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Peer effects on appropriate antibiotic prescribing within a patient-sharing physician network in China

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Abstract

Background Resource limitations frequently impede efforts to enhance antibiotic prescribing practices. Previous studies have suggested that physicians' behaviors can be influenced by their peers, potentially amplifying the effect of interventions through peer effects. This study aimed to examine the peer effects on physicians' appropriateness of antibiotic prescribing and to identify key physicians within their networks.

Methods We extracted outpatient records from a regional electronic medical records database in Yinzhou, China. Physicians who prescribed more than 100 outpatient antibiotics prescription annually were included. We constructed physician networks by connecting physicians who shared at least ten patients in the same year and calculated networks' descriptive indicators. We then estimated the magnitude of peer effects on antibiotic prescribing by regressing the rate of appropriate antibiotic prescription for each physician in the current year on the average rate of their peers in the previous year.

Results We included 2,586 physicians, generating 13,856 physician-year observations, with an overall annual appropriate antibiotic prescribing rate of 60.7%. After adjustment, an 1% increase in the appropriate antibiotic prescribing rate among peers in the previous year is significantly associated with a 0.62% (95% CI 0.58, 0.66) increase in an individual physician's rate in the current year. Physicians with higher network centrality associate with greater effects on their peers, compared with those with lower centrality (stratified by degree centrality: 0.57[95% CI = 0.53, 0.61] vs 0.05 [0.04, 0.06]).

Conclusions Peer effect provides a promising solution to improve intervention efficiency by targeting influential opinion leaders and facilitate the diffusion of appropriate antibiotic prescribing.

Plain language summary

A growing body of literature has revealed that an individual's behavior may be shaped by the behaviors of their peers. This study aimed to explored how physicians influence one another when prescribing antibiotics. Using electronic health records from a district in China, we constructed a social network by connecting physicians who shared patients and examined whether their antibiotic prescribing behaviors affected one another. We found that physicians were more likely to prescribe antibiotics appropriately when their peers had done so in the previous year, with the effect being particularly pronounced among physicians occupying central positions within the network. These findings suggest that interventions targeting influential physicians may represent an efficient strategy to strengthen antimicrobial stewardship and reduce inappropriate antibiotic use.

The inappropriate prescribing of antibiotics is one of the most prevalent low-value clinical practices globally[1], leading to greatly increased risk of antimicrobial resistance (AMR) and unnecessary health expenditures[2–4]. Antimicrobial stewardship (AMS) programs have thus been proposed worldwide, which typically comprise a set of evidence-based, multi-disciplinary interventions[5]. Educational interventions (such as physician training, audit, and feedback) represent a key component[6,7], however, their implementation may be significantly hindered by human and economic resource limitations, especially in low- and middle-income countries[6]. Therefore, such interventions need to incorporate strategies to ensure the effective use of limited resources and to achieve lasting impacts on antibiotic prescribing.

Previous studies have observed that physicians' attitudes and practice patterns may be shaped by their peers[8], arising from physician interactions such as patient referrals, clinical advice, and information exchange[9–11], as well as from hierarchical authority[12,13], and collectively reinforced

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prescribing etiquette[14,15], To capture such dynamics, researchers have introduced social network analysis to depict peer effects among physicians, often using patient-sharing relationships extracted from medical records as a proxy[9,16,17]. Employing this approach, associations have been found between the characteristics of physicians' professional networks and their practice patterns[17,18]. Furthermore, the extent to which physicians' behaviors were influenced by peers, particularly in the adoption of updated medical practices such as genomic test[19], imaging technologies[20,21], or novel drugs[22–25], has been extensively studied. While such research has increased over the past decade[11], there is limited evidence on how peers contribute to the de-adoption of low-value clinical practices[26,27].

China is one of the largest antibiotic consumers, accounting for 10% of total consumption by defined daily doses[1,3]. Meanwhile, over 50% of antibiotic prescriptions at Chinese tertiary and secondary hospitals were inappropriate[28], with the rate exceeding 70% at primary healthcare facilities, as reported by our previous research[29]. Efforts to curb the prevalent inappropriate antibiotic prescribing have been complicated by the large and diverse physician population, which exceeded four million in number in 2021[30]. Thus, considering the limited healthcare resources, there needs to be more cost-effective strategies for AMS. In this study, we aim to construct a physician network, based on patient-sharing relationships, using data extracted from regional electronic health records, and examine whether the appropriateness of antibiotic prescriptions was associated with other physicians' practices and how this effect varied across populations with different characteristics. Additionally, utilizing social network analysis methods, we tried to identify the more influential physicians with a stronger effect on their peers within the professional network, who can serve as potential targets for future interventions.

Methods

Data sources and data collection

We conducted a retrospective study using data from the Chinese Electronic Health Records Research in Yinzhou (CHERRY)[31]. This integrated database comprises administrative data containing demographic characteristics of patients, inpatient and outpatient electronic medical records (EMRs) from hospitals and primary healthcare facilities, patient health insurance database, and other relevant databases. All data elements are linked through unique identifiers assigned to each patient or healthcare provider. Since its inception in 2009, the CHERRY database has achieved registration of over 98% of permanent residents (~1.0 million) and all healthcare providers (5.8 thousand) in Yinzhou. Detailed descriptions of the database's components and methodologies are available in a previously published protocol[31].

We extracted outpatient EMRs between 2010 and 2023 from the database. These data contained outpatient prescription information, including patient codes, drug names, prescription dates, and physician codes, as well as related patient diagnoses with disease names and ICD-10 codes (International Classification of Diseases, Tenth Revision)[32]. Patients' sociodemographic characteristics were also included in the data extraction. Ethical approval was obtained from the Peking University Institutional Review Board (IRB00001052-24013). All data were de-identified, thereby the requirement of informed consent was exempted by the Peking University Institutional Review Board.

Study samples

The unit of observation and analysis was physician-year. We included all physicians who prescribed antibiotics, classified under the Anatomical Therapeutic Chemical classification J01[33], as documented in outpatient EMRs within the study period. Physicians at hospitals for Chinese medicine or special surgery were excluded. Physicians with fewer than 100 antibiotic prescriptions in any given year were excluded from the analysis for that specific year.

Patient-sharing physician networks construction

Aligning with previous research, we constructed physician networks by connecting physicians who shared patients within the same year, identified from outpatient EMRs[9,16,17]. The nodes in the network were defined as physicians, and the edges were defined as connections between a pair of physicians. Connections were established when physicians shared at least ten patients in a year (accounting for ~20% of all patient-sharing relationships; Supplementary Table 1), a threshold validated in a previous study to likely represent referral or advice relationships[9]. To assess the robustness of the threshold, we conducted additional sensitivity analyses by applying both absolute and relative thresholds, as described in the sensitivity analysis section. Network edges were weighted by the number of shared patients, implying that more shared patients indicate a stronger connection between two physicians[26].

Measurements and covariates

Network integration was assessed using both network-level indicators and physician-level centrality measures. Network-level indicators included network diameter, average distance of nodes, network density, and cluster coefficient (transitivity). Lower diameter or average distance, alongside higher density or clustering coefficient, signified a greater level of network integration. Physician-level network position was measured using three widely applied centrality measures, including degree, closeness centrality, and betweenness centrality, to depict physicians' position within the network, following prior literature[21,27,34]. Higher values of these centrality measures indicate a physician's more central position and potential for greater influence within the network. A detailed explanation of indicators was provided in the Supplementary Table 2.

We calculated the annual appropriate antibiotic prescribing rate for each physician, defined as the physician's number of appropriate antibiotic prescriptions divided by his/her total number of antibiotic prescriptions in a given year. The appropriateness of antibiotic prescriptions was determined following the methodology developed and validated in the previous studies[28,29]. We classified disease conditions into three categories: tier-1, where antibiotics are almost always justified (e.g., pneumonia); tier-2, where antibiotics are only sometimes justified (e.g., sinusitis); and tier-3, where antibiotics are almost never justified (e.g., hypertension). The detailed ICD-10 codes of each tier were reported in the Supplementary Table 3. All diagnoses in each antibiotic prescription were categorized based on this framework, with antibiotic prescriptions containing only tier-3 diagnoses deemed inappropriate. Prescriptions associated with Tier-1 or Tier-2 diagnoses were considered appropriate.

To estimate the peer effect on appropriate antibiotic prescribing, we incorporated several physician-level covariates potentially associated with antibiotic prescribing behavior. These included physician-level centrality measures, the level of affiliated hospitals (primary care, secondary, and tertiary hospitals), and the year. Additional covariates were the annual patient volume (the number of patients managed by a physician per year), as well as the annual proportion of male patients, older patients (≥65 years old)[35], and patients with Charlson comorbidity index (CCI) of ≥2 (indicator of moderate comorbidity burden; related ICD-10 codes were reported in Supplementary Table 4)[36]. To facilitate interpretation, we categorized continuous covariates, including physician centralities and characteristics, into three groups (low, medium, and high) based on tertile cut-off points.

Statistical analyses

We first characterized sampled physicians and reported their appropriate antibiotic prescribing rate. Then we described the annual physician networks by network-level measurements and visualized by the Fruchterman-Rheingold algorithm[37]. Subsequently, we estimated the peer effect by regressing the appropriate rate of individual physicians in the current (t) year on the average appropriate rate of their peer physicians in the previous year (t-1). Consistent with previous studies, the average rate among peers was calculated by averaging the rate of all other peer physicians, weighted by the normalized number of patients shared with the individual physician[22,26]. We applied the mixed-effect model for regression, incorporating the previously mentioned covariates as fixed effects and random intercepts at both physician- and hospital-levels. Variance inflation factors were calculated to test potential multicollinearity of variates (Supplementary Table 8). Since the appropriate rate approximated a normal distribution ranging from 0 and 100% (Supplementary Fig. 1), a linear model was used without transformation of the rate. The peer effect, reflected by the regression coefficient of the peers' rate, was interpreted as the expected change in the individual physician's prescribing rate resulting from a change in the peers' rate. We further conducted a series of stratified analyses to determine whether the peer effect varied among different types of physicians. Specifically, we examined the variations in peer effect generated by peer physicians with different relative levels of centrality, hospital affiliations, and hospital tiers. All analyses were performed using R Statistical Software (version 4.12). A two-sided $p < 0.05$ was considered statistically significant.

Sensitivity analysis

We conducted a series of sensitivity analyses to validate the robustness of the results. First, we generated random physician networks using parameters (number of nodes, number of edges, network density) from the real physician network to randomize physician connections. We then simulated peers' appropriate prescribing rate within these random networks and re-estimated the main models. Second, we varied the threshold for establishing physician connections to test whether different thresholds affected the results. We used absolute thresholds of five or 20 patients and relative thresholds retaining the top 10%, 20%, or 30% of the closest physician connections. Third, we calculated the peers' appropriate rate using unweighted networks to examine whether edge weights influenced the estimates.

Results

Study sample

We included 2586 individual physicians from 5 hospitals and 29 primary care facilities in Yinzhou, resulting in 13,856 physician-year observations. The characteristics of these observations are presented in Table 1. On average, each physician managed 7721.9 [SD = 7433.3] patients annually, of whom 47.4% [14.5%] were male, 24.4% [17.9%] were aged 65 or older, and 2.2% [6.9%] had a CCI of 2 or higher. Most observations were from primary healthcare physicians (62.6%), followed by physicians from tertiary hospitals (21.9%) and secondary hospitals (15.4%).

The number of patients shared among physician pairs prior to applying thresholds to construct the physician network is reported in Supplementary Table 1. Overall, 68.5%, 14.0%, 8.0%, and 9.5% of physician-physician pairs shared 1–4, 5–9, 10-19, and >20 patients.

Antibiotic prescribing

The average appropriate antibiotic prescribing rate of all physicians was 60.7% [SD = 24.1%]. Density distribution of these rates is represented in Supplementary Fig. 1. Before adjustment for covariates, physicians with a low proportion of male patients had a higher appropriate antibiotic prescribing rate (63.6%, reference), compared with those with medium (60.3%, $p < 0.001$) and high proportions (58.1%, $p = 0.001$). Similarly, physicians with a low proportion of elderly patients exhibited a higher rate (62.2%, reference), compared with those with medium (58.7%, $p < 0.001$) and high proportions (61.3%, $p = 0.013$). Notably, physicians at tertiary (65.7%, $p < 0.001$) or secondary (63.7%, $p < 0.001$) hospitals had significantly higher appropriate prescribing rates, compared with their counterparts in primary care facilities (58.2%, reference).

Characteristics of patients who were prescribed antibiotics by sample physicians are reported in Supplementary Tables 5 and 6. Overall, 13.1%, 42.8%, and 44.2% of patients who received antibiotics were diagnosed with tier-1, −2, and −3 diseases. The most common diseases leading to antibiotic prescriptions were viral upper respiratory infection (tier-3), acute pharyngitis (tier-2), acute bronchitis (tier-3), oral infectious diseases (tier-2), and urinary tract infections (tier-1).

Network description

Characteristics of the physician networks between 2010 and 2023 are depicted in Table 2. Among the networks, the median number of physicians (network nodes) was 1225 [range = 1115–1514], and the median number of connections between physicians (network edges) was 43,978 [29,345–50,672]. Of all connections, 46.6% [38.4%–50.6%] were formed between physicians across different hospitals, and 33.8% [27.3%–41.4%] were between physicians across hospitals of different tiers. Each physician was connected to an average of 35.4 [25.4–40.4] physicians. The median and ranges of network diameter, average distance of nodes, network density, and cluster coefficient were 289.5 [79.0–455.0], 32.3 [29.4–35.4], 0.06 [0.04–0.07], and 0.43 [0.42–0.45], respectively. Graphical depictions of networks are presented in Supplementary Figs. 2 and 3, with primary care physicians centering their patient-sharing around physicians from secondary or tertiary hospitals.

The relationship between physician characteristics and network centrality metrics (degree, closeness centrality, or betweenness centrality) is reported in the Supplementary Table 7. Generally, physicians with higher centrality tended to have higher patient volumes, a lower proportion of elder patients, a higher proportion of patients with CCI ≥ 2, and were more likely to be affiliated with a tertiary hospital.

Peer effect analysis

Overall, for each 1% increase in the appropriate antibiotic prescribing rate among peer physicians in the previous year, the rate for an individual physician in the current year increased by 0.62% (Table 3). After adjusting for other covariates, physicians with higher proportion of male patients (low proportion: reference; medium proportion: coefficient = −1.40 [95% CI = −2.15, −0.65]; high proportion: −1.71 [−2.70, −0.71]) and physicians with higher proportions of elder patients (low proportion: reference; medium proportion: −2.50 [3.46, −1.54]; high proportion: −2.89 [−4.16, −1.62]) were significantly associated with lower appropriate prescribing rates. Compared with physicians at primary care facilities, the coefficient for physicians at secondary or tertiary hospitals was positive but statistically insignificant (primary care facilities: reference; secondary hospitals: 2.26 [−3.81, 8.32]; tertiary hospitals: 3.62 [−3.42, 10.66]). To avoid potential multicollinearity on three types of centralities, regression models, including only one type of centrality at a time, were conducted. The estimations for peer effect were stable in these models (in all three models: 0.62 [0.58, 0.66], Supplementary Table 9). Additionally, no significant interactions were found between peer effects and centrality measures (Supplementary Table 10).

Stratified analyses

Stratified analyses were performed to evaluate the influence of peer physicians' centrality, relative to any individual physician, on the magnitude of peer effect (Table 4). Peer effects were more pronounced for physicians with higher centrality, compared with those with lower centrality (stratified by degree: 0.57 [95% CI = 0.53, 0.61] vs 0.05 [0.04, 0.06]; stratified by closeness centrality: 0.57 [0.57, 0.60] vs 0.01 [0.06, 0.07]; stratified by betweenness centrality: 0.58 [0.55, 0.62] vs 0.06 [0.05, 0.07]). Additional stratified analyses comparing peer physicians within the same hospital with those at different hospitals revealed stronger peer effects among physicians within the same hospital (0.52 [0.49, 0.56] vs 0.29 [0.25, 0.32], Supplementary Table 11). Results were consistent across further stratifications by both relative centrality and whether within the same hospital, as well as by hospital level of peer physicians (Supplementary Tables 12 and 13).

Sensitivity analysis

The regression coefficients from repeating the main analysis using randomly generated networks are presented in Supplementary Table 14. We conducted a total of 1000 simulations to calculate the confidence interval. The estimated peer effect from the random networks was markedly smaller than the results from the real network (random networks: 0.00 [95% CI = −0.05, 0.04] vs real network: 0.62 [0.58, 0.66]). Results of the sensitivity analysis with threshold adjustments are reported in Supplementary Tables 15 and 16. Applying stricter thresholds yielded peer-effect estimates comparable to the main analysis (absolute thresholds: ten shared patients

Table 1 | Characteristics and appropriate antibiotic prescribing rate of sample physicians

Characteristics	Groups	Characteristics values	Observations[a]	Appropriate antibiotic prescribing rate (%)	*p* value[b]
		Mean (SD)	*N* (%)	Mean (SD)	
Overall	-	-	13856 (100.0)	60.7 (24.1)	-
Patient volume	Overall	7721.9 (7433.3)	-	-	-
	Low	2364.1 (1007.5)	4406 (31.8)	60.8 (25.0)	Ref.
	Medium	5957.9 (1239.6)	4689 (33.8)	61.4 (24.0)	0.427
	High	14417.4 (9159.8)	4761 (34.4)	59.8 (23.5)	0.014
Proportion of male patients (%)	Overall	47.4 (14.5)	-	-	-
	Low	34.9 (17.9)	4569 (33.0)	63.6 (24.4)	Ref.
	Medium	49.4 (1.3)	4711 (34.0)	60.3 (24.0)	<0.001
	High	57.8 (6.9)	4576 (33.0)	58.1 (23.7)	<0.001
Proportion of patients age ≥ 65 (%)	Overall	24.4 (17.9)	-	-	-
	Low	5.2 (4.3)	4062 (29.3)	62.2 (24.1)	Ref.
	Medium	19.7 (4.5)	4764 (34.4)	58.7 (25.1)	<0.001
	High	44.4 (11.3)	5030 (36.3)	61.3 (23.2)	0.013
Proportion of patients with CCI ≥ 2 (%)	Overall	2.2 (6.9)	-	-	-
	Low	0.0 (0.1)	4427 (32.0)	59.5 (26.9)	Ref.
	Medium	0.6 (0.3)	4674 (33.7)	56.1 (23.2)	<0.001
	High	5.8 (10.9)	4755 (34.3)	66.2 (21.1)	<0.001
Level of hospitals	Primary Care	-	8678 (62.6)	58.2 (23.6)	Ref.
	Secondary	-	2138 (15.4)	63.7 (26.3)	<0.001
	Tertiary	-	3040 (21.9)	65.7 (22.9)	<0.001
Year[c]	2011	-	1040 (7.5)	37.5 (22.9)	Ref.
	2012	-	1113 (8.0)	45.1 (23.6)	<0.001
	2013	-	1136 (8.2)	51.7 (23.6)	<0.001
	2014	-	1163 (8.4)	58.6 (23.3)	<0.001
	2015	-	1148 (8.3)	64.3 (22.7)	<0.001
	2016	-	1070 (7.7)	65.5 (21.5)	<0.001
	2017	-	1190 (8.6)	65.0 (21.0)	<0.001
	2018	-	995 (7.2)	61.3 (22.0)	<0.001
	2019	-	973 (7.0)	62.8 (21.9)	<0.001
	2020	-	978 (7.1)	71.0 (19.1)	<0.001
	2021	-	992 (7.2)	72.9 (20.0)	<0.001
	2022	-	1032 (7.4)	72.2 (20.7)	<0.001
	2023	-	1026 (7.4)	63.4 (22.1)	<0.001

SD standard deviation, *CCI* Charlson Comorbidity Index, *Ref.* reference

[a]The unit of observation was physician-year.

[b]The *p* value were derived from Mann–Whitney test. All *p* value were two-sided. As pairwise comparisons were conducted within groups, significance levels should be adjusted by Bonferroni correction: for three-category variables, $p < 0.017$.

[c]The observations in 2010 were excluded because there was no t-1 year (2009) data to construct the physician network for peer effect analysis.

[main analysis]: 0.62 [0.58, 0.66], 20 shared patients: 0.55[0.52, 0.59]; relative thresholds: top 20% connections: 0.70[0.65, 0.74], top 10% connections: 0.62[0.58, 0.66]). By contrast, when more relaxed thresholds were applied, the effects observed were smaller but remained statistically significant (absolute thresholds: five shared patients: 0.25[0.20, 0.30]; relative thresholds: top 30% connections: 0.27[0.22, 0.32]). Additionally, analysis using an unweighted network yielded a significant but smaller peer effect estimate (unweighted networks: 0.32 [0.26, 0.37] vs weighted network: 0.62 [0.58, 0.66], Supplementary Table 17).

Discussion

Our analysis revealed that the appropriateness of individual physicians' antibiotic prescriptions was significantly associated with their peers' practice, with each 1% increase in the peers' appropriateness rate in the previous year corresponding to a 0.6% increase in the individual's rate in the current year, after controlling for potential confounding factors. For context, nationwide evaluations in China have reported appropriateness rates of approximately 43% in secondary and tertiary hospitals[28], and only 25% in primary care facilities[29], highlighting that the 0.6 multiplier improvement by peer effects holds considerable potential at the population level. We also observed an asymmetry in the peer effect that physicians are predominantly influenced by peers with higher centrality in their facilities, while influence from those with lower centrality was less pronounced. However, there was no clear association between a physician's own network centrality and the appropriateness of their prescribing practices.

Our research contributes new evidence from China to the existing research on peer effects on physician behaviors. Previous studies have explored how patient-sharing connections shaped physicians' behavioral patterns, suggesting that physicians connected to peers who had adopted novel practices were more likely to embrace such novelties themselves, such as innovative tests[19], technologies[20], or drugs[22–25]. Our study not only echoes previous findings but also extends them by showing that peer effects can also be observed in the de-adoption of low-value practices. Additionally, through sensitivity analyses comparing weighted and unweighted networks, our results provide further evidence supporting earlier observations that a more pronounced effect from the stronger connections in explaining practice diffusion[38,39]. These phenomena resonate with established theories of diffusion of innovation or social contagion[11], which propose that clinical knowledge is disseminated via interactions among physicians, thereby influencing physicians' practices[22]. Within these frameworks, certain individuals were found to play a key role in facilitating knowledge transfer and behavior change through competence or social accessibility, often regarded as "opinion leaders"[40,41]. Our study observed the significance of strong connections and the asymmetric peer effects distinguished by network centrality, underscoring the value of centrality as a proxy for identifying influential physicians. Distinct from formal professional titles, high social network centrality captures the informal aspect of influence in clinical decision-making, operating alongside hierarchical authority or institutional position[10,40].

Beyond the mechanisms of diffusion, our study also uncovered distinct contextual patterns within Chinese healthcare settings. We found that physicians received peer effect predominantly from peers within the same healthcare facilities, inconsistent with a previous study on the end-of-life care of cancer patients in the U.S., which indicated a stronger effect from external physicians[26]. This discrepancy might stem from less cohesive care coordination of infections across different facilities in our study[42,43]. More importantly, the stronger internal effect aligns with the concept of

Table 2 | Characteristics of patient-sharing networks of sampled physicians, 2010–2023

Year	Median	Range
Numbers of nodes (physicians)	1225	(1115, 1514)
Numbers of edges (connections)	43978	(29,345, 50,672)
With physicians in other hospitals	20384	(11,268, 23,912)
(%)	46.6	(38.4, 50.6)
With physicians in other levels of hospitals	15263	(8016, 19,565)
(%)	33.8	(27.3, 41.4)
Average numbers of edges per physicians	35.4	(25.4, 40.4)
With physicians in other hospitals	16.5	(9.7, 20.4)
With physicians in other levels of hospitals	11.9	(6.9, 16.7)
Network diameter	289.5	(79.0, 455.0)
Average distance of nodes	32.3	(29.4, 35.4)
Network density	0.06	(0.04, 0.07)
Cluster coefficient (transitivity)	0.43	(0.42, 0.45)

Table 3 | Influence of the appropriate antibiotic prescribing rate among peer physicians in the previous year on the rate of an individual physician in the current year

Characteristics[a]	Groups	Coeff.	S.E.	*p* value[b]	95% CI
Peer effect[c]	-	0.62	0.02	<0.001	(0.58, 0.66)
Degree	Low	ref	-	-	
	Medium	1.60	0.43	<0.001	(0.75, 2.45)
	High	1.40	0.64	0.029	(0.14, 2.65)
Closeness centrality	Low	ref	-	-	
	Medium	−1.11	0.38	0.004	(−1.86, −0.35)
	High	−0.87	0.52	0.096	(−1.89, 0.15)
Betweenness centrality	Low	ref	-	-	
	Medium	0.22	0.36	0.546	(−0.49, 0.93)
	High	−0.01	0.48	0.986	(−0.95, 0.93)
Patient volume	Low	ref	-	-	
	Medium	0.81	0.41	0.047	(0.01, 1.61)
	High	1.36	0.54	0.012	(0.30, 2.42)
Proportion of male patients (%)	Low	ref	-	-	
	Medium	−1.40	0.38	<0.001	(−2.15, −0.65)
	High	−1.71	0.51	0.001	(−2.70, −0.71)
Proportion of patients age ≥ 65 (%)	Low	ref	-	-	
	Medium	−2.50	0.49	<0.001	(−3.46, −1.54)
	High	−2.89	0.65	<0.001	(−4.16, −1.62)
Proportion of patients with CCI ≥ 2 (%)	Low	ref	-	-	
	Medium	0.46	0.40	0.248	(−0.32, 1.25)
	High	3.85	0.51	<0.001	(2.84, 4.86)
Level of hospitals	Primary Care	ref	-	-	
	Secondary	2.26	2.97	0.453	(−3.81, 8.32)
	Tertiary	3.62	3.45	0.303	(−3.42, 10.66)

CCI Charlson Comorbidity Index, *Coeff.* coefficient, *S.E.* standard error, *95% CI* 95% confidence intervals, *Ref* reference

[a]The fixed effect of years was omitted from the table for conciseness.

[b]All *p* value were two-sided.

[c]The peer effect was the regression estimation of the appropriate antibiotic prescribing rate among peer physicians in the previous year on the rate of an individual physician in the current year. The estimations were derived from linear mixed-effects models, with covariates as fixed effects and random intercepts at both physician- and hospital levels.

Table 4 | Stratified analysis of the influence of the appropriate antibiotic prescribing rate among peer physicians (stratified by relative centrality) in the previous year on the rate for an individual physician in the current year

Characteristics[a]	Groups	By degree				By closeness centrality				By betweenness centrality			
		Coeff.	S.E.	*p* value[b]	95% CI	Coeff.	S.E.	*p* value	95% CI	Coeff.	S.E.	*p* value	95% CI
Peer effect[c, d]	-	-	-	-	-	-	-	-	-	-	-	-	-
From physicians with higher centrality	-	0.57	0.02	<0.001	(0.53, 0.61)	0.57	0.02	<0.001	(0.57, 0.60)	0.58	0.02	<0.001	(0.55, 0.62)
From physicians with lower centrality	-	0.05	0.01	<0.001	(0.04, 0.06)	0.06	0.01	<0.001	(0.06, 0.07)	0.06	0.01	<0.001	(0.05, 0.07)
Patient volume	Low	Ref	-	-	-	Ref	-	-	-	Ref	-	-	-
	Medium	1.02	0.37	0.006	(0.29, 1.74)	1.10	0.37	0.003	(1.10, 1.83)	1.06	0.37	0.004	(0.34, 1.79)
	High	1.74	0.46	<0.001	(0.84, 2.64)	1.69	0.46	<0.001	(1.69, 2.59)	1.69	0.46	<0.001	(0.80, 2.59)
Proportion of male patients (%)	Low	Ref	-	-	-	Ref	-	-	-	Ref	-	-	-
	Medium	−1.36	0.38	<0.001	(−2.11, −0.62)	−1.36	0.38	<0.001	(−1.36, −0.62)	−1.29	0.38	0.001	(−2.03, −0.55)
	High	−1.72	0.51	0.001	(−2.71, −0.73)	−1.70	0.50	0.001	(−1.70, −0.71)	−1.56	0.50	0.002	(−2.54, −0.57)
Proportion of patients age ≥ 65 (%)	Low	Ref	-	-	-	Ref	-	-	-	Ref	-	-	-
	Medium	−2.49	0.49	<0.001	(−3.45, −1.54)	−2.55	0.49	<0.001	(−2.55, −1.60)	−2.48	0.49	<0.001	(−3.43, −1.53)
	High	−2.82	0.64	<0.001	(−4.07, −1.57)	−3.00	0.64	<0.001	(−3.00, −1.75)	−2.82	0.64	<0.001	(−4.07, −1.57)
Proportion of patients with CCI ≥ 2 (%)	Low	Ref	-	-	-	Ref	-	-	-	Ref	-	-	-
	Medium	0.52	0.40	0.194	(−0.26, 1.30)	0.51	0.40	0.201	(0.51, 1.29)	0.42	0.40	0.294	(−0.36, 1.20)
	High	3.74	0.51	<0.001	(2.74, 4.74)	3.68	0.51	<0.001	(3.68, 4.68)	3.69	0.51	<0.001	(2.69, 4.69)
Level of hospitals	Primary care	Ref	-	-	-	Ref	-	-	-	Ref	-	-	-
	Secondary	2.70	2.94	0.366	(−3.30, 8.69)	2.51	2.93	0.399	(2.51, 8.48)	2.52	2.92	0.396	(−3.44, 8.48)
	Tertiary	3.47	3.41	0.318	(−3.49, 10.43)	3.24	3.40	0.348	(3.24, 10.18)	3.37	3.40	0.329	(−3.56, 10.30)

CCI, Charlson Comorbidity Index, *Coeff*. coefficient, *S.E.* standard error, *95% CI* 95% confidence intervals, *Ref.* reference.

[a]The fixed effect of years was omitted from the table for conciseness.

[b]All *p* value were two-sided.

[c]The estimations were derived from linear mixed-effects models, with covariates as fixed effects and random intercepts at both physician- and hospital-levels.

[d]Based on the relative centrality (degree, closeness centrality, or betweenness centrality) of the peer physicians compared to the individual physicians, peer effects are stratified into those physicians with higher centrality and those physicians with lower centrality.

"prescribing etiquette" reported in prior qualitative interviews[12,14,15], which suggested an implicit norm whereby physicians, particularly junior staff, tend to endorse prescription patterns already established by senior colleagues, even when alternative choices might be more reasonable[13,44]. This dynamic reflects the inherent hierarchical structures of medical practice[45], and illustrates how professional discretion is embedded within organizational authority and culture[14,46,47], thereby normative expectations within clinical teams could surpass individual decision-making[12,15]. Consequently, prescribing decision-making is not merely guided by clinical evidence, but becomes a relational practice in which authority, etiquette, and peer norms jointly define what is considered appropriate[12–15]. These dynamics highlight both the challenges and opportunities of leveraging peer influence, as established hierarchical structures, cultural etiquette, and other connections could serve as facilitators for the dissemination of evidence-based practices.

From a policy perspective, our results illustrated the feasibility of interventions that leverage peer effects by identifying and targeting influential physicians to maximize impact at the group level with minimal resource expenditure[27]. Conventional strategies for improving prescribing behaviors, such as educational training or prescription audits, require substantial resources, especially given the vast number of healthcare facilities in China[30]. In contrast, interventions targeting opinion leaders facilitate the progressive diffusion of evidence-based practices to achieve broader impacts through knowledge transfer within peer interactions[14,48,49]. Thus, the observed peer effect of 0.62 holds considerable promise for translating into meaningful improvements in appropriate antibiotic prescribing, especially given the relatively low baseline appropriateness rates nationwide. The pragmatic strategies include identifying influential physicians through qualitative interviews or social network methods, facilitating training opportunities for them, and implementing stricter audits of their prescriptions. The positive effect of such interventions has been reported in a Cochrane review[40]. Furthermore, prior research underscored that peer effect could be strengthened by more cohesive physician connections, which might be attributed to more frequent information exchange and social support[50,51]. Closer physician connections also contribute to enhanced continuity of care[52], reduced reduplicative medication[53], lower healthcare costs[54], and improved patient health outcomes[17,55]. Thus, policymakers and administrators should actively foster physicians' professional networks and promote regular physician communication, along with collaboration within and between healthcare facilities, to improve physicians' prescribing behaviors and subsequently patient outcomes.

Disappointingly, among the three centrality measures, we only found that an increase in degree centrality was associated with slightly improved appropriateness of antibiotic prescriptions, suggesting that "opinion leaders" were not always the ones who prescribed antibiotics more rationally. On one hand, high centrality reflects the extensive patient sharing of these influential physicians with their peers, indicating that these physicians might be more senior and experienced[34,56]. However, according to Burt's structural hole theory, physicians with less centrality could act as a "bridge" within the network, offering them an advantage in accessing information, and are less adherent to the "prescribing etiquette"[27,57]. Thus, complexity was observed in the relationship between physicians' centrality and their clinical practice in previous research. While multiple prior studies have reported a positive association between centrality and evidence-based practice[58–60], one study found a correlation between higher centrality and increased rate of potentially inappropriate medications prescribing[27]. Given the high influence of opinion leaders and appropriateness of their prescriptions, we again advocate for targeted interventions for these physicians and to strengthen physician connections, thereby improving prescribing behavior at the group level.

This study has several limitations. First, we identified physician relationships based on EMRs from a single district in China, though most patients seek healthcare within their local regions, our approach might have overlooked potential patient-sharing connections among physicians across districts. Second, our results on peer effect should be interpreted within the specific context and may not be directly generalized to other areas in China with different physician network structures[16]. However, the gradual establishment of compact medical alliances nationwide is expected to strengthen physicians' connections and promote the generalizability of our methods and findings[43,61]. Third, our findings are subject to potential bias due to unmeasured confounding. Physicians' antibiotic prescribing decisions are affected by both physician and patient characteristics. While we controlled for aggregated patient characteristics at the physician level, factors such as patients' age, sex and disease, as well as physicians' practicing department, years in practice, and professional title were not included due to data access. This may overlook the impact of specific physician or patient distinctions, though we attempted to control for unobservable variables by introducing random intercepts at the physician and facility levels. Fourth, our data did not allow the identification of patients' medical episodes and thus the use of advanced methods to construct physician connections based on shared clinical episodes, which align better with clinical practice and do not require setting the patient-sharing threshold[62]. To avoid arbitrariness in threshold decisions, we conducted sensitivity analyses regarding thresholds to validate the robustness of our results. However, future research should consider constructing a physician network by identifying medical episodes to enhance the clinical relevance of results. Finally, although the strength of our study lies in including a broad population of physicians and measuring the extent of peer effects, qualitative research remains valuable for revealing the subjective perceptions and mechanisms driving prescribing behaviors[14,48]. Future studies should consider employing qualitative or mixed-method approaches to provide a more comprehensive understanding of the mechanisms underlying peer effects in physician prescribing.

In conclusion, our findings suggest that physicians' appropriateness of antibiotic prescription was influenced by their peer physicians, particularly by those with higher centrality within the same healthcare facilities. Leveraging the peer effect provides a promising solution to increase intervention efficiency by targeting influential opinion leaders and facilitating the diffusion of improved prescribing behaviors.

Data availability

The data that support the findings of this study are available from the Centers for Disease Control and Prevention of Yinzhou, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of the Centers for Disease Control and Prevention of Yinzhou.

Code availability

The codes used to conduct this analysis, including the disease classifications, network construction, data cleaning, and covariate processing, were uploaded to a GitHub repository[63].

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Author contributions

Z.G., H.H., and X.G. conceived and designed the study. Z.G., C.L., K.L., H.Lin, and P.S. collected and analyzed the data. Z.G. and M.F. drafted the paper. H.Li, D.Z. and X.G. critically reviewed and edited the paper. L.S. and X.G. supervised the conduction of the project. All authors reviewed and approved the final version.

Competing interests

The authors declare no competing interests.

Additional information

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