

Study on Human Migration Process From Rural and Urban Areas to Urban Area in Amravati

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Abstract

This study investigates the patterns and determinants of human migration from rural and urban areas to the urban region of Amravati, Maharashtra, India. Primary data were collected from 400 respondents using snowball sampling across different localities of Amravati. The study employs statistical tools including a two-sample Z-test for proportions, Chi-square test of independence, two-way ANOVA, Pearson correlation, and binary logistic regression to analyse the migration data. Key findings reveal that education (37.5%) and employment (31.5%) are the dominant reasons for migration. A significant difference in first-time migration rates was observed between males and females ($p = 0.0021$). Gender and reasons for migration were found to be significantly associated ($p \approx 0$). Age groups significantly differ in migration behaviour ($p = 0.0137$), while duration of stay shows no significant association with gender ($p = 0.297$). A logistic regression model achieved 70% prediction accuracy for future migration likelihood. Rural-to-urban migration (61%) predominates over urban-to-urban migration (39%), driven by better educational and economic opportunities.

Keywords: Rural-urban migration, internal migration, Amravati, snowball sampling, logistic regression, Chi-square test, ANOVA, push-pull factors

1. Introduction

Migration has emerged as a universal phenomenon in the contemporary world, accelerated by the expansion of transport networks and communication technologies. It constitutes one of the three fundamental demographic components of population change—alongside fertility and mortality—and exerts profound influence on the size, composition, and spatial distribution of populations. Unlike fertility and mortality, migration operates beyond strictly biological frameworks, implicating social, economic, and political dimensions of human life.

In India, industrialisation and economic development have historically been accompanied by large-scale population movements from rural to urban settings. The 2011 Census identifies four major internal migration streams: rural-to-rural (R-R), rural-to-urban (R-U), urban-to-urban (U-U), and urban-to-rural (U-R). Of these, rural-to-urban migration has received the most scholarly attention because of its scale and consequences for urbanisation.

Amravati, a city in the Vidarbha region of Maharashtra, presents a compelling case study. As a regional educational and administrative hub, it attracts migrants from surrounding rural districts as well as from other urban centres. This paper applies rigorous statistical analysis to primary survey data to uncover the socio-demographic profile of migrants, identify the principal drivers of migration, and develop a predictive model for future migration behaviour. Objectives of the Study

1. To examine the proportions of males and females migrating for the first time.
2. To determine whether a significant association exists between gender and reasons for migration.
3. To examine whether age group is associated with reasons for migration.
4. To investigate the relationship between gender and duration of stay.
5. To suggest a suitable predictive model for future migration.

The scholarly discourse on internal migration in India is rich and multidisciplinary. Srivastava (2016) examined construction-sector labour migration and found that while migrant workers face poor living conditions at destinations,

remittances positively impact origin households through higher consumption and investment in children's education. Garg and Agarwal (2020) analysed rural-urban migration trends using Census data for 2001 and 2011, highlighting that urban-sector wages and unemployment rates are key determinants consistent with the Harris-Todaro model, and that the COVID-19 pandemic severely disrupted established migration patterns.

Ahmed (2021) investigated how migration shapes educational attainment and social development in India, documenting both positive knowledge-transfer effects and disruptive consequences for children's schooling. Their case study from Monywa, Myanmar, systematically mapped push and pull factors driving migration, offering a framework applicable to the Indian context. Singh and Varghese (2010) found that in the Indo-Gangetic plains, rural-urban outmigration primarily involves surplus unskilled labour and that household size and education positively predict migration propensity.

Kallio (2016) explored the interface between human migration and biodiversity conservation, noting that population movements alter land-use patterns in origin regions. Singh and Smarandache (2022) documented structural changes in migration flows to Jaipur over two consecutive decades, observing a shift away from education- and business-driven migration toward marriage-driven flows and a widening gender gap in migration motives. Collectively, this literature underscores that migration is multi-causal and that gender and age operate as critical moderating variables—context that motivates the present study's focus on Amravati.

Research Methodology

Data Collection

Primary data were collected through personal interviews and a structured questionnaire administered across multiple localities of Amravati city to minimise response bias. The questionnaire comprised 16 items capturing socio-demographic characteristics (gender, age, education, occupation, annual income, marital status, family structure) and migration-specific variables (reason for migration, type of move, age at migration, duration of stay, and likelihood of future migration). Data were recorded in both physical and Google Forms formats.

Sampling Design

A snowball sampling technique was adopted. An initial set of respondents from the target population was identified, and each participant was subsequently asked to refer additional members of the migrant community. This approach is particularly suited to hard-to-reach populations where no exhaustive sampling frame exists. The final sample comprised 400 respondents aged 16 years and above.

Analytical Framework

The data were analysed using the following statistical techniques, implemented in Python, R, and SPSS:

- Two-sample Z-test for proportions – to compare first-time migration rates between males and females.
- Chi-square test of independence – to assess association between (i) gender and reasons for migration, and (ii) gender and duration of stay.
- Two-way ANOVA (without replication) – to examine the joint effects of age group and migration reason on migration counts.
- Pearson correlation – to quantify the linear relationship between present age and age at first migration.
- Binary logistic regression – to model the probability of future migration as a function of migration reason and current educational enrolment.

Sample Profile

Table 1 presents the key socio-demographic and migration characteristics of the 400 respondents.

Table 1: Socio-Demographic Profile of Respondents (n = 400)

Variable	Category	Frequency	Percentage (%)
Gender	Male	232	58%
	Female	168	42%
Age Group	16–25	188	47%
	26–35	66	17%
	36–45	61	15%
	46–55	48	12%
	56 and above	37	9%
	Marital Status	Single	218
	Married	153	38%
	Divorcee/Widow	29	7%
Family Structure	Nuclear	154	39%
	Joint	135	34%
	Single	111	28%
Type of Move	Rural–Urban	245	61%
	Urban–Urban	155	39%
Duration of Stay	Long-term (≥1 year)	278	70%
	Short-term (6 months)	122	30%
First-time Migrant	Yes	266	67%
	No	134	33%

Table 2: Distribution of Reasons for Migration

Reason for Migration	Frequency	Percentage (%)
Education	150	37.50%
Employment	126	31.50%
Marriage	36	9.00%
Family Reunification	30	7.50%
Retirement	14	3.50%
Children’s Education	13	3.25%
Daily Wages	13	3.25%
Covid-19	12	3.00%
Business-Related	5	1.25%
Family Migration	1	0.25%
Total	400	100%

Data Analysis and Results

Test for Difference in Proportions of First-Time Migrants by Gender

To examine whether first-time migration rates differ significantly between males and females, a two-sample large-sample Z-test for proportions was applied.

H₀: $P_1 = P_2$ (proportions of first-time migrants are equal across gender)

H₁: $P_1 \neq P_2$ (proportions differ)

Given: n_1 (females) = 168, x_1 = 126 first-time migrants; n_2 (males) = 232, x_2 = 140 first-time migrants. The sample proportions are $\hat{O}_1 = 0.75$ and $\hat{O}_2 = 0.6034$. The pooled estimate $\hat{O} = 0.6649$ yields a test statistic $|Z| = 3.07$. At $\alpha = 0.05$, the critical value is $Z_\alpha = 1.96$.

Result: Since $|Z| = 3.07 > 1.96$, and the Python-computed p-value = $0.0021 < 0.05$, H_0 is rejected. The proportions of males and females migrating for the first time are significantly different. Females show a higher first-time migration rate (75%) compared to males (60%), possibly reflecting the increasing role of education in motivating female migration.

Association Between Gender and Reasons for Migration (Chi-Square Test)

A Pearson Chi-square test of independence was conducted on a 5×2 contingency table (migration reasons \times gender).

Table 3: Cross-Tabulation – Gender by Reason for Migration

Reason	Female	Male	Total
Education	81	69	150
Employment	42	84	126
Family Reunification	7	23	30
Marriage	33	3	36
Others	5	53	58
Total	168	232	400

Result: The Chi-square statistic is highly significant ($p = 1.72 \times 10^{-16}$, $df = 4$). H_0 is rejected at the 5% level. There is a strong association between gender and migration motive. Notably, females migrate predominantly for education (48%) and marriage (20%), whereas males migrate primarily for employment (36%) and other economic reasons. This finding diverges from the national pattern in the 2011 Census, where marriage accounted for 46% of female migration, suggesting shifting gender dynamics in Amravati’s migration landscape.

Association Between Age Group and Reasons for Migration (Two-Way ANOVA)

A two-way ANOVA without replication was performed with age groups as rows (Factor A) and migration reasons as columns (Factor B), using the observed frequency matrix.

Table 4: ANOVA Summary Table

Source of Variation	SS	df	MS	F	p-value	F critical
Rows (Age Groups)	6155.07	5	1231.01	3.81	0.0137	2.71
Columns (Reasons)	1989.33	4	497.33	1.54	0.2287	2.87
Error	6456.27	20	322.81	—	—	—
Total	14600.67	29	—	—	—	—

Result: Age group (Factor A) shows a significant effect on migration counts ($F = 3.81$, $p = 0.0137 < 0.05$). Migration is not uniformly distributed across age groups; the 16–25 cohort dominates, particularly for education-driven migration, while employment and business motives emerge above age 25. Migration reasons (Factor B) do not differ significantly across groups ($p = 0.2287$), indicating no single reason dominates uniformly.

Association Between Gender and Duration of Stay (Chi-Square Test)

To determine whether the duration of migration (short-term: 6 months; long-term: ≥ 1 year) is independent of gender, a chi-square test with Yates’ continuity correction was applied to the 2×2 contingency table.

Table 5: Gender by Duration of Stay

Gender	Short-term (6 mo.)	Long-term (≥ 1 yr.)	Total
Female	122	46	168
Male	156	76	232
Total	278	122	400

Result: $\chi^2_{\text{aal}} = 1.09$ (with Yates' correction), $df = 1$, $p = 0.297 > 0.05$. H_0 is accepted. Duration of stay is independent of gender; the decision to settle temporarily or permanently in Amravati is not determined by the migrant's sex.

Predictive Logistic Regression Model

To predict the probability of future migration ($Y = 1$: Yes, $Y = 0$: No) based on current reason for migration (X_1) and school/college enrolment status (X_2), a binary logistic regression model was estimated using statsmodels (Python).

Estimated model: $\text{logit}(p) = -1.8288 + 0.3681 X_1 + 0.8868 X_2$

Table 6: Logistic Regression Coefficients

Predictor	Coefficient (b)	Std. Error	z-value	p-value	95% CI
Constant	-1.8288	0.2257	-8.103	0.0000	[-2.27, -1.39]
Reason (X_1)	0.3681	0.0780	4.718	0.0000	[0.215, 0.521]
College/School (X_2)	0.8868	0.2457	3.609	0.0003	[0.405, 1.368]

The model achieved 79.4% accuracy on the training set and 70% on the test set (20 records). Selected conditional probability estimates:

- $P(\text{migrate} \mid \text{education reason, currently enrolled}) = 0.7106$ (71.1%)
- $P(\text{migrate} \mid \text{education reason, not enrolled}) = 0.5029$ (50.3%)
- $P(\text{migrate} \mid \text{family reunification, currently enrolled}) = 0.1883$ (18.8%)
- $P(\text{migrate} \mid \text{family reunification, not enrolled}) = 0.3603$ (36.0%)

Interpretation: Both predictors are highly significant ($p < 0.001$). Educational motivation and active academic enrolment substantially increase the probability of future migration, consistent with the life-course hypothesis that education-related moves recur across academic transitions.

Pearson Correlation: Present Age vs. Age at First Migration

A Pearson correlation analysis between present age group and age group at first migration yields $r = 0.5417$ ($p = 6.93 \times 10^{-32}$). The moderate-to-strong positive correlation indicates that migrants who moved at a younger age tend to be younger in the current sample, and that migration age is significantly associated with current age. The heat map and scatter plot confirm an upward trend, consistent with a pattern where early educational migration tends to occur among younger cohorts.

Rural-Urban vs. Urban-Urban Migration: Reason Profile

Cross-tabulation of migration type against specific reasons reveals informative patterns:

- Retirement (3.5%), children's education (3.3%), daily wages (3.3%), and Covid-19 displacement (3.0%) are exclusively rural-to-urban phenomena with zero urban-to-urban incidence.
- Education drives both streams but is proportionally stronger in rural-to-urban (21.3%) vs. urban-to-urban (16.3%).
- Employment is the leading reason for urban-to-urban migration (17.5% vs. 14.0% rural-to-urban), reflecting job-transfer and career-advancement motives among urban professionals.
- Business migration favours urban-to-urban routes (0.8% vs. 0.5%).

Discussion

The findings confirm that Amravati's migration landscape is shaped by a distinct interplay of educational aspirations and economic necessity. Education displacing employment as the primary migration motive (37.5% vs. 31.5%) is a notable departure from the national pattern reported in literature, where economic reasons dominate for male migrants and marriage for female migrants. This shift may reflect Amravati's role as a university city attracting students from Vidarbha's predominantly agricultural hinterland.

The significant association between gender and migration motive, combined with the finding that female first-time migration rates exceed male rates, suggests an ongoing transformation in women's migration agency. Increasing female participation in higher education appears to be reshaping the traditional marriage-dominated female migration narrative documented in the 2011 Census. This aligns with macro-level observations that rising education levels are positively associated with female migration.

The dominance of the 16–25 age cohort (54% migrating first at this age) and the significant ANOVA result for age groups reinforce the life-course perspective: migration is concentrated in the transition from adolescence to early adulthood, driven by educational progression and labour-market entry. The absence of a gender–duration association implies that once the decision to migrate is taken, men and women do not systematically differ in how long they remain away—settlement behaviour is gender-neutral.

The logistic regression model's 70% test accuracy is modest but meaningful given the categorical nature of predictors and the complexity of migration decisions. The model's high sensitivity (all actual 'Yes' cases correctly predicted) with low specificity indicates a tendency to over-predict future migration, which may reflect the general mobility orientation of the young, educated sample.

Conclusions

This study provides a statistically rigorous characterisation of migration to Amravati. The principal conclusions are as follows:

6. Education (37.5%) and employment (31.5%) are the dominant drivers of migration, with education especially prominent among females and employment among males.
7. Female migrants show a significantly higher first-time migration rate than males (75% vs. 60%, $p = 0.0021$), indicating greater female participation in migration, likely driven by educational aspirations.
8. Gender and migration reason are strongly associated ($p \approx 0$), with females gravitating toward education and marriage and males toward employment and economic motives.
9. Migration behaviour varies significantly across age groups ($p = 0.0137$), concentrated in the 16–25 cohort, consistent with educational and early labour-market transitions.
10. Duration of stay is independent of gender ($p = 0.297$), indicating that settlement duration is not a gendered outcome.
11. The logistic regression model predicts that educationally motivated, currently enrolled migrants have a 71.1% probability of future migration, making them the most mobile sub-group.
12. Rural-to-urban migration (61%) significantly exceeds urban-to-urban flows (39%), driven by access to education, healthcare, and economic opportunity unavailable in rural hinterlands.

These findings carry implications for urban planners and policymakers in Amravati: expanding higher educational infrastructure in source districts may moderate rural-to-urban pressure, while targeted employment programmes for male migrants and support services for young female students can optimise migration's developmental benefits.

References

- Ahmed, M. (2021). Study on human migration and its impact on education and society in India.
- Garg, A., & Agarwal, P. (2020). Analysis of rural-urban migration in India and impact of COVID-19. *International Journal of Policy Sciences and Law*, 1(4).
- Gupta, S.C., & Kapoor, V.K. (1970). *Fundamentals of Mathematical Statistics* (1st ed.). Sultan Chand and Sons.
- Kallio, E. (2016). Human migration: Implications and opportunities for conservation.
- Office of the Registrar General & Census Commissioner. (2011). *Census of India 2011*. Government of India.
- Singh, N.P., & Varghese, N. (2010). Labour migration and its implications on rural economy of Indo-Gangetic plains of India.
- Singh, R., & Smarandache, F. (2022). Structural dynamics of various causes of migration in Jaipur (July 2022).
- Srivastava, R. (2016). Labour migration to the construction sector in India and its impact on rural poverty.
- Thet, K.K. Pull and push factors of migration: A case study in the urban area of Monywa Township, Myanmar.