least 2 km versus 55% of rural females, and 36% of rural males travel beyond 10 km compared with only 15% of rural females. These patterns align with earlier studies but extend them with a macroscopic, data-driven perspective.

Prior work links restricted female mobility in Uttar Pradesh to socio-cultural norms that limit independent travel, e.g., requirements for young women to obtain permission from male family members (Hebert et al., 2019). Evidence from contraceptive-use studies further suggests that rural women face stronger constraints on longer trips than their urban counterparts, consistent with higher travel frictions for accessing dispersed services (Mishra et al., 2014). These constraints are compounded by well-documented disadvantages in education, employment, and health outcomes for women in Uttar Pradesh, which reduce both the necessity and feasibility of longer-distance travel (Srivastava, 2010). Our contribution complements these micro-level findings with a macroscopic, state-representative perspective: we quantify the distance thresholds at which male travel probabilities markedly exceed female probabilities and show that these gaps persist across multiple cutoffs (e.g., 5, 10,



(a) Rural

(b) Urban

Fig. 2 Disparities in male and female travel mobility in Uttar Pradesh (rural (**a**), urban (**b**)). The y-axis shows the fraction of the population traveling at least the distance on the x-axis. For details, see Section 3

Table 1 Probability of traveling at least 1, 2, 5, 10, 15, 25 or 35 km for all the male population of India (first two rows) and the male population of the 35 states and union territories obtained from Eq. (2)

	1	2	5	10	15	25	35
INDIA	0.8843	0.7886	0.5709	0.3514	0.2318	0.1281	0.0951
	0.8717	0.7542	0.4857	0.2413	0.1336	0.0679	0.0564
ANDAMAN & NICOBAR ISLANDS	0.8147	0.6828	0.4213	0.2039	0.1064	0.0378	0.0210
	0.9010	0.7658	0.3985	0.1013	0.0274	0.0124	0.0121
ANDHRA PRADESH	0.8854	0.7947	0.5901	0.3790	0.2576	0.1420	0.0989
	0.8864	0.7746	0.5062	0.2514	0.1376	0.0693	0.0582
ARUNACHAL PRADESH	0.7183	0.5695	0.3242	0.1554	0.0882	0.0434	0.0323
	0.6338	0.4733	0.2405	0.1040	0.0566	0.0287	0.0226
ASSAM	0.8171	0.6782	0.4054	0.1983	0.1198	0.0772	0.0704
	0.7989	0.6424	0.3458	0.1453	0.0826	0.0566	0.0539
BIHAR	0.8805	0.7696	0.5120	0.2709	0.1611	0.0913	0.0783
	0.8317	0.6861	0.3857	0.1620	0.0867	0.0542	0.0509
CHANDIGARH	0.9500	0.8541	0.5000	0.1258	0.0287	0.0139	0.0139
	0.9511	0.8651	0.5568	0.1948	0.0644	0.0286	0.0278
CHHATTISGARH	0.8728	0.7650	0.5212	0.2845	0.1638	0.0698	0.0445
	0.8763	0.7395	0.4130	0.1549	0.0772	0.0527	0.0515
DADRA & NAGAR HAVELI	0.6777	0.5300	0.2987	0.1427	0.0786	0.0326	0.0194
	0.7711	0.6149	0.3299	0.1288	0.0557	0.0164	0.0099
DAMAN & DIU	0.8072	0.6401	0.3188	0.1220	0.0736	0.0599	0.0592
	0.6748	0.4727	0.1822	0.0601	0.0386	0.0339	0.0337
GOA	0.9218	0.8506	0.6703	0.4544	0.3117	0.1544	0.0848
	0.8864	0.7838	0.5422	0.2998	0.1750	0.0790	0.0545
GUJARAT	0.8803	0.7884	0.5837	0.3725	0.2493	0.1281	0.0803
	0.9010	0.7751	0.4406	0.1531	0.0666	0.0421	0.0413
HARYANA	0.9073	0.8288	0.6428	0.4392	0.3162	0.1936	0.1458
	0.8653	0.7422	0.4676	0.2327	0.1386	0.0883	0.0812
HIMACHAL PRADESH	0.8893	0.7837	0.5320	0.2874	0.1717	0.0949	0.0798
	0.7561	0.6086	0.3500	0.1659	0.0935	0.0484	0.0386
JAMMU & KASHMIR	0.9104	0.8270	0.6222	0.4014	0.2774	0.1709	0.1390
	0.8975	0.7910	0.5246	0.2615	0.1416	0.0700	0.0587
JHARKHAND	0.8983	0.7971	0.5468	0.2934	0.1694	0.0851	0.0683
	0.8840	0.7474	0.4094	0.1404	0.0636	0.0421	0.0413
KARNATAKA	0.8907	0.8035	0.6045	0.3944	0.2698	0.1465	0.0980
	0.8869	0.7817	0.5319	0.2846	0.1623	0.0748	0.0552
KERALA	0.8789	0.7712	0.5236	0.2858	0.1700	0.0873	0.0683
	0.9032	0.7961	0.5200	0.2466	0.1275	0.0633	0.0552
LAKSHADWEEP	0.5223	0.2884	0.0540	0.0050	0.0017	0.0015	0.0015
	0.7052	0.4214	0.0637	0.0116	0.0109	0.0109	0.0109
MADHYA PRADESH	0.8843	0.7792	0.5331	0.2920	0.1728	0.0865	0.0665
	0.8618	0.7229	0.4082	0.1609	0.0805	0.0503	0.0481
MAHARASHTRA	0.8852	0.7946	0.5897	0.3768	0.2529	0.1328	0.0867
	0.8713	0.7677	0.5377	0.3142	0.1970	0.0999	0.0706
MANIPUR	0.8582	0.7532	0.5290	0.3148	0.2004	0.0997	0.0656
	0.8455	0.7209	0.4582	0.2339	0.1365	0.0744	0.0620
MEGHALAYA	0.8121	0.6861	0.4455	0.2533	0.1691	0.1107	0.0963
	0.7882	0.6166	0.3034	0.1220	0.0788	0.0667	0.0661

Table 1 (continued)

	1	2	5	10	15	25	35
MIZORAM	0.4462	0.3340	0.1951	0.1123	0.0767	0.0459	0.0332
	0.6822	0.4886	0.2013	0.0672	0.0390	0.0312	0.0307
NAGALAND	0.6676	0.5246	0.3045	0.1560	0.0937	0.0471	0.0326
	0.7041	0.5110	0.2111	0.0648	0.0334	0.0247	0.0243
NCT OF DELHI	0.9236	0.8577	0.6929	0.4911	0.3499	0.1771	0.0869
	0.8974	0.8052	0.5819	0.3399	0.2003	0.0735	0.0315
ODISHA	0.8836	0.7821	0.5475	0.3153	0.1958	0.1023	0.0774
	0.8558	0.7255	0.4391	0.2008	0.1084	0.0610	0.0547
PUDUCHERRY	0.9321	0.8606	0.6648	0.4208	0.2632	0.1060	0.0497
	0.9281	0.8271	0.5254	0.2149	0.0998	0.0589	0.0570
PUNJAB	0.9193	0.8337	0.6063	0.3483	0.2047	0.0905	0.0621
	0.8755	0.7432	0.4292	0.1697	0.0824	0.0492	0.0469
RAJASTHAN	0.8931	0.8069	0.6104	0.4055	0.2867	0.1732	0.1309
	0.8797	0.7463	0.4241	0.1615	0.0786	0.0506	0.0491
SIKKIM	0.7681	0.6270	0.3745	0.1865	0.1083	0.0557	0.0430
	0.7352	0.5662	0.2823	0.1085	0.0552	0.0316	0.0286
TAMIL NADU	0.9284	0.8596	0.6810	0.4663	0.3278	0.1835	0.1262
	0.8909	0.7860	0.5338	0.2853	0.1660	0.0856	0.0694
TRIPURA	0.8459	0.7015	0.3899	0.1539	0.0772	0.0471	0.0446
	0.8647	0.7276	0.4148	0.1663	0.0847	0.0537	0.0514
UTTAR PRADESH	0.8939	0.8025	0.5885	0.3652	0.2402	0.1293	0.0933
	0.8531	0.7260	0.4501	0.2152	0.1180	0.0621	0.0529
UTTARAKHAND	0.8780	0.7675	0.5124	0.2710	0.1575	0.0809	0.0651
	0.8433	0.7011	0.3977	0.1650	0.0859	0.0521	0.0488
WEST BENGAL	0.8726	0.7756	0.5664	0.3662	0.2604	0.1697	0.1404
	0.8325	0.7147	0.4768	0.2681	0.1664	0.0862	0.0627

For any state, the first row provides the probability for the rural population while the second row provides that of the urban population

20 km). These threshold-based metrics translate directly into policy targets–identifying where additional facilities or reliable transport could most effectively narrow gender gaps in mobility and access.

While gendered mobility has been studied in Europe (Nobis & Lenz, 2005; Rosenbloom & Plessis-Fraissard, 2009), Indian evidence is largely city-specific (see, e.g., Rajkot Mahadevia and Advani (2016) and Visakhapatnam Jain and Tiwari (2020)) which overlooks India's regional heterogeneity. Our state-level models reveal substantial inter-state variation reflecting diverse socioeconomic and geographic contexts. For example, in Punjab (northwestern India), roughly one-seventh of rural males travel less than 2 km, whereas in Nagaland (northeast) nearly half do. Such contrasts call for state-specific strategies rather than uniform national policies. Quantifying these variations provides a foundation for equitable, region-tailored mobility interventions.

Across the four population groups, rural males travel farther than urban males, whereas urban females travel farther than rural females. This supports the hypothesis that rural women face restricted mobility, in line with survey-based findings (Venter et al., 2007) and comparative evidence from Pakistan (Adeel, 2018). Broader migration research also shows men are more likely to make longer-distance moves to urban centers, while women are over-

Table 2 Probability of traveling at least 1, 2, 5, 10, 15, 25 or 35 km for all the female population of India (first two rows) and the female population of the 35 states and union territories obtained from Eq. (2)

	1	2	5	10	15	25	35
INDIA	0.7614	0.6117	0.3465	0.1587	0.0870	0.0443	0.0358
	0.8325	0.7009	0.4296	0.2048	0.1100	0.0512	0.0398
ANDAMAN & NICOBAR ISLANDS	0.7556	0.6019	0.3293	0.1363	0.0627	0.0189	0.0102
	0.9103	0.7734	0.3811	0.0811	0.0233	0.0159	0.0159
ANDHRA PRADESH	0.7886	0.6547	0.4064	0.2119	0.1266	0.0661	0.0504
	0.8343	0.6994	0.4190	0.1905	0.0984	0.0457	0.0369
ARUNACHAL PRADESH	0.6998	0.5382	0.2792	0.1148	0.0567	0.0236	0.0171
	0.6335	0.4595	0.2099	0.0751	0.0346	0.0152	0.0121
ASSAM	0.6428	0.4494	0.1768	0.0513	0.0234	0.0146	0.0139
	0.7626	0.5996	0.3109	0.1236	0.0638	0.0367	0.0334
BIHAR	0.7299	0.5765	0.3171	0.1383	0.0691	0.0259	0.0163
	0.7870	0.6401	0.3663	0.1650	0.0878	0.0434	0.0353
CHANDIGARH	0.9267	0.8064	0.4286	0.0954	0.0190	0.0074	0.0074
	0.9334	0.8305	0.5046	0.1710	0.0615	0.0318	0.0311
CHHATTISGARH	0.7361	0.5544	0.2509	0.0820	0.0392	0.0249	0.0239
	0.7989	0.6237	0.2896	0.0911	0.0449	0.0328	0.0323
DADRA & NAGAR HAVELI	0.8183	0.6841	0.4159	0.1966	0.1024	0.0410	0.0277
	0.7193	0.5491	0.2689	0.0978	0.0439	0.0186	0.0151
DAMAN & DIU	0.8379	0.6842	0.3545	0.1130	0.0394	0.0130	0.0112
GOA	0.6908	0.4867	0.1796	0.0438	0.0191	0.0136	0.0134
	0.9158	0.8365	0.6348	0.3999	0.2534	0.1073	0.0525
	0.8893	0.7855	0.5366	0.2859	0.1592	0.0662	0.0444
GUJARAT	0.6722	0.5388	0.3315	0.1843	0.1173	0.0610	0.0405
	0.8519	0.7058	0.3821	0.1369	0.0606	0.0333	0.0314
HARYANA	0.6836	0.5551	0.3535	0.2072	0.1389	0.0795	0.0568
	0.8455	0.7244	0.4700	0.2480	0.1469	0.0771	0.0611
HIMACHAL PRADESH	0.7345	0.5809	0.3210	0.1443	0.0778	0.0379	0.0296
	0.7827	0.6446	0.3895	0.1919	0.1069	0.0480	0.0333
JAMMU & KASHMIR	0.7338	0.5951	0.3613	0.1905	0.1165	0.0614	0.0452
	0.9081	0.8077	0.5461	0.2746	0.1457	0.0662	0.0534
JHARKHAND	0.7689	0.6042	0.3066	0.1111	0.0490	0.0216	0.0184
	0.8202	0.6560	0.3227	0.1023	0.0436	0.0257	0.0248
KARNATAKA	0.7966	0.6577	0.3945	0.1913	0.1073	0.0537	0.0421
	0.8495	0.7217	0.4451	0.2067	0.1051	0.0434	0.0323
KERALA	0.8290	0.6940	0.4178	0.1942	0.1031	0.0495	0.0400
	0.8636	0.7384	0.4557	0.2066	0.1024	0.0434	0.0343
LAKSHADWEEP	0.3582	0.1537	0.0158	0.0005	0.0000	0.0000	0.0000
	0.6165	0.3356	0.0411	0.0015	0.0008	0.0008	0.0008
MADHYA PRADESH	0.7675	0.6053	0.3150	0.1240	0.0624	0.0343	0.0307
	0.8234	0.6663	0.3461	0.1235	0.0577	0.0342	0.0325
MAHARASHTRA	0.8142	0.6873	0.4394	0.2330	0.1382	0.0683	0.0496
	0.8480	0.7336	0.4928	0.2737	0.1653	0.0800	0.0557
MANIPUR	0.7665	0.6292	0.3829	0.1932	0.1092	0.0472	0.0298
	0.8039	0.6525	0.3603	0.1516	0.0801	0.0465	0.0423
MEGHALAYA	0.7062	0.5565	0.3140	0.1496	0.0844	0.0409	0.0299
	0.7798	0.6005	0.2772	0.0972	0.0573	0.0470	0.0466

Table 2 (continued)

	1	2	5	10	15	25	35
MIZORAM	0.3196	0.2267	0.1224	0.0654	0.0418	0.0217	0.0133
	0.6539	0.4445	0.1535	0.0381	0.0193	0.0154	0.0153
NAGALAND	0.5981	0.4533	0.2485	0.1212	0.0703	0.0329	0.0213
	0.6992	0.5045	0.2037	0.0576	0.0263	0.0176	0.0171
NCT OF DELHI	0.8625	0.7602	0.5392	0.3217	0.2009	0.0889	0.0479
	0.8756	0.7760	0.5514	0.3221	0.1927	0.0734	0.0311
ODISHA	0.7845	0.6200	0.3134	0.1111	0.0493	0.0242	0.0217
	0.8160	0.6643	0.3614	0.1424	0.0695	0.0375	0.0341
PUDUCHERRY	0.8764	0.7656	0.5085	0.2591	0.1366	0.0482	0.0277
	0.8705	0.7270	0.3880	0.1285	0.0548	0.0333	0.0324
PUNJAB	0.7758	0.6450	0.4072	0.2167	0.1275	0.0565	0.0341
	0.8496	0.7171	0.4301	0.1923	0.0991	0.0498	0.0428
RAJASTHAN	0.7577	0.5656	0.2349	0.0671	0.0344	0.0272	0.0270
	0.8356	0.6899	0.3847	0.1557	0.0791	0.0467	0.0436
SIKKIM	0.6992	0.5376	0.2804	0.1195	0.0637	0.0327	0.0268
	0.7625	0.5862	0.2744	0.0894	0.0404	0.0238	0.0225
TAMIL NADU	0.8524	0.7338	0.4799	0.2536	0.1485	0.0750	0.0579
	0.8239	0.6897	0.4182	0.1973	0.1048	0.0474	0.0360
TRIPURA	0.6985	0.4955	0.1842	0.0424	0.0159	0.0098	0.0095
	0.7966	0.6274	0.3050	0.1021	0.0482	0.0308	0.0298
UTTAR PRADESH	0.6980	0.5496	0.3111	0.1483	0.0823	0.0365	0.0241
	0.8341	0.7045	0.4369	0.2130	0.1168	0.0555	0.0430
UTTARAKHAND	0.7187	0.5589	0.2961	0.1264	0.0665	0.0333	0.0271
	0.8073	0.6639	0.3853	0.1753	0.0954	0.0514	0.0442
WEST BENGAL	0.7382	0.5733	0.2960	0.1242	0.0702	0.0452	0.0419
	0.7718	0.6409	0.4049	0.2179	0.1309	0.0619	0.0403

For any state, the first row provides the probability for the rural population while the second row provides that of the urban population

represented in short-distance rural moves (Fawcett, 2019), with notable contrasts in north and south India in women's rural-to-urban migration (Singh, 2019). Cultural and religious factors (e.g., influence of Islam in northern India) have been identified as reasons for lower female mobility in parts of northern India (Fawcett, 2019). These results underscore the interplay of socioeconomic, cultural, and geographic influences, motivating nuanced, state-specific policy design.

At the all-India level, the group-specific curves in Figure 1 do not intersect (except at $x = 0$), implying no distance threshold at which the national-level ordering reverses. In some states, however, crossovers do occur. For instance, in Gujarat (see Figure S11 in the appendix), urban females are more likely to travel short distances than rural females up to about 6.77 km, beyond which rural females exhibit greater mobility. Similar patterns are reported in Tanzania, where female workers are allocated farms farther from their homes resulting in longer commutes (Bryceson & Howe, 1993; Turner & Fouracre, 1995). These findings highlight the multifaceted nature of mobility disparities and the need for data-driven, state-specific interventions.

In Table 5, we report the average trip length among trips up to $\bar{x} = 50$ km as calculated from Eq. (4). At the all-India level, the expected distances are: rural male 8.13 km, urban male 6.19 km, rural female 4.69 km, and urban female 5.68 km. We also run a sensitivity check using only the raw Census bins (midpoint-weighted grouped mean over the six closed bins [0, 1], [2, 5], [6, 10], [11, 20], [21, 30], [31, 50] and excluding 51+). The corresponding averages are rural male 8.92 km, urban male 7.29 km, rural female 5.17 km, and urban female 6.44 km. Thus, our model's values are lower by 0.48 to 1.11 km (about 9 to 15%). This direction and magnitude are plausible since the midpoint assumption may overweight the upper halves of longer bins. However, importantly, the substantive ordering and gaps are unchanged (rural male >urban male and urban female >rural female).

We conclude with data-informed suggestions that follow from the patterns identified in our analyses. Given the consistently higher tail probabilities for rural males and the lower tail probabilities for rural females (Fig. 1), it may be useful to place incremental emphasis on rural accessibility. This is enabled both through improvements to rural roads plus public transport (to reduce long-distance burdens observed in $P(x)$ for rural workers) and through the nearer siting of essential services (healthcare, schools, employment centers) where our estimates indicate tighter mobility constraints for women. To address gender gaps, especially in states where the disparities are large, measures that enhance perceived and actual safety and reliability (e.g., women-focused options or targeted security enhancements) could be considered alongside modest fare support; our results suggest such steps may be most relevant where female tails fall off steeply. Finally, because several states show distinct profiles—including cases with crossover distances (e.g., the rural–urban female pattern in Gujarat)—state-specific adaptations appear warranted. Thus, interventions might be tailored to the fitted curves and local threshold distances, focusing facility placement and service coverage where the modeled marginal benefits are likely to be greatest.

4 Conclusions

To date, the 2011 Census remains the largest household travel dataset in India. Prior household travel studies typically rely on far smaller samples. For example, a study from Rajkot (an urban city in Gujarat; population ≈1.4 million in 2011) analyzes 2848 households for trips up to 30 km and includes work, education, and shopping purposes (Mahadevia & Advani, 2016). It reports longer trip lengths for men than for women and longer trips among higher-income groups for both sexes. Using our state-level model for Gujarat, we obtain a comparable summary by evaluating the conditional mean up to $\bar{x} = 30$ km from Eq. (4) with coefficients in Tables 3 and 4; under the assumption that Rajkot resembles the broader state pattern, the average trip length for urban males (5.1 km) is slightly larger than for urban females (4.7 km). A second study from Chennai (an urban city in Tamil Nadu; population ≈ 4.7 million in 2011) analyzes 116 households and 2064 person-trips (Srinivasan, 2004). It concludes that men incur higher travel costs because they travel farther to work. Consistent with this pattern, our fitted tails imply about 6.7 and 12 percentage points higher male travel at the 1 km and 5 km thresholds, respectively (Tables 1 and 2). A third study from Bangalore (an urban city in Karnataka; population ≈8.4 million in 2011) covers 9075 individuals from 2522 households (Page, 2015). It finds that 40% of women versus 29% of men take trips shorter than 15 min, again indicating longer trips for men. While that study reports a distribution of time to destination, our work focuses on distance.

Table 3 Coefficients for equation (2) obtained from a nonlinear least squares fit for the rural male and urban male population of all India (first row) and the 35 states and union territories

	A		α		β	
	Rural	Urban	Rural	Urban	Rural	Urban
INDIA	0.9211	0.9460	0.1343	0.1457	0.9575	1.0459
ANDAMAN & NICOBAR ISLANDS	0.9851	0.9879	0.2084	0.1056	0.8988	1.3574
ANDHRA PRADESH	0.9287	0.9438	0.1317	0.1283	0.9237	1.0893
ARUNACHAL PRADESH	0.9723	0.9797	0.3421	0.4680	0.7732	0.7206
ASSAM	0.9310	0.9464	0.2187	0.2389	0.9554	0.9899
BIHAR	0.9246	0.9495	0.1384	0.1951	1.0501	1.0405
CHANDIGARH	0.9861	0.9722	0.0520	0.0516	1.6213	1.5333
CHHATTISGARH	0.9650	0.9485	0.1414	0.1397	0.9808	1.2003
DADRA & NAGAR HAVELI	0.9878	0.9915	0.3949	0.2625	0.7099	0.9050
DAMAN & DIU	0.9408	0.9663	0.2293	0.4103	1.0720	0.9434
GOA	0.9706	0.9538	0.0840	0.1268	0.9924	1.0190
GUJARAT	0.9541	0.9587	0.1341	0.1090	0.9028	1.2950
HARYANA	0.8861	0.9199	0.1105	0.1583	0.9573	1.0550
HIMACHAL PRADESH	0.9236	0.9647	0.1277	0.2915	1.0629	0.8365
JAMMU & KASHMIR	0.8743	0.9431	0.1081	0.1150	1.0286	1.1234
JHARKHAND	0.9355	0.9587	0.1151	0.1290	1.0876	1.2453
KARNATAKA	0.9362	0.9503	0.1242	0.1267	0.9233	1.0428
KERALA	0.9373	0.9457	0.1384	0.1080	1.0158	1.1687
LAKSHADWEEP	0.9985	0.9891	0.6509	0.3539	0.9380	1.3131
MADHYA PRADESH	0.9394	0.9520	0.1314	0.1568	1.0279	1.1335
MAHARASHTRA	0.9443	0.9427	0.1296	0.1467	0.9201	0.9474
MANIPUR	0.9538	0.9412	0.1609	0.1793	0.8962	0.9721
MEGHALAYA	0.9091	0.9340	0.2315	0.2572	0.8716	1.0391
MIZORAM	0.9832	0.9693	0.8285	0.3972	0.4493	0.9168
NAGALAND	0.9763	0.9758	0.4161	0.3614	0.6814	0.9446
NCT OF DELHI	1.0179	0.9892	0.0781	0.1095	0.9484	1.0024
ODISHA	0.9316	0.9462	0.1335	0.1653	0.9978	1.0518
PUDUCHERRY	0.9788	0.9431	0.0719	0.0793	1.0958	1.3528
PUNJAB	0.9463	0.9533	0.0891	0.1399	1.1170	1.1655
RAJASTHAN	0.8961	0.9510	0.1271	0.1352	0.9329	1.1985
SIKKIM	0.9618	0.9718	0.2758	0.3182	0.8310	0.8940
TAMIL NADU	0.9103	0.9344	0.0819	0.1242	1.0323	1.0667
TRIPURA	0.9556	0.9487	0.1758	0.1539	1.0907	1.1371
UTTAR PRADESH	0.9244	0.9489	0.1220	0.1683	0.9785	1.0183
UTTARAKHAND	0.9389	0.9515	0.1391	0.1799	1.0321	1.0671
WEST BENGAL	0.8749	0.9483	0.1574	0.1944	0.9134	0.8809

The above city-level studies use modest sized samples and are not state-representative. One of the few analyses using the entire national 2011 Census data is Singh (2017), which—although not proposing a new mobility model—provides complementary insights to our work. These include longer distances are more likely traveled by public transport, very short trips rely on walking and bicycles, trip lengths correlate with district density, and women are more likely to walk to work for sub-1 km trips.

A limitation of our analysis is that we do not differentiate by mode of transport. For shorter distances, many travelers in India rely on walking and bicycles (Nayka & Sridhar,

Table 4 Coefficients for equation (2) obtained from a nonlinear least squares fit for the rural female and urban female population of all India (first row) and the 35 states and union territories

	A		α		β	
	Rural	Urban	Rural	Urban	Rural	Urban
INDIA	0.9667	0.9630	0.2834	0.1911	0.8577	0.9611
ANDAMAN & NICOBAR ISLANDS	0.9922	0.9841	0.2828	0.0956	0.8588	1.4532
ANDHRA PRADESH	0.9561	0.9649	0.2498	0.1884	0.8427	0.9864
ARUNACHAL PRADESH	0.9848	0.9886	0.3636	0.4632	0.7994	0.7723
ASSAM	0.9861	0.9672	0.4497	0.2816	0.8618	0.9243
BIHAR	0.9870	0.9667	0.3197	0.2490	0.8100	0.9035
CHANDIGARH	0.9926	0.9689	0.0768	0.0712	1.4992	1.4344
CHHATTISGARH	0.9762	0.9677	0.3151	0.2329	0.9518	1.0800
DADRA & NAGAR HAVELI	0.9762	0.9855	0.2059	0.3352	0.9246	0.8674
DAMAN & DIU	0.9889	0.9866	0.1790	0.3759	1.1036	0.9665
GOA	0.9796	0.9619	0.0898	0.1223	1.0235	1.0450
GUJARAT	0.9767	0.9687	0.4089	0.1659	0.6444	1.1258
HARYANA	0.9637	0.9439	0.3979	0.1787	0.6381	0.9500
HIMACHAL PRADESH	0.9730	0.9724	0.3187	0.2529	0.8221	0.8471
JAMMU & KASHMIR	0.9634	0.9486	0.3233	0.1019	0.7537	1.1522
JHARKHAND	0.9821	0.9753	0.2682	0.2038	0.9434	1.0943
KARNATAKA	0.9614	0.9701	0.2377	0.1686	0.8888	1.0042
KERALA	0.9622	0.9673	0.1957	0.1520	0.9678	1.0528
LAKSHADWEEP	1.0001	0.9992	1.0266	0.4843	0.8668	1.1751
MADHYA PRADESH	0.9698	0.9676	0.2742	0.2016	0.9304	1.0690
MAHARASHTRA	0.9582	0.9549	0.2156	0.1733	0.8737	0.9164
MANIPUR	0.9785	0.9583	0.2727	0.2290	0.8049	0.9759
MEGHALAYA	0.9749	0.9534	0.3586	0.2626	0.7589	1.0484
MIZORAM	0.9987	0.9847	1.1435	0.4331	0.3805	0.9393
NAGALAND	0.9864	0.9829	0.5233	0.3653	0.6267	0.9411
NCT OF DELHI	0.9785	0.9938	0.1515	0.1338	0.8922	0.9329
ODISHA	0.9785	0.9663	0.2488	0.2113	0.9826	1.0145
PUDUCHERRY	0.9784	0.9676	0.1350	0.1437	1.0205	1.2062
PUNJAB	0.9786	0.9583	0.2602	0.1708	0.7920	1.0348
RAJASTHAN	0.9731	0.9567	0.2863	0.1885	1.0465	1.0554
SIKKIM	0.9748	0.9776	0.3690	0.2784	0.8012	0.9837
TAMIL NADU	0.9475	0.9669	0.1694	0.2010	0.9615	0.9455
TRIPURA	0.9905	0.9703	0.3629	0.2352	0.9722	1.0427
UTTAR PRADESH	0.9818	0.9603	0.3675	0.1896	0.7402	0.9557
UTTARAKHAND	0.9746	0.9573	0.3405	0.2248	0.8232	0.9443
WEST BENGAL	0.9586	0.9720	0.3189	0.2675	0.8851	0.7856

2018; Singh & Sarkar, 2022), likely due to the costs of owning a private vehicle. Census tabulations indicate that nearly 70% of trips under 5 km are by foot or bicycle, whereas only about 2.3% are by car/jeep/van. Similar patterns appear in other developing countries, although women's bicycle use is often more restricted (Rosenbloom & Plessis-Fraissard, 2009). We further note that Census records "by foot" up to 10 km and "by bicycle" up to 50 km. Separate mode-specific models (e.g., bicycles and cars) are developed in Goel (2018), which fit lognormal, Weibull, and exponential distributions to the share commuting

Table 5 Expected travel distances for travel up to 50 km for the four Census groups for all of India (first row) and the 35 states and union territories

	Male		Female	
	Rural	Urban	Rural	Urban
INDIA	8.13	6.19	4.69	5.68
ANDAMAN & NICOBAR ISLANDS	5.98	4.80	4.69	4.56
ANDHRA PRADESH	8.92	6.37	5.61	5.46
ARUNACHAL PRADESH	4.60	3.51	4.00	3.15
ASSAM	5.00	4.26	2.73	4.09
BIHAR	6.44	4.73	4.56	4.88
CHANDIGARH	5.54	6.22	5.00	5.73
CHHATTISGARH	7.34	4.85	3.44	3.74
DADRA & NAGAR HAVELI	4.52	4.59	5.71	3.79
DAMAN & DIU	3.84	2.64	4.58	2.79
GOA	11.30	7.47	10.07	7.31
GUJARAT	9.18	5.12	5.15	4.72
HARYANA	9.70	5.62	5.41	6.24
HIMACHAL PRADESH	6.75	4.77	4.45	5.48
JAMMU & KASHMIR	8.48	6.57	5.19	6.90
JHARKHAND	7.06	4.83	4.14	4.14
KARNATAKA	9.41	7.10	5.31	5.87
KERALA	6.93	6.36	5.46	5.86
LAKSHADWEEP	1.63	2.03	1.04	1.75
MADHYA PRADESH	7.09	4.90	4.15	4.36
MAHARASHTRA	9.12	7.64	6.12	6.95
MANIPUR	7.85	5.92	5.57	4.58
MEGHALAYA	5.69	3.64	4.50	3.51
MIZORAM	3.16	2.85	2.17	2.51
NAGALAND	4.56	3.01	3.87	3.00
NCT OF DELHI	12.86	8.88	8.40	8.62
ODISHA	7.47	5.42	4.15	4.60
PUDUCHERRY	10.42	5.97	7.02	4.69
PUNJAB	8.32	5.12	6.07	5.44
RAJASTHAN	9.03	5.00	3.24	4.76
SIKKIM	5.16	3.80	3.92	3.70
TAMIL NADU	10.67	6.88	6.42	5.58
TRIPURA	4.76	4.95	2.87	3.94
UTTAR PRADESH	8.48	5.71	4.58	5.80
UTTARAKHAND	6.66	4.86	4.10	4.98
WEST BENGAL	7.71	6.72	3.86	5.98

Values are computed with $\bar{x} = 50$ in equation (4)

exactly x km. Our approach instead models the survival $P(x)$—the probability of traveling at least x km—to facilitate comparisons across the target groups and states.

We conclude by reiterating that the drivers of gender and socioeconomic differences merit continued study (see also Sect. 3). International evidence shows historically restricted access to, and lower willingness or opportunity to drive, among women (Matthies et al., 2002; Pickup, 1984), yet even within North America there is no consensus on why trip lengths differ by gender. For instance, Matthies et al. (2002) emphasizes household responsibilities, whereas Hanson and Johnston (1985) stress greater distance sensitivity among women, as reasons for shorter trip lengths by women. A natural extension of our work would compare our 2011 Census estimates with the next Indian census, currently expected in 2027, to assess how mobility patterns have evolved alongside India's accelerated economic growth.

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Data availability The data available on https://github.com/bissi1/IndiaTravelPatterns.

Declarations

Conflict of interest The authors declare no conflict of interest.

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