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Cross-city referral dependency in Saudi Arabia: a retrospective cross-sectional, diagnosis-level analysis of city-to-city referral volume and destination

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Research Article

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Cross-city referral dependency in Saudi Arabia: a retrospective cross-sectional, diagnosis-level analysis of city-to-city referral volume and destination

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Abstract

Background: Referral volume and destination show where a health system's capacity falls short. Saudi studies, however, have described referrals only by specialty and administrative region. We quantified cross-city referral dependency, tested whether it is diagnosis-specific after accounting for the referring city, and explored whether cities and diagnoses form distinct referral profiles.

Methods: We analysed five quarterly files of aggregated national referral records from the Saudi National Open Data Portal (Q4 2024 – Q4 2025), which were recenlty made it open for public. A scripted pipeline harmonised city names, assigned regions and classified diagnoses with ICD-10-AM. For each referring city we computed a cross-city dependency index (DI), the share of its referrals sent to another city. The main analysis was a quasi-binomial regression of cross-city referral on referring city, ICD-10 chapter and age group in cities with adequate local data coverage (at least 100 same-city referrals). Exploratory cluster analyses were tested against a permutation null benchmark.

Results: Of 460,953 referrals, 8.7% crossed city boundaries, and 62.8% of these also crossed an administrative-region boundary. The DI ranged from 0.4% (Riyadh) to 100%, but seven cities recorded fewer than 100 same-city referrals, so their high DIs may partly reflect data coverage. Among the 12 coverage-adequate cities, referring city accounted for 84% of the explained deviance, diagnosis chapter for 8% and age for under 1%, and cities differed in which diagnoses they referred out. After adjustment, cross-city referral was most likely for rehabilitation and other health-status factors (OR 10.23, 95% CI 6.67–15.71), congenital malformations (3.93), eye diseases (3.83), neoplasms (3.57) and mental and behavioural disorders (2.49), relative to circulatory diseases, and least likely for pregnancy and childbirth (0.34). Riyadh, Jeddah and Makkah received 91.5% of cross-city referrals. Only two of four

cluster analyses exceeded the null benchmark (an outbound city typology, $p = 0.04$; nine specialised codes, $p = 0.01$).

Conclusions: Cross-city referral in Saudi Arabia is driven mainly by where a patient is referred from, but is additionally concentrated in rehabilitation, congenital, ophthalmic, oncological and mental-health care, and converges on three hubs. City-to-city, diagnosis-level monitoring, interpreted alongside data-coverage checks, can help health clusters target specialised capacity.

Trial registration: Not applicable.

Keywords: Patient referral; Health services accessibility; Regional health planning; Specialised care; Health information systems; Saudi Arabia

Background

Referral volume and destination are among the most direct signals of where a health system's capacity falls short of its population's needs. When a city refers a patient elsewhere, the referral often marks a local deficit: an unavailable sub-specialty, missing equipment or no available bed. In Saudi Arabia, the national e-referral system has made such signals measurable at scale. An analysis of more than 600,000 requests from 2020–2021 found that referrals rose year on year, peaked in autumn and winter, and were dominated by surgical and medical specialties [1]. Referral drivers differed by region: unavailable sub-specialty care accounted for 68.86% of referrals in the Central and 67.93% in the Eastern region, while Southern regions had more referrals due to unavailable equipment (18.44%) and beds (6.24%) and the highest share of emergency referrals (44.06%) [1].

Referral flow also reveals friction that volume alone cannot. Of 632,763 national referral requests, 74.13% were accepted. All life-saving referrals were accepted, but external referrals were 32% less likely to be accepted than internal ones [2]. Patients who need care beyond their local facility therefore face both distance and a lower probability of acceptance.

Since 2022, service delivery has been restructured into regional health clusters, semi-autonomous entities intended to tailor services to local population needs, and non-emergency hospital admission now requires referral through a primary health centre (PHC) [3]. PHC density and staffing vary widely between regions [4, 5], region of residence independently predicts healthcare use [6], and weak referral processes have long-standing consequences for chronic disease management [7]. Under this model, referrals that leave a city are especially informative, because they indicate care that a local network does not provide.

Existing Saudi evidence describes referrals by broad specialty, urgency and administrative region [1, 2]. Earlier work documented e-referral implementation in a single network [8], and

other studies examined facility distribution or utilisation without referral flows [4, 8]. To our knowledge, no published study has combined diagnosis-level detail with city-to-city mapping of referral volume and destination, so planners cannot see which conditions drive cross-city flow, from which cities, and towards which hubs.

We therefore asked: **do certain cities depend more on cross-city referrals for specific diseases, and do cities and diseases form distinct groups based on their referral patterns?** Our objectives were to:

1. quantify each city's cross-city dependency, with explicit checks of local data coverage;
2. estimate the separate contributions of referring city, diagnosis and age to cross-city referral, and test whether diagnosis-specific dependency differs between cities;
3. characterise the concentration of cross-city inflow on receiving hubs;
4. explore, and formally test, typologies of cities and diagnoses by referral behaviour.

Methods

Study design, data source and reporting

This was a retrospective, cross-sectional study of routinely collected, aggregated referral records from Saudi Arabia, Q4 2024 to Q4 2025, reported according to the RECORD statement [9] (Additional file 1: Table S39). Data were obtained from the Saudi National Open Data Portal, where the dataset "Referral of Medical Cases", published by the Center For National Health Insurance, is openly available as quarterly Excel files on 15 september 20216 [10]. The files covering Q4 2024 to Q4 2025 were downloaded on 17 September 2026; they contain aggregated referral counts only, with no patient-level or identifiable information. Each row gave the number of referrals for one combination of gender, referring city,

receiving city, age group (0–17, 18–29, 30–39, 40–49, 50–59, 60–69, 70–79 and ≥80 years) and diagnosis coded in ICD-10-AM. A same-city referral is a referral between hospitals in the same city; patients are referred to another city when the required, usually specialised, service is not available locally. Counts were analysed as recorded; small counts were not suppressed, so combinations absent from the data represent true zeros. Each referral record carries a single (principal) diagnosis code, so that counts are referrals rather than referral–diagnosis pairs. Some geographic units are health regions or directorates rather than single cities (for example, Asir and Qassim); we refer to all of them as cities.

Data preparation

The raw extracts were processed with a scripted, five-stage pipeline (see Software and reproducibility); the flow of rows and referrals from the raw extracts to the analysis dataset is shown in Additional file 1: Fig. S1.

Loading and data-quality review. The extracts were combined and the quarter read from each file name, with all values read as text to prevent automatic type conversion. Before any change, a data-quality review documented missing values, duplicates, spelling variants, unexpected categories, invalid or extreme counts and malformed codes, with the rows and referrals affected by each.

Cleaning and region assignment. City names were harmonised with a standardisation dictionary. Records labelled with the Eastern Province directorate ("East", "Eastern" or "Eastern Region" in the city columns) were merged with Al-Ahsa into a single unit, so that no city-level unit carries a region name. Exact duplicate rows and rows with missing, non-numeric, zero or negative counts were removed. The referring provider region was recorded only in Q4 2025; for the other quarters it was derived from a city-to-region lookup built from Q4 2025, assigning each city the region holding the majority of its referrals. Applied to Q4

2025 itself, the lookup reproduced the recorded region for 100.0% of referrals; no city was linked to more than one region. Cities absent from Q4 2025, and all receiving cities, were assigned regions from the same table and the administrative geography of Saudi Arabia. Rows describing the same group were merged by summing their counts, and the pipeline verified that the referral total was unchanged.

Diagnosis coding. Diagnoses were coded in ICD-10-AM and classified with ICD-10-AM only; no other classification was used. Each code was assigned to its ICD-10-AM chapter from the chapter code ranges. ICD-10-AM supplementary codes for chronic conditions (U78–U88; 3.1% of referrals) were kept as a separate group, and codes outside the ICD-10-AM chapters (activity codes U53 and U66; 0.02%) as an unclassified group. All codes had a valid ICD-10-AM format, and 96.8% of referrals carried a code within ICD-10-AM Chapters 1–21 (A00–Z99). Chapter ranges follow the ICD-10-AM classification [11], 10th Edition. Diagnoses were not imputed. Analyses use the chapter level, and individual codes are reported at the category level.

Data-quality flags. Two signals were flagged without altering counts: count heaping (a value at least four times as frequent as its neighbouring values within a city) and changes in reporting coverage (city-quarter totals below half or above twice the city's median quarter).

Analysis dataset. Referrals involving facilities outside Saudi Arabia were excluded (519 referrals; Additional file 1: Table S2). Records were aggregated over quarters and genders within each combination of referral type, referring city, receiving city, age group and ICD-10 code, giving 12,806 records, 2,659 codes, 19 referring and 16 receiving cities.

Local data coverage

Four cities recorded no same-city referrals and three recorded fewer than 100 (Al-Baha 1, Al-Jouf 51, Hail 57), although all have hospitals. Their dependency indices may therefore reflect

how local care is captured by the referral data rather than an absence of local services. We defined coverage-adequate cities a priori as those with at least 100 same-city referrals (12 cities, 95.6% of referrals) and used them for the main multivariable analysis and for sensitivity analyses of all headline results.

Cross-city dependency index

For each referring city *c*, the cross-city dependency index (DI) was defined as:

$$DI_c = \frac{cross-city\ referrals_c}{same-city\ referrals_c + cross-city\ referrals_c}$$

The DI was calculated overall and for each ICD-10 chapter, with Wilson 95% confidence intervals [12]. Comparisons with the national proportion (exact binomial tests with Benjamini–Hochberg correction [13]) are reported in Additional file 1; because the number of referrals is very large, inference relies on confidence intervals and effect sizes.

Descriptive statistics

Referral volumes were summarised by referral type, age group, chapter and city. Associations were described with Pearson's chi-square test and bias-corrected Cramér's V [14] on referral-weighted tables, for all cities and for coverage-adequate cities.

Multivariable analysis (main analysis)

To separate the contributions of referring city, diagnosis and age, we fitted a binomial regression to referral-weighted cells (referring city × ICD-10 chapter × age group) of the coverage-adequate cities, with the cross-city share as outcome and city, chapter and age group as categorical predictors (references: Riyadh, circulatory diseases, 18–29 years). A quasi-binomial scale (Pearson chi-square / residual df) accounted for over-dispersion. City entered as a fixed effect because, with 12 cities and complete separation in cities without same-city records, a random-effects model would be poorly identified. The contribution of

each factor was summarised as the deviance lost when it was dropped, with quasi-binomial F tests. A city × chapter interaction tested whether cities differ in which diagnoses they refer out; at the city × chapter level the interaction model is saturated, so the test uses the deviance of the main-effects model fitted to city × chapter cells.

Sensitivity analyses

We repeated the headline results (cross-city share, associations, chapter ranking and hub concentration) for coverage-adequate cities. To address nested geography, each city was assigned to its administrative region and cross-city referrals were divided into those staying within, and those crossing, a regional boundary; health-cluster boundaries could not be assigned from the data. We also report the share of supplementary (U-coded) referrals by city. Finally, using the quarter-level file, we computed the DI by quarter and by gender and repeated the headline results excluding cities with count heaping, city-quarters with changes in reporting coverage, and both (Additional file 1: Tables S36–S38).

Exploratory cluster analysis

Cluster analyses were exploratory. We clustered (A) the 15 cities with same-city referrals by local referral profile, (B) all 19 referring cities by outbound profile (chapter, age and destination mix, and the DI), (C) the 22 ICD-10 chapters and (D) the 100 highest-volume codes by referral behaviour. City profiles were shrunk towards the national profile (Dirichlet prior of $0.5 \times K$ pseudo-referrals per block) and Hellinger-transformed [15]; this shrinkage and the rule that every cluster must contain at least two members were introduced after an initial analysis in which a city with a single same-city referral formed its own cluster. Disease features were the age distribution, cross-city rate, log volume, and the repetition rate and number of receiving cities, the last two adjusted for volume (residuals on log volume) because both rise mechanically with volume.

K-Means and Ward clustering [16] were compared for k = 2–8 (2–10 for codes) using the silhouette coefficient [17] and the Davies–Bouldin index [18], selecting the highest silhouette without singleton clusters. Validation comprised: (i) a null benchmark, in which every feature was permuted independently across entities (100 permutations) and the full selection procedure re-run; (ii) sensitivity to analytic choices (each feature block dropped or double-weighted; the volume adjustment removed; the prior strength varied; Analysis B restricted to coverage-adequate cities); (iii) multinomial bootstrap, leave-one-out and seed stability and agreement between algorithms, using the adjusted Rand index (ARI) [19]; and (iv) for Analysis B, comparison with simpler partitions: each city's main destination, its administrative region and Louvain communities of the cross-city flow network [20].

Hub analysis and mapping

Cross-city flows were summarised in an origin–destination matrix. Concentration of inflow was measured with the Herfindahl–Hirschman Index (HHI) and the top-three share. Regions were mapped at their administrative capitals.

Software and reproducibility

All processing used Python 3. Data preparation used pandas, openpyxl and RapidFuzz; analysis used pandas, NumPy, SciPy, statsmodels, scikit-learn, NetworkX, matplotlib, seaborn and, optionally, GeoPandas, with a fixed random seed 42. The pipeline is openly available (see Availability of data and materials) as two scripts: 01_data_preparation.py (raw extracts to analysis dataset, with data-quality, region-mapping and ICD-10-AM chapter reports) and 02_referral_dependency_analysis.py (all tables, figures and sensitivity analyses). The pipeline is deterministic, and a re-run reproduces the analysis dataset exactly. Use of a large language model: Claude (Claude Opus 5.5; Anthropic; accessed through claude.ai, 2026) was used to assist with drafting and debugging the analysis code and with language

editing. The author reviewed and verified all code, results and text and takes full responsibility for the content of the article.

Ethics

The study used aggregated, de-identified secondary data with no individual-level information. The data are publicly available open data from the Saudi National Open Data Portal; ethical approval was therefore not required (see Declarations).

Results

Referral volume and characteristics

The analysis dataset contained 460,953 referrals, of which 39,883 (8.7%) crossed city boundaries (Table 1; Additional file 1: Fig. S1). Cross-city records were smaller than same-city records (median 6 vs 12 referrals per record) and less often repeated across quarters or genders (18.3% vs 31.2%). Crude cross-city shares were highest for congenital malformations (34.1%), eye (31.4%) and ear diseases (31.3%) and lowest for pregnancy and childbirth (2.5%) (Additional file 1: Fig. S3); children and adolescents had the highest crude share (11.8%) (Additional file 1: Fig. S2).

Table 1 Referral volume and record characteristics by referral type, Q4 2024 – Q4 2025.

Characteristic	Same-city	Cross-city
Referrals, n (%)	421,070 (91.3)	39,883 (8.7)
Code-cell records, n	9,493	3,313
Distinct ICD-10 codes, n	2,491	1,081
Referring cities, n	15	19
Receiving cities, n	15	15
Referrals per record, median (IQR)	12 (4–32)	6 (1–21)
Repeated records, %	31.2	18.3

IQR, interquartile range. Referrals involving facilities outside Saudi Arabia are excluded. Al-Ahsa includes the former Eastern directorate unit.

Cross-city dependency by city

The DI varied from 0.4% in Riyadh to 100% (Table 2; Fig. 1). Ten cities sent more than 85% of their referrals elsewhere, but seven of them had fewer than 100 same-city referrals, so their DIs should be read as upper bounds that partly reflect data coverage. Among coverage-adequate cities, Tabuk (92.6%), Taif (91.3%) and Hafr Al-Batin (86.8%) remained highly dependent, Najran (46.0%) and Jazan (31.5%) were intermediate, and Riyadh, Al-Ahsa, Madinah, Jeddah and Asir had DIs below 4%. Highly dependent cities typically sent most referrals to one destination; Al-Jouf, Northern Borders and Qurayyat each sent at least 99% to Riyadh. Dependency varied across cities within every chapter (Fig. 2; Additional file 1: Table S6).

Table 2 Cross-city dependency index (DI) by referring city, ranked from most to least dependent. National DI = 8.7%.

Referring city	Same-city, n	Cross-city, n	DI, % (95% CI)	Destinations, n	Main destination (share)
Northern Borders†	0	3,912	100.0 (99.9–100.0)	7	Riyadh (99%)
Qunfudah†	0	2,715	100.0 (99.9–100.0)	5	Makkah (55%)
Qurayyat†	0	3,800	100.0 (99.9–100.0)	5	Riyadh (99%)
Bisha†	0	2,007	100.0 (99.8–100.0)	4	Riyadh (51%)
Al-Baha†	1	2,181	100.0 (99.7–100.0)	5	Jeddah (74%)
Al-Jouf†	51	5,229	99.0 (98.7–99.3)	4	Riyadh (100%)
Tabuk	164	2,063	92.6 (91.5–93.6)	6	Riyadh (66%)
Taif	156	1,639	91.3 (89.9–92.5)	3	Jeddah (73%)
Hail†	57	411	87.8 (84.5–90.5)	2	Riyadh (86%)
Hafr Al-Batin	267	1,758	86.8 (85.3–88.2)	4	Riyadh (91%)
Najran	1,164	990	46.0 (43.9–48.1)	7	Riyadh (86%)
Jazan	2,998	1,378	31.5 (30.1–32.9)	4	Asir (57%)
Makkah	12,361	3,434	21.7 (21.1–22.4)	4	Jeddah (87%)
Qassim	6,359	1,335	17.4 (16.5–18.2)	3	Riyadh (100%)
Asir	34,625	1,228	3.4 (3.2–3.6)	9	Riyadh (63%)
Jeddah	134,977	4,357	3.1 (3.0–3.2)	9	Makkah (92%)
Madinah	23,317	467	2.0 (1.8–2.1)	5	Jeddah (56%)
Al-Ahsa‡	12,657	239	1.9 (1.6–2.1)	3	Riyadh (99%)

Referring city	Same-city, n	Cross-city, n	DI, % (95% CI)	Destinations, n	Main destination (share)
Riyadh	191,916	740	0.4 (0.4–0.4)	14	Al-Ahsa (30%)

† Fewer than 100 same-city referrals: DI may partly reflect incomplete capture of local referrals; excluded from the main multivariable analysis. ‡ Includes the former Eastern directorate unit. CI, Wilson confidence interval.

Contributions of city, diagnosis and age

In the 12 coverage-adequate cities (1,409 cells; dispersion 17.1), referring city accounted for 83.6% of the explained deviance, ICD-10 chapter for 8.1% and age group for 0.4% (Table 3). The city × chapter interaction was significant ($F = 1.6$, $df = 215$, $p = 2.7 \times 10^{-7}$) and accounted for 8.6% of the deviance among city × chapter cells: cities differed not only in how much but also in which diagnoses they referred elsewhere.

Table 3 Contribution of referring city, ICD-10 chapter and age group to cross-city referral (quasi-binomial regression, 12 coverage-adequate cities).

Term	df	Deviance explained	Share of explained deviance, %	F	p
Referring city	11	53,527	83.6	284.8	$<10^{-300}$
ICD-10 chapter	21	5,199	8.1	14.5	1.7×10^{-46}
Age group	7	242	0.4	2.0	0.049
City × chapter interaction	215	5,986	8.6*	1.6	2.7×10^{-7}

*Deviance explained: deviance lost when the term is dropped from the main-effects model. *Relative to the null deviance of city × chapter cells. Null deviance 81,181; residual deviance 17,118.*

After adjustment for city and age, cross-city referral was most likely for factors influencing health status, mainly rehabilitation (OR 10.23, 95% CI 6.67–15.71), congenital malformations (3.93, 2.44–6.34), eye diseases (3.83, 1.96–7.49), neoplasms (3.57, 1.68–7.57), mental and behavioural disorders (2.49, 1.29–4.82) and nervous-system diseases (1.81, 1.27–2.60), relative to circulatory diseases (Table 4; Fig. 3). It was least likely for pregnancy and childbirth (0.34, 0.20–0.59), infectious (0.47), respiratory (0.51) and endocrine diseases (0.56). Injury and poisoning, despite its large crude cross-city volume, did not differ from circulatory diseases after adjustment (0.97, 0.71–1.32), indicating that its crude excess

reflects the cities that refer it. No age group differed significantly from 18–29 years (ORs 0.89–1.37; Additional file 1: Table S12).

Table 4 Adjusted odds ratios of cross-city referral by ICD-10 chapter (12 coverage-adequate cities; adjusted for referring city and age group).

ICD-10 chapter	Adjusted OR (95% CI)	ICD-10 chapter	Adjusted OR (95% CI)
Health-status factors	10.23 (6.67–15.71)	External causes	1.09 (0.70–1.70)
Congenital malformations	3.93 (2.44–6.34)	Injury and poisoning	0.97 (0.71–1.32)
Eye	3.83 (1.96–7.49)	Digestive	0.83 (0.56–1.24)
Neoplasms	3.57 (1.68–7.57)	Perinatal	0.63 (0.41–0.96)
Ear	2.80 (0.72–10.87)	Supplementary codes	0.59 (0.35–0.99)
Mental and behavioural	2.49 (1.29–4.82)	Symptoms and signs	0.58 (0.42–0.81)
Skin	2.14 (0.99–4.63)	Endocrine and metabolic	0.56 (0.39–0.82)
Nervous system	1.81 (1.27–2.60)	Respiratory	0.51 (0.39–0.68)
Musculoskeletal	1.40 (0.80–2.43)	Infectious	0.47 (0.31–0.72)
Genitourinary	1.22 (0.85–1.74)	Blood and immune	0.45 (0.18–1.10)
Circulatory (reference)	1	Pregnancy and childbirth	0.34 (0.20–0.59)

Quasi-binomial confidence intervals. Age-group and city estimates are given in Additional file 1: Tables S12 and S13.

Sensitivity analyses

Restricting to coverage-adequate cities lowered the cross-city share from 8.7% to 4.5% and the association between city and referral type from V = 0.81 to 0.57, but left the chapter ranking essentially unchanged (Spearman $\rho = 0.96$; mental and behavioural disorders then ranked first at 23.9%) and the three main hubs unchanged (87.8% of inflow) (Additional file 1: Table S9).

Overall, 62.8% of cross-city referrals also crossed an administrative-region boundary (Additional file 1: Table S10). Referrals from the northern cities (Al-Jouf, Hail, Northern Borders, Qurayyat, Tabuk) left the Northern region almost entirely, whereas most cross-city referrals from Jeddah (93.5%), Makkah (90.7%), Qunfudah (99.4%) and Taif (82.7%) stayed within the Western region. Supplementary U codes made up 0.1–7.1% of referrals by city, exceeding 5% only in Hail (Additional file 1: Table S11).

City-level dependency was stable over time: Spearman correlations between quarterly and pooled city DIs ranged from 0.97 to 0.99 (Additional file 1: Fig. S18; Table S36), although the national cross-city share varied between quarters (from 11.0% in Q2 2025 to 6.4% in Q4 2025). The DI was higher for male than for female patients (9.7% vs 7.6%), but cities ranked almost identically by gender (ρ = 0.97; Additional file 1: Table S37). Excluding the eight cities with count heaping (Al-Baha, Asir, Bisha, Jazan, Makkah, Najran, Qassim and Tabuk; 15.7% of referrals) lowered the cross-city share to 6.5% but left the chapter ranking (ρ = 0.96) and the three main hubs (96.5% of inflow) essentially unchanged. Excluding the nine city-quarters with changes in reporting coverage (1.5% of referrals) gave a cross-city share of 8.1% (ρ = 0.99; top-three hub share 91.7%), and excluding both gave 6.5% (ρ = 0.95; 96.7%) (Additional file 1: Table S38).

Concentration of cross-city inflow on hubs

Cross-city inflow was highly concentrated (HHI = 3,780): Riyadh, Jeddah and Makkah received 91.5% of all cross-city referrals (Table 5; Fig. 4). Riyadh received referrals from 18 of 19 referring cities, with no single origin contributing more than 24%. Jeddah and Makkah formed a reciprocal pair within the Western region (Jeddah sent 92% of its cross-city referrals to Makkah, and Makkah 87% to Jeddah), and Asir acted as a southern hub, receiving 57% of Jazan's cross-city referrals. Nine receiving cities each received less than 0.5% of national inflow.

Table 5 Leading receiving cities by cross-city inflow.

Receiving city	Inflow, n	Share of national inflow, %	Origin cities, n	Main origin (share)	Leading chapter (share of inflow)
Riyadh	22,158	55.6	18	Al-Jouf (24%)	Injury and poisoning (14%)
Jeddah	8,424	21.1	14	Makkah (36%)	Injury and poisoning (19%)
Makkah	5,908	14.8	14	Jeddah (68%)	Circulatory (21%)
Asir	1,877	4.7	8	Bisha (42%)	Respiratory (20%)
Madinah	815	2.0	7	Tabuk (68%)	Injury and poisoning (24%)

Receiving city	Inflow, n	Share of national inflow, %	Origin cities, n	Main origin (share)	Leading chapter (share of inflow)
Al-Ahsa	453	1.1	6	Riyadh (49%)	Circulatory (25%)
Other 9 cities	248	0.6	—	—	—

HHI of national cross-city inflow = 3,780; top-three share = 91.5%.

Exploratory typologies

Only two of the four cluster analyses showed more structure than the null benchmark (Additional file 1: Table S29; Fig. S17). The outbound typology of referring cities (Analysis B; observed silhouette 0.243 vs null 95th percentile 0.233; p = 0.04) comprised four groups (Table 6; Figs. 5–6): a **Riyadh-oriented high-dependency group** of eight northern and southern cities (mean DI 89%; 84.7% of cross-city referrals to Riyadh); a **Jeddah-bound western group** of four Makkah-region cities (69.6% to Jeddah; injury 23.6% of the outbound mix); **low-dependency regional centres** (Al-Ahsa, Asir, Madinah, Qassim; mean DI 6.1%), whose few outbound referrals went mainly to Riyadh and were weighted towards health-status factors; and the **major centres** (Riyadh, Jeddah, Jazan), whose outbound referrals were weighted towards circulatory and endocrine disease and older patients. The typology was stable to resampling, to dropping the age or chapter features and to moderate changes in prior strength, but agreed only partly with Ward clustering (ARI 0.59), depended on the destination and dependency blocks (ARI 0.45 and 0.48 when dropped) and changed substantially when restricted to coverage-adequate cities (ARI 0.32) (Additional file 1: Table S30). It overlapped moderately with each city's main destination (ARI 0.51) and less with flow-network communities (0.34; modularity 0.41) and administrative region (0.20) (Additional file 1: Table S31).

Table 6 Exploratory typology of referring cities by outbound referral profile (Analysis B), with validation.

Group	Cities	Cross-city referrals, n	Mean DI, %	Distinguishing features (group mean)
B1 Riyadh-oriented high dependency	Al-Jouf†, Bisha†, Hafr Al-Batin, Hail†, Najran, Northern Borders†, Qurayyat†, Tabuk	20,170	89.0	84.7% to Riyadh; 2.1% to Jeddah; digestive 7.6%
B2 Jeddah-bound western group	Al-Baha†, Makkah, Qunfudah†, Taif	9,969	78.3	69.6% to Jeddah; injury and poisoning 23.6%; 10.9% to Riyadh
B3 Low-dependency regional centres	Al-Ahsa, Asir, Madinah, Qassim	3,269	6.1	Health-status factors 13.7%; skin 4.4%; mainly to Riyadh
B4 Major centres	Jazan, Jeddah, Riyadh	6,475	11.7	Circulatory 24.1%; endocrine 6.9%; aged ≥80 13.7%

Validation: null benchmark p = 0.040; bootstrap ARI 1.00; leave-one-out ARI median 1.00 (minimum 0.64); agreement with Ward 0.59; restricted to 12 coverage-adequate cities ARI 0.32; agreement with main-destination partition 0.51. † Fewer than 100 same-city referrals. Group means of shares are shrunk profiles; mean DI is unshrunk.

Among the 100 highest-volume codes (Analysis D; p = 0.01), Ward clustering separated nine codes with high cross-city rates (mean 31.1%) reaching many receiving cities (mean 6.9) — rehabilitation (Z50), fractures of the femoral head (S72) and acetabulum (S32), multiple injuries (T07), hydrocephalus (G91), anoxic brain damage and encephalopathy (G93), hydronephrosis (N13) and one supplementary code (U80) — from 91 high-volume, frequently repeated codes (Additional file 1: Tables S26–S27). This split depended on the cross-city rate and on the volume adjustment (Additional file 1: Table S30).

The local-profile typology (Analysis A; p = 0.29) and the chapter typology (Analysis C; p = 0.15) did not exceed the null benchmark and were sensitive to analytic choices; they are reported only in Additional file 1 (Tables S16 and S24).

Discussion

Principal findings

Where a patient is referred from explains most of whether the referral leaves the city: in coverage-adequate cities, referring city accounted for 84% of the explained deviance and age for almost none. Diagnosis nonetheless mattered independently. Rehabilitation, congenital, ophthalmic, oncological, mental-health and neurological referrals were two to ten times as likely to cross city boundaries as circulatory referrals, and cities differed in which of these diagnoses they referred out. Cross-city inflow converged on Riyadh, Jeddah and Makkah. Cluster analyses added little beyond these results: only an outbound typology of cities and a small group of specialised codes exceeded a null benchmark, and the city typology was sensitive to excluding low-coverage cities.

Interpretation and comparison with previous Saudi studies

Our findings are consistent with, and extend, the national e-referral analyses, which attributed most Central and Eastern referrals to unavailable sub-specialty care and found more equipment-, bed- and emergency-related referrals in the south [1]. At city level, Riyadh and Al-Ahsa were among the least dependent referring cities while Riyadh was the dominant receiving hub, suggesting that Central-region sub-specialty needs are largely met within Riyadh, which also serves the rest of the country. The northern cities sent almost all cross-city referrals across a regional boundary, mostly to Riyadh, whereas the Jeddah–Makkah exchange and most referrals from Taif and Qunfudah stayed within the Western region. The latter pattern looks more like a division of services within one regional network than dependency in the usual sense, and argues for monitoring referrals that cross region or cluster boundaries separately from those that do not.

The diagnosis-specific excess was concentrated in services that are typically provided only in specialised centres. Rehabilitation (Z50) stood out both in the adjusted model and at code level, together with complex orthopaedic trauma, hydrocephalus and anoxic brain injury, pointing to rehabilitation and neurosurgical capacity as the main specialised drivers of travel. For neoplasms the adjusted odds of cross-city referral were high, but the volume was very small (about 1,350 referrals, 0.3% of the total), far below what a national referral dataset would be expected to contain. This suggests that most oncology referrals follow a separate pathway not captured here; specialised cancer services in Saudi Arabia are concentrated in three regions [21], so our data probably understate oncology-related travel. External referrals are less often accepted than internal ones [2]. Our data contain recorded referrals only, so the cities most reliant on external referral may face additional unmet need not visible in these counts.

Comparison with international evidence

Centralising complex care in high-volume centres is standard practice internationally and can improve efficiency and outcomes, but shifts travel time and cost onto patients and raises equity concerns [21]. Referral pathways for suspected cancer vary substantially between jurisdictions[22], and referral destination reflects specialisation, trial access and perceived expertise as much as proximity [23], with pathways that differ by socioeconomic position [24]. Problems in primary-to-specialty referral are common across systems [25]; in Saudi Arabia, 65% of medical directorates have rated primary-to-secondary referral systems as weak [3].

Implications and hypotheses for planning

Because the design is descriptive and lacks acceptance, waiting-time, travel and outcome data, the following are hypotheses for planners rather than tested recommendations. First,

rehabilitation and neurosurgical services are candidate targets for regional capacity or outreach, particularly for the northern cities, which refer almost exclusively to Riyadh. Second, regional centres with low dependency (Al-Ahsa, Asir, Madinah, Qassim) might absorb some referrals from neighbouring dependent cities. Third, routine monitoring should distinguish referrals that cross region or cluster boundaries from those within a regional network, and should be paired with checks of local data coverage, since dependency near 100% in several cities probably reflects incomplete capture of local referrals. Forecasting referral demand by city and diagnosis is a natural next step; machine-learning methods often improve demand forecasts over classical time-series models, although gains are context-dependent[26, 27], and interpretable or explainable models are preferable for planning use [28, 29]. Longer, patient-level series than ours would be required.

Strengths and limitations

Strengths. To our knowledge, this is the first Saudi study combining diagnosis-level detail with city-to-city referral flows. It uses national-scale data, separates city, diagnosis and age effects in a multivariable model, reports effect sizes, makes data coverage explicit, and tests its exploratory clustering against a null benchmark and alternative analytic choices. The full pipeline, from raw extracts to figures, is scripted and openly available.

Limitations.

- **Coverage and system scope.** Seven cities recorded fewer than 100 same-city referrals, and the data appear to capture few oncology referrals. DIs in low-coverage cities are upper bounds; the main model was restricted to coverage-adequate cities, but some coverage-adequate cities (e.g., Tabuk, Taif) may also be partly affected.

- **Aggregated data and unit of count.** Records are aggregated rather than patient-level; if a referral can carry several codes, counts are referral–diagnosis pairs. Tests assume independence only approximately, so inference emphasises effect sizes.
- **Geography.** Units mix cities and health regions; the Eastern Province directorate unit was merged with Al-Ahsa, so this unit covers a wider area than Al-Hofuf; health-cluster boundaries could not be assigned; and the referring region for four quarters was derived from a lookup.
- **Diagnosis coding.** Chapters were assigned from the ICD-10-AM chapter structure, and individual codes depend on validation against the licensed ICD-10-AM tabular list; supplementary codes (3.1%) could not be assigned to a body system.
- **Data quality.** Count heaping and changes in reporting coverage were present in some cities; excluding the eight affected cities or the nine affected city-quarters lowered the cross-city share (to 6.5% and 8.1%, respectively) but did not change the chapter ranking ($\rho \geq 0.95$) or the three main hubs.
- **Missing context.** No population denominators, acceptance, reasons, urgency, travel or outcome data were available, so dependency cannot be equated with unmet need. The open files contain only the variables released by the publisher.
- **Exploratory clustering.** Cluster structure was weak, two of four typologies did not exceed the null benchmark, the shrinkage and no-singleton rules were introduced post hoc, and the city typology was sensitive to excluding low-coverage cities.

Conclusions

Cross-city referral in Saudi Arabia depends mainly on the referring city, but is additionally concentrated in rehabilitation, congenital, ophthalmic, oncological, mental-health and neurological care, and converges on Riyadh, Jeddah and Makkah. Diagnosis-level, city-to-

city monitoring of referral volume and destination — interpreted together with checks of local data coverage and with acceptance data — can help health clusters decide where specialised capacity and outreach are most needed.

List of abbreviations

ARI: Adjusted Rand index

CI: Confidence interval

DI: Cross-city dependency index

HHI: Herfindahl–Hirschman Index

ICD-10-AM: International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification

IQR: Interquartile range

KSA: Kingdom of Saudi Arabia

OR: Odds ratio

PHC: Primary health centre

Q: Quarter

RECORD: REporting of studies Conducted using Observational Routinely-collected health Data

Declarations

Ethics approval and consent to participate

Not applicable. The study analysed publicly available, aggregated and de-identified open data published by the Center for National Health Insurance on the Saudi National Open Data Portal; no individual-level or identifiable information was accessed, so ethics approval and informed consent were not required.

Consent for publication

Not applicable.

Availability of data and materials

The quarterly files analysed during the current study are openly available from the Saudi National Open Data Portal (https://open.data.gov.sa), dataset "Referral of Medical Cases". The complete analysis pipeline (01_data_preparation.py and 02_referral_dependency_analysis.py) is openly available under the MIT License at https://github.com/ndhassani/cross-city-referral-dependency .

Competing interests

The author declares no competing interests.

Funding

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Authors' contributions

NA conceived and designed the study, curated the data, wrote the software, performed the formal analysis and visualisation, and wrote and revised the manuscript. The author read and approved the final manuscript.

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Supplementary Information

Additional file 1 (.docx): Supplementary methods S1–S12, Supplementary Tables S1–S39 (Table S39 is the completed RECORD checklist) and Supplementary Figs. S1–S18.

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Figure titles and legends

Fig. 1 Cross-city dependency index by referring city, with 95% Wilson confidence intervals. Colours indicate a significant difference from the national proportion after Benjamini–Hochberg correction. n is the total number of referrals originating in the city. Cities with fewer than 100 same-city referrals (Table 2) may have incomplete capture of local referrals.

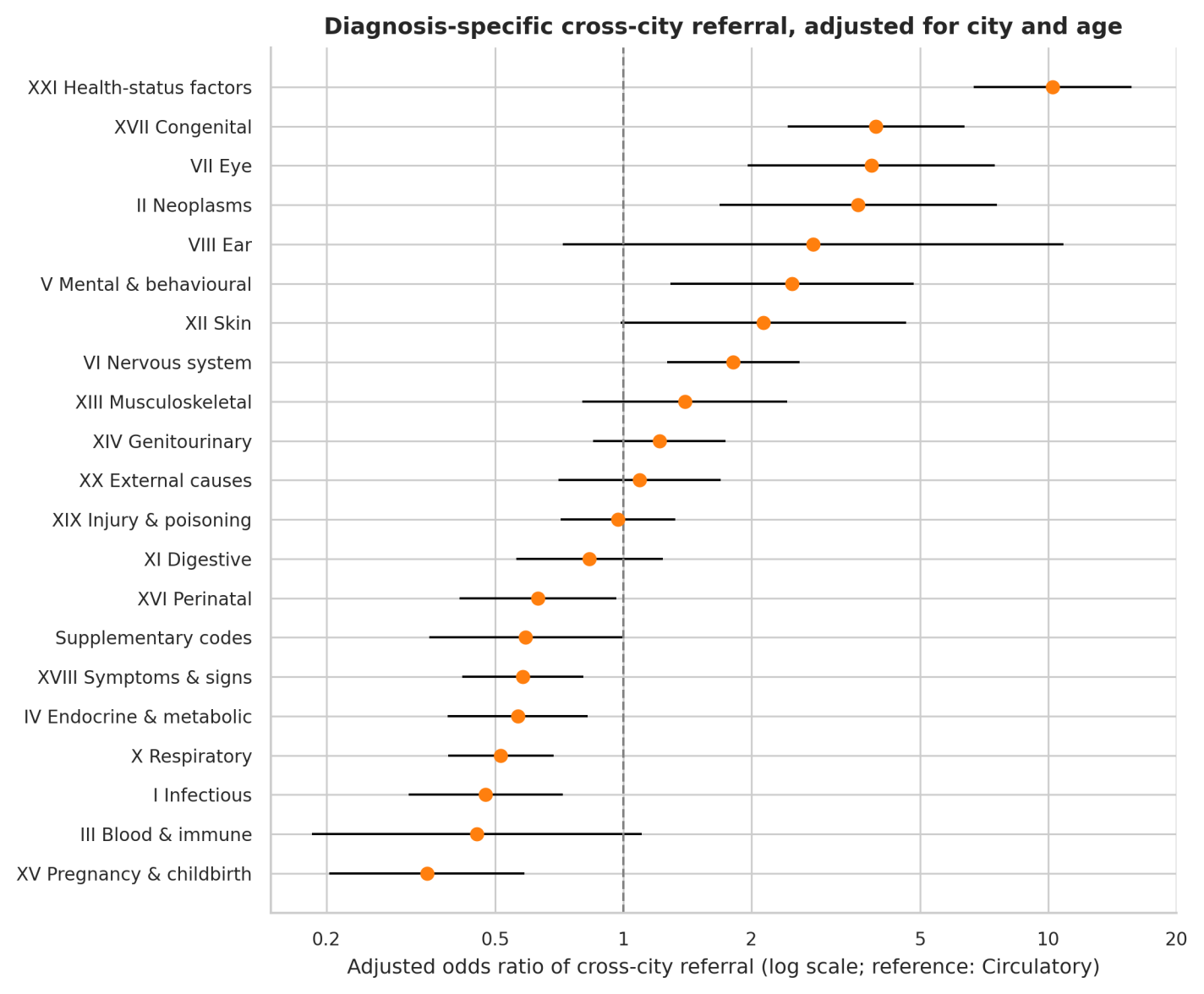
Fig. 2 Cross-city dependency index (%) by referring city and ICD-10 chapter. Blank cells indicate no referrals; outlined cells have fewer than 20 referrals. Cities are ordered from most dependent (top) to least dependent.

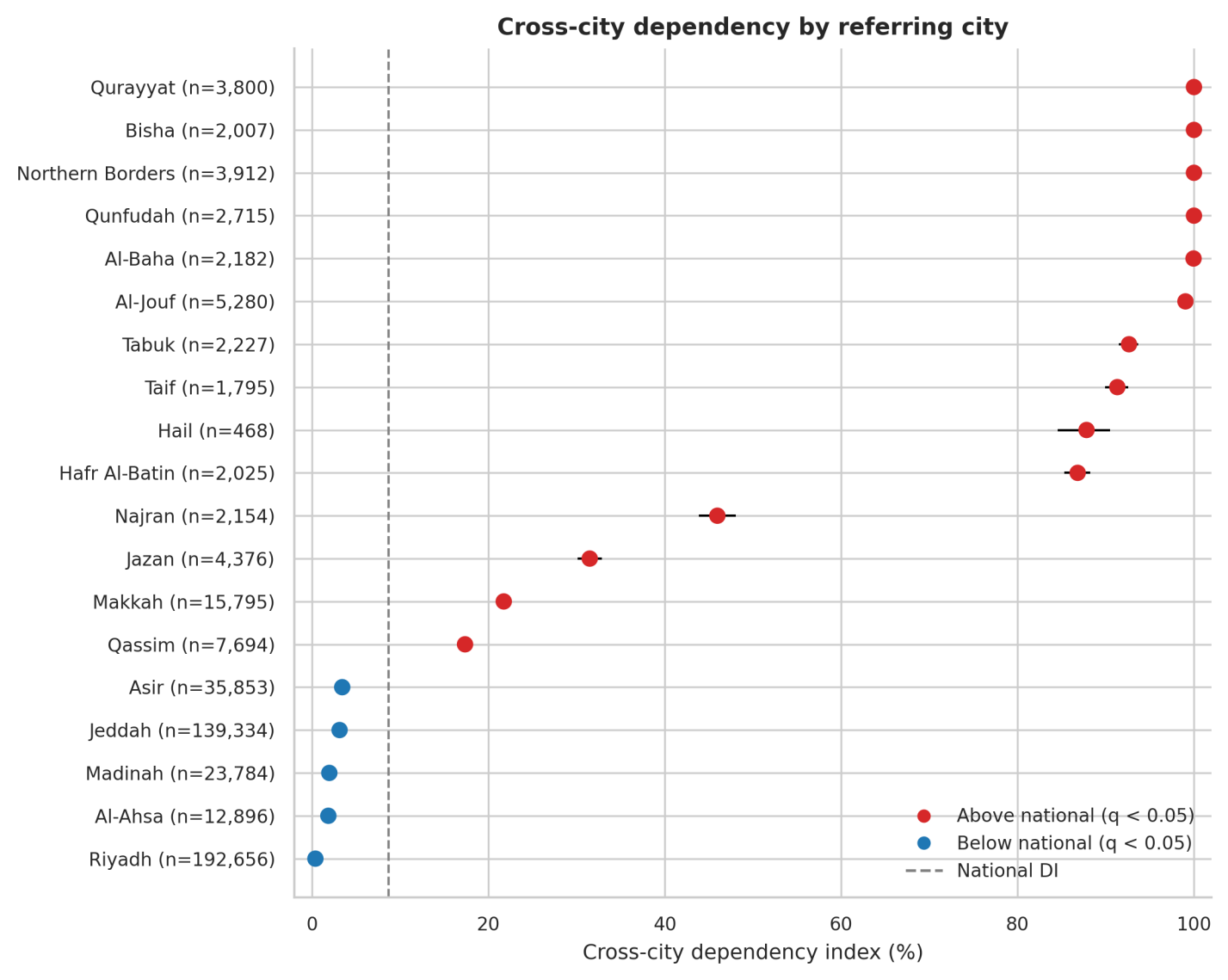
Fig. 3 Adjusted odds ratios (95% CI) of cross-city referral by ICD-10 chapter, from a quasi-binomial regression with referring city and age group as covariates (12 coverage-adequate cities). Reference: circulatory diseases.

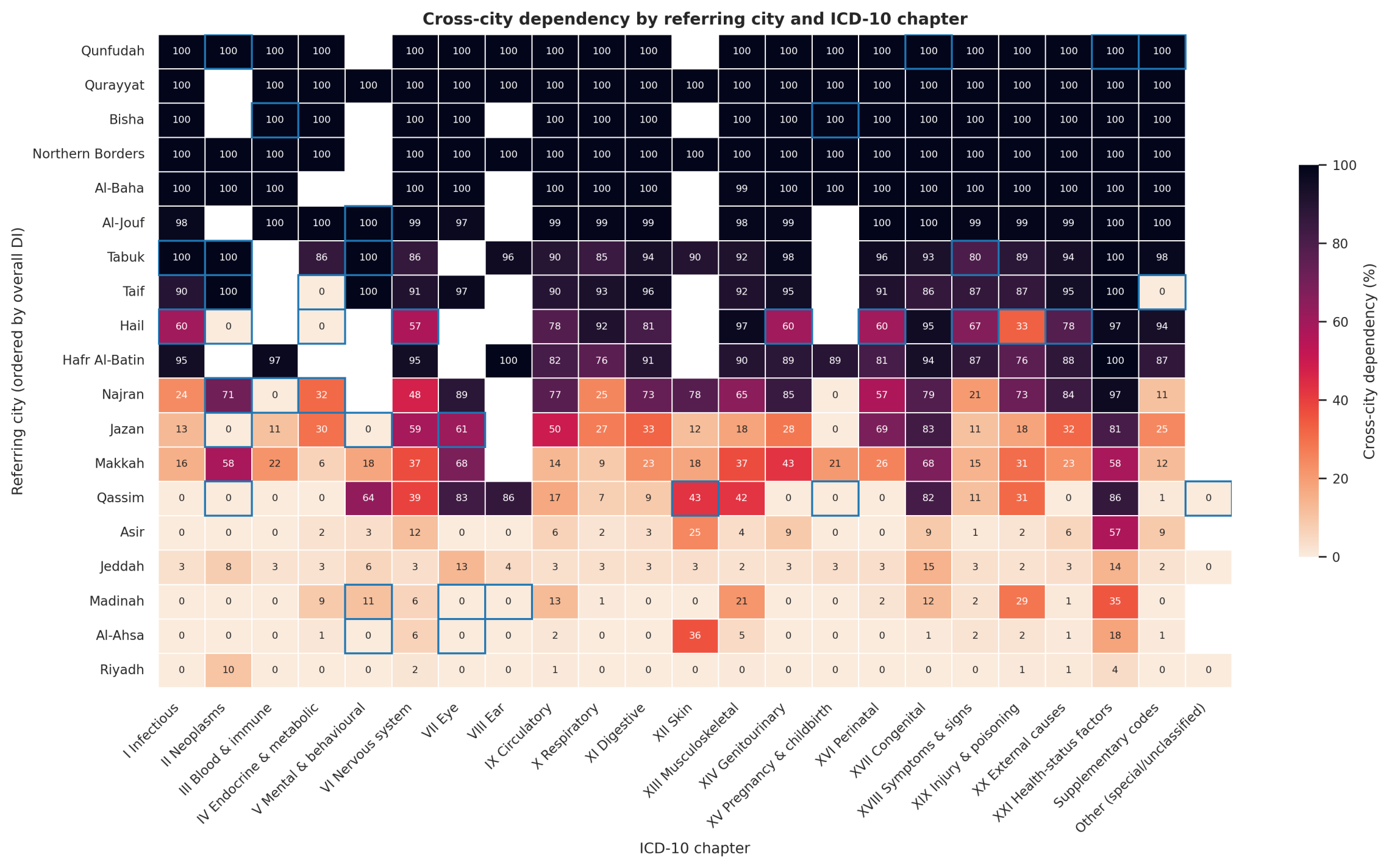
Fig. 4 Geography of referrals. (a) Same-city referral volume (circle area), coloured by local-profile cluster (Analysis A, exploratory); hollow markers indicate cities without same-city referrals. (b) Cross-city flows, with line width proportional to the square root of volume and colour showing the origin city's outbound group (Analysis B); rings show inflow received. Regions are plotted at their administrative capitals; Al-Ahsa (including the former Eastern directorate unit) at Al-Hofuf; coordinates are approximate.

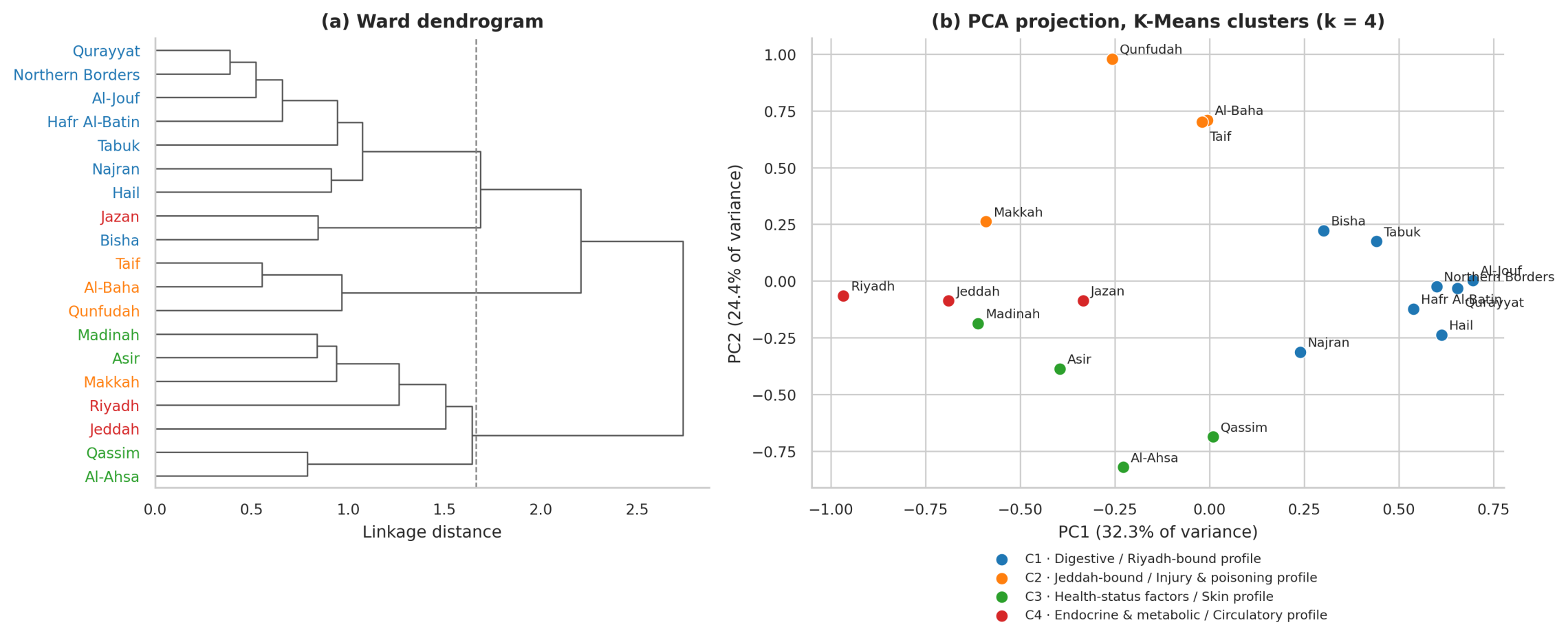
Fig. 5 Exploratory typology of referring cities by outbound profile (Analysis B). (a) Ward dendrogram with the cut at k = 4; leaf labels coloured by the final K-Means cluster. (b) Projection onto the first two principal components. C1 = B1 Riyadh-oriented high dependency; C2 = B2 Jeddah-bound western group; C3 = B3 low-dependency regional centres; C4 = B4 major centres.

Fig. 6 Profiles of the four outbound city groups by feature block: ICD-10 chapter mix, age mix, and destination and dependency. Cell values are group means; colour shows the mean z-score relative to all cities.


Diagnosis-specific cross-city referral, adjusted for city and age
XXI Health-status factors
XVII Congenital
VII Eye
II Neoplasms
VIII Ear
V Mental & behavioural
XII Skin
VI Nervous system
XIII Musculoskeletal
XIV Genitourinary
XX External causes
XIX Injury & poisoning
XI Digestive
XVI Perinatal
Supplementary codes
XVIII Symptoms & signs
IV Endocrine & metabolic
X Respiratory
I Infectious
III Blood & immune
XV Pregnancy & childbirth
0.2
0.5
1
2
5
10
20
Adjusted odds ratio of cross-city referral (log scale; reference: Circulatory)

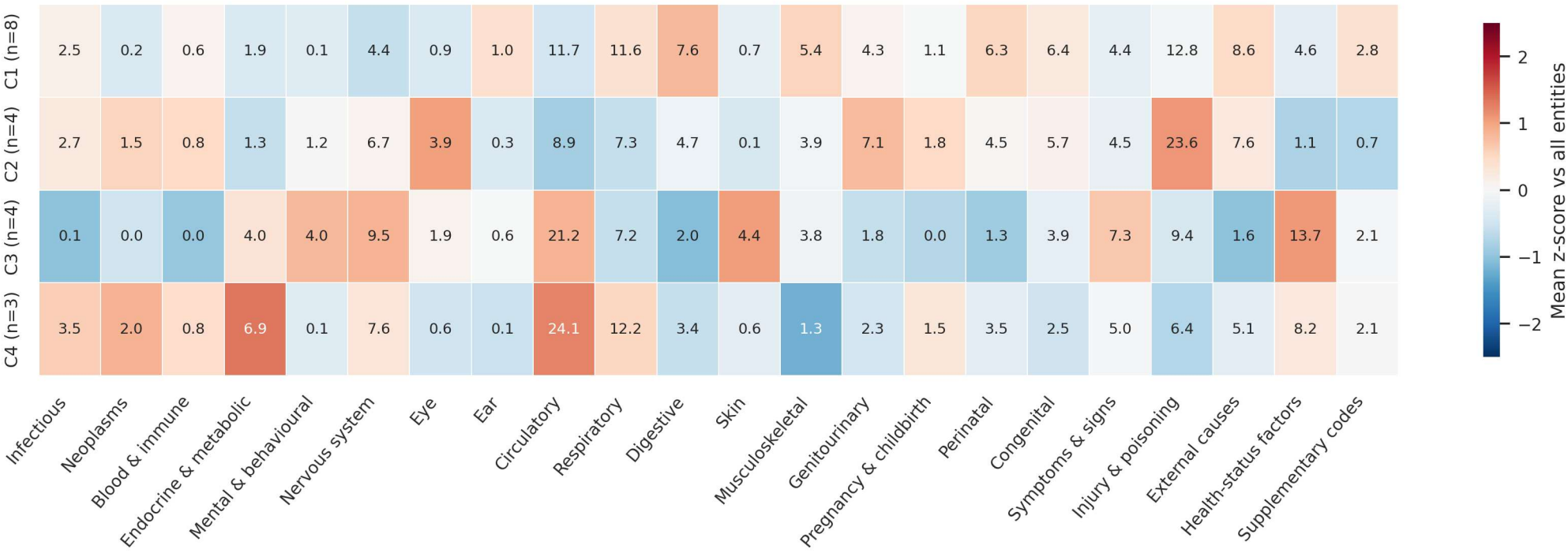

Cross-city dependency by referring city
Qurayyat (n=3,800)
Bisha (n=2,007)
Northern Borders (n=3,912)
Qunfudah (n=2,715)
Al-Baha (n=2,182)
Al-Jouf (n=5,280)
Tabuk (n=2,227)
Taif (n=1,795)
Hail (n=468)
Hafr Al-Batin (n=2,025)
Najran (n=2,154)
Jazan (n=4,376)
Makkah (n=15,795)
Qassim (n=7,694)
Asir (n=35,853)
Jeddah (n=139,334)
Madinah (n=23,784)
Al-Ahsa (n=12,896)
Riyadh (n=192,656)
Above national (q < 0.05)
Below national (q < 0.05)
National DI
0
20
40
60
80
100
Cross-city dependency index (%)


Cross-city dependency by referring city and ICD-10 chapter
Referring city (ordered by overall DI)
Qunfudah 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100
Qurayyat 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100
Bisha 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100
Northern Borders 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100 100
Al-Baha 100 100 100 100 100 100 100 100 100 100 100 99 100 100 100 100 100 100 100 100 100 100 100
Al-Jouf 98 100 100 100 99 97 99 99 99 98 99 100 100 99 99 99 100 100
Tabuk 100 100 86 100 86 96 90 85 94 90 92 98 96 93 80 89 94 100 98
Taif 90 100 0 100 91 97 90 93 96 92 95 91 86 87 87 95 100 0
Hail 60 0 0 57 78 92 81 97 60 60 95 67 33 78 97 94
Hafr Al-Batin 95 97 95 100 82 76 91 90 89 89 81 94 87 76 88 100 87
Najran 24 71 0 32 48 89 77 25 73 78 65 85 0 57 79 21 73 84 97 11
Jazan 13 0 11 30 0 59 61 50 27 33 12 18 28 0 69 83 11 18 32 81 25
Makkah 16 58 22 6 18 37 68 14 9 23 18 37 43 21 26 68 15 31 23 58 12
Qassim 0 0 0 0 64 39 83 86 17 7 9 43 42 0 0 0 82 11 31 0 86 1 0
Asir 0 0 0 2 3 12 0 0 6 2 3 25 4 9 0 0 9 1 2 6 57 9
Jeddah 3 8 3 3 6 3 13 4 3 3 3 3 2 3 3 3 15 3 2 3 14 2 0
Madinah 0 0 0 9 11 6 0 0 13 1 0 0 21 0 0 2 12 2 29 1 35 0
Al-Ahsa 0 0 0 1 0 6 0 0 2 0 0 36 5 0 0 0 1 2 2 1 18 1
Riyadh 0 10 0 0 0 2 0 0 1 0 0 0 0 0 0 0 0 0 1 1 4 0 0
I Infectious
II Neoplasms
III Blood & immune
IV Endocrine & metabolic
V Mental & behavioural
VI Nervous system
VII Eye
VIII Ear
IX Circulatory
X Respiratory
XI Digestive
XII Skin
XIII Musculoskeletal
XIV Genitourinary
XV Pregnancy & childbirth
XVI Perinatal
XVII Congenital
XVIII Symptoms & signs
XIX Injury & poisoning
XX External causes
XXI Health-status factors
Supplementary codes
Other (special/unclassified)
ICD-10 chapter
Cross-city dependency (%)
100
80
60
40
20
0

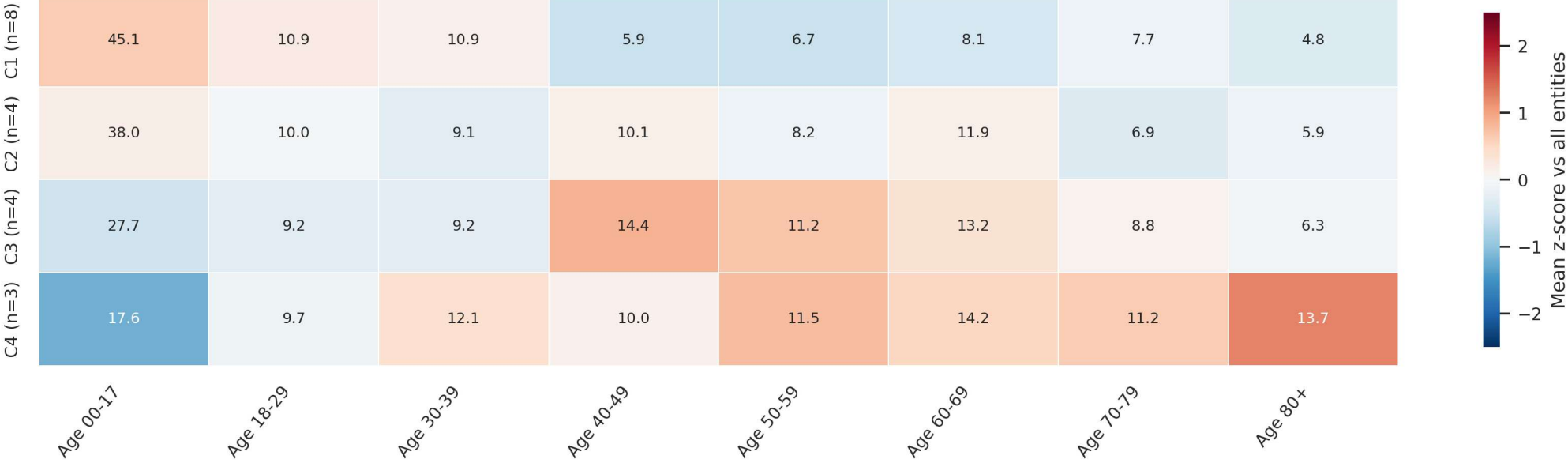

(a) Ward dendrogram
Qurayyat
Northern Borders
Al-Jouf
Hafr Al-Batin
Tabuk
Najran
Hail
Jazan
Bisha
Taif
Al-Baha
Qunfudah
Madinah
Asir
Makkah
Riyadh
Jeddah
Qassim
Al-Ahsa
0.0
0.5
1.0
1.5
2.0
2.5
Linkage distance
(b) PCA projection, K-Means clusters (k = 4)
PC2 (24.4% of variance)
PC1 (32.3% of variance)
Qunfudah
Al-Baha
Taif
Makkah
Bisha
Tabuk
Al-Jouf
Northern Borders
Hafr Al-Batin
Qurayyat
Hail
Riyadh
Jeddah
Jazan
Madinah
Najran
Asir
Qassim
Al-Ahsa
C1 · Digestive / Riyadh-bound profile
C2 · Jeddah-bound / Injury & poisoning profile
C3 · Health-status factors / Skin profile
C4 · Endocrine & metabolic / Circulatory profile

Analysis B (cross-city outbound profiles): cluster profiles

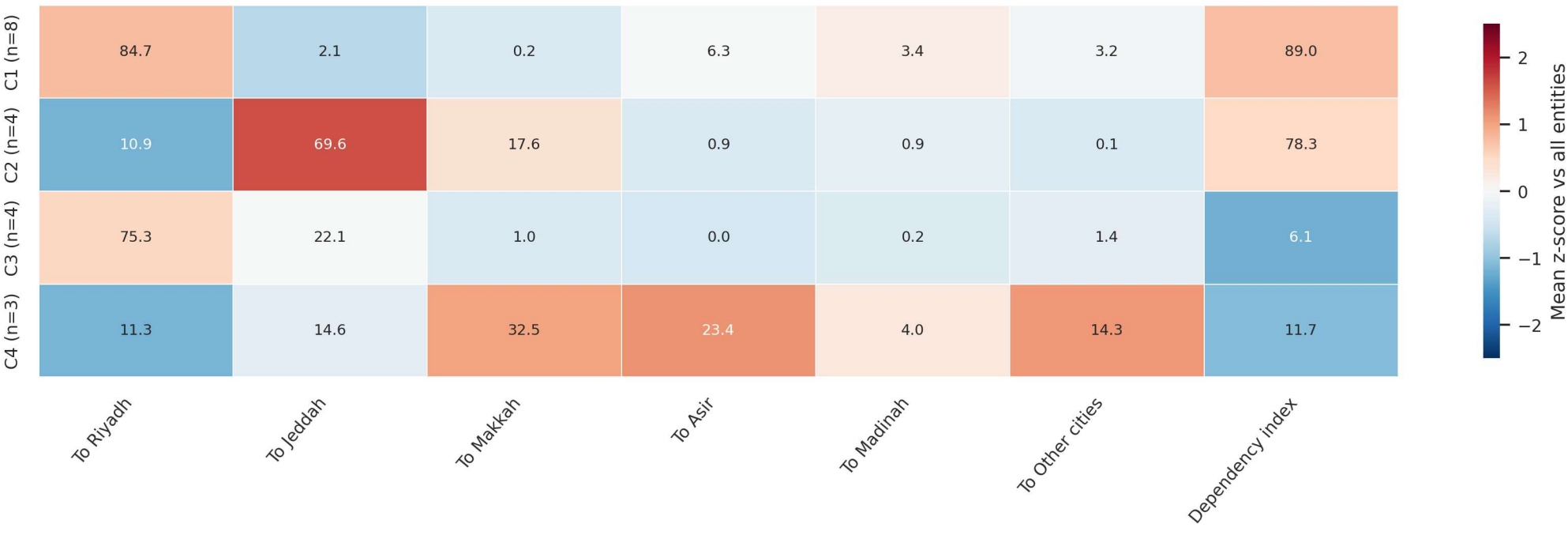
ICD-10 chapter (% of referrals)

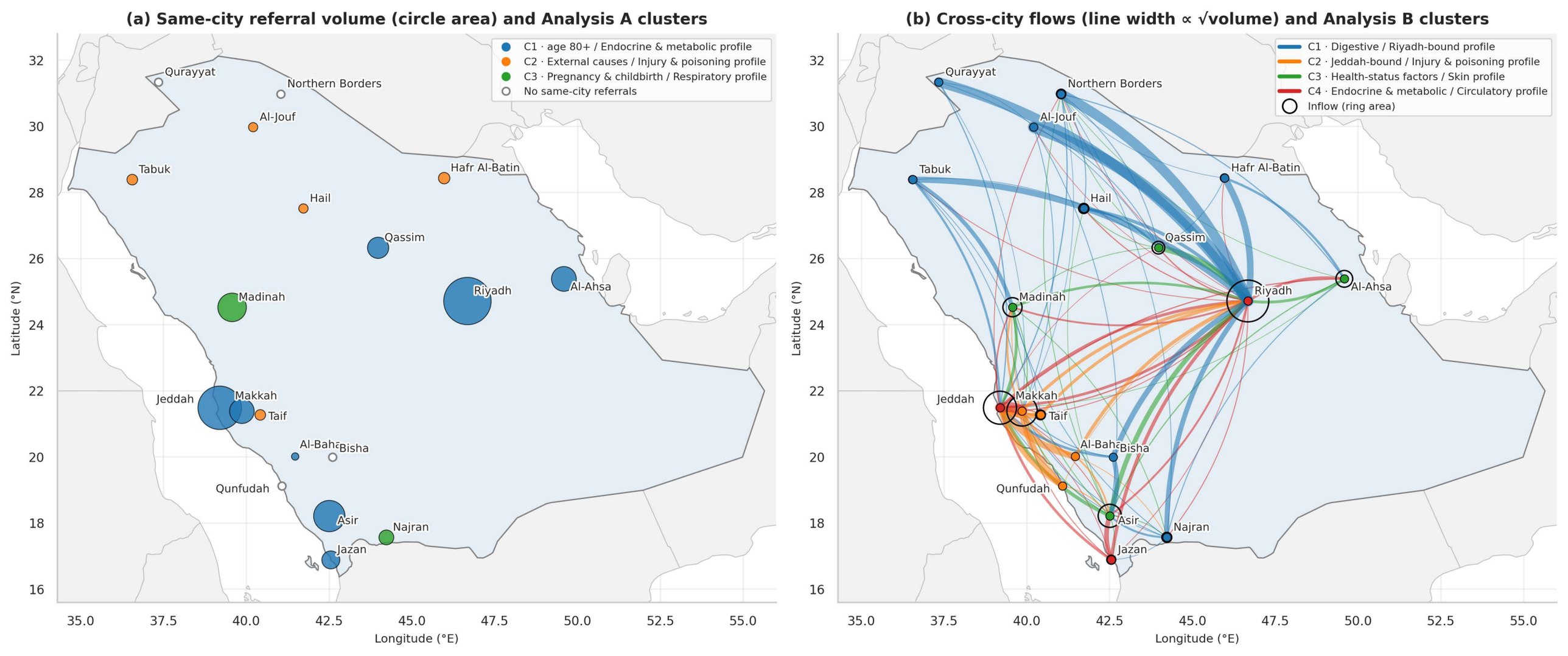


Age group (% of referrals)



Destination and dependency (%)




(a) Same-city referral volume (circle area) and Analysis A clusters
C1 · age 80+ / Endocrine & metabolic profile
C2 · External causes / Injury & poisoning profile
C3 · Pregnancy & childbirth / Respiratory profile
No same-city referrals
Qurayyat
Northern Borders
Al-Jouf
Tabuk
Hafr Al-Batin
Hail
Qassim
Madinah
Riyadh
Al-Ahsa
Jeddah
Makkah
Taif
Al-Baha
Bisha
Qunfudah
Asir
Najran
Jazan
Latitude (°N)
Longitude (°E)
(b) Cross-city flows (line width ∝ √volume) and Analysis B clusters
C1 · Digestive / Riyadh-bound profile
C2 · Jeddah-bound / Injury & poisoning profile
C3 · Health-status factors / Skin profile
C4 · Endocrine & metabolic / Circulatory profile
Inflow (ring area)
Qurayyat
Northern Borders
Al-Jouf
Tabuk
Hafr Al-Batin
Hail
Qassim
Madinah
Riyadh
Al-Ahsa
Jeddah
Makkah
Taif
Al-Baha
Bisha
Qunfudah
Asir
Najran
Jazan
Latitude (°N)
Longitude (°E)

Supplementary Files

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