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Identifying opioid prescribing patterns for high-volume prescribers via cluster analysis

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Abstract

Objective: Despite recent decreases in opioid prescribing rates, evidence suggests there is substantial variation in the way opioids are prescribed by providers. This study aims to identify patterns in high-volume opioid prescribing.

Methods: We conducted partitioning-around-medoids cluster analysis using the IQVIA Prescriber Profile dataset, including the number of opioid prescriptions filled at US retail pharmacies aggregated at the prescriber-level from July 2016 through June 2017. Clustering was used to identify prescription patterns within a sample of 10,000 high-volume opioid prescribers (defined as the top 10% of prescribers by number of opioid prescriptions during the 12-month period). Clustering variables included prescription counts by opioid type, and prescriber specialty, age, and region.

Results: Family medicine (32%), internal medicine (23%), and orthopedics (11%) were the most common highvolume prescribing specialties. Across specialties, hydrocodone and oxycodone were the most-frequently prescribed opioid types. Thirty-five clusters of prescribers were obtained, consistently comprised of a single majority specialty and region. All majority high-prescribing specialties were represented in Southern clusters, indicating consistently high volume opioid prescribing across specialties in the region. Prescribing patterns varied by drug type and region - across every Northeastern cluster, oxycodone prescribing was higher than hydrocodone. While clusters of pain medicine specialists had the highest median total prescriptions, emergency medicine specialist clusters had some of the lowest.

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Contributors

Nisha Nataraj led the study design, development and interpretation of results, conducted data analysis, drafted and edited the manuscript, and approved the final manuscript as submitted.

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Conflicts of Interest

The authors have no relevant conflicts of interest to disclose.

Conclusions: These results provide a clearer picture of current patterns among high-volume prescribers, who accounted for almost two-thirds of all opioid prescriptions. In light of the ongoing opioid overdose epidemic, this knowledge is critical for prevention activities.

Keywords

Prescription opioids; Analgesics; Prescribing; Cluster analysis

1. Introduction

While opioid prescribing has been decreasing in the United States since 2013, the amount of opioids prescribed is still three times higher than in 1999 (Guy et al., 2017). Despite the emergence of illicitly-manufactured fentanyl in recent years as a driver of opioid overdose deaths, overdoses from prescription opioids continue to remain a concern. In 2017, over 35% of opioid overdose deaths involved a prescription opioid (Scholl et al., 2018). Evidence suggests there is substantial variation in the quantity of opioids prescribed, both at the regional level (Guy et al., 2017), and by prescriber specialty (Guy and Zhang, 2018; Levy et al., 2015). Although the rate of opioid prescribing is high in the United States (Centers for Disease Control and Prevention, 2017), a large portion of all opioid prescriptions come from a small group of prescribers, and varies considerably by prescriber specialty (Guy and Zhang, 2018).

Given the significant role that high-volume prescribers play in opioid prescribing, this study focuses on understanding and identifying patterns among these prescribers. A better understanding of prescribing in this population will help effectively target public health prevention efforts to reduce high opioid prescription rates.

2. Material and Methods

We examined data from the IQVIA Prescriber Profile. The dataset provides the number of opioid prescriptions filled in over 59,000 U.S. retail pharmacies aggregated at the prescriber level. This dataset represents approximately 90% of all retail prescriptions in the 2017 fiscal year across the country, and is weighted to produce national estimates. High-volume prescribers were defined as the top 10% of prescribers based on the number of total opioid prescriptions during a 12-month period (July 1, 2016 through June 30, 2017). Total prescriptions for a given prescriber are comprised of the weighted aggregate prescriptions they wrote for hydrocodone, oxycodone, tramadol, morphine, fentanyl, hydromorphone, oxymorphone, codeine, and other opioids not listed above. For our analysis, we excluded those buprenorphine prescriptions typically prescribed for conditions other than pain, as well as cough and cold formulations from the total prescriptions. Veterinarians and prescribers missing prescription information for the time period considered were also excluded from our analysis (44,121 prescribers). Of the remaining 970,902 prescribers in the dataset, we retained only prescribers above the 90th percentile and then excluded prescribers with missing age (18,076 prescribers) to ensure that any clustering variables had no missing information. Consequently, 79,014 prescribers were identified as high-volume with complete age and prescription information available. This population accounted for almost two-thirds

(64%) of the total opioid prescriptions dispensed in the time period examined. In order to keep the clustering computationally feasible, we limited our study population to a random, representative analytic sample of 10,000 of the 79,014 high volume prescribers, obtained using the **R** function *sample_n* from the package *dplyr* (Wickham et al., 2017).

We conducted partitioning-around-medoids (PAM) cluster analysis to identify prescription patterns among high-volume prescribers based on provider characteristics. Clustering is a useful methodology for multivariate data exploration that allows us to segment subjects into groups that are most similar to each other, given a set of variables. PAM is a partitioning clustering method that divides objects into disjoint, non-overlapping clusters, based on a pre-specified number of clusters. The PAM algorithm was selected because it is robust (i.e., less sensitive) to outliers and is capable of identifying a representative object or individual (i.e., medoid) for each cluster identified (Kaufman and Rousseeuw, 2009). We iteratively ran the PAM algorithm with the number of clusters ranging from 2 to 40 to obtain multiple clusterings. The final number of clusters was then selected based on the clustering with the highest Silhouette coefficient, which is a combined measure that evaluates the homogeneity of clusters as well as how well-separated clusters are (Kaufman and Rousseeuw, 2009). Silhouette widths greater than 0.7 and closer to 1.0 suggest that a strong clustering structure has been found (Kaufman and Rousseeuw, 2009). Analysis was carried out in R version 3.4.3 (R Core Team, 2017) using the package *cluster* (Maechler, 2017) to calculate the Gower distance (function *daisy*) and carry out PAM clustering (function *pam*).

Clustering variables were at the provider-level and included quantitative variables of age and prescription counts (for specific opioid types and total opioid prescriptions dispensed), as well as categorical variables of prescriber specialty and U.S. census region of the prescriber (West, Midwest, Northeast, and South). Specific opioid types considered included hydrocodone, oxycodone, and tramadol, which were the most frequently prescribed opioid types, accounting for 83% of all total opioid prescriptions in the sample. Prescriber specialties considered included family medicine, internal medicine, surgery, pain medicine, dentistry/oral surgery, emergency medicine, physical medicine and rehabilitation, obstetrics and gynecology, general practice, psychiatry, neurology, radiology, orthopedics, pediatrics, oncology, hospitalists, palliative medicine, nurse practitioner, physician assistant, and other. The residual “Other” category included specialists of pathology, neurophysiology, podiatry, occupational medicine, ophthalmology, optometry, dermatology, student health care, unspecified, and others. A representative category for a given categorical variable in a cluster was defined as the majority level or value that appeared in more than half the prescribers within a given cluster. Clusters were characterized by the representative category for categorical variables (specialty and region) and by comparing the cluster median with the sample median for quantitative variables (prescription counts and age). Sensitivity analysis was conducted by clustering on a second random sample of 10,000 prescribers. In addition, a total of ten random samples of 10,000 prescribers each were used to validate the final number of clusters obtained for a given random sample (determined via the silhouette coefficient)

3. Results

The characteristics of the analytic sample, all high-volume prescribers, and all opioid prescribers with complete age and prescription information present obtained from the IQVIA Prescriber Profile are provided in Table 1. Amongst all opioid prescribers, the five most common specialties were internal medicine (23.8%), family medicine (15%), surgery (10.5%), emergency medicine (6.7%), and obstetrics/gynecology (5.7%). The most common specialties among the sampled high-volume prescribers were family medicine (32.2%), internal medicine (22.9%), orthopedics (11.4%), emergency medicine (6.8%), and pain medicine (5.8%). The median age for high-volume prescribers in the sample was 53 years (compared with 50 years for all prescribers). The mean number of prescriptions for every opioid type was much higher than the median, highlighting that the distributions were skewed by the presence of some outliers with extremely high numbers of prescriptions (Table 2). Overall, as well as across all specialties, hydrocodone had the highest mean number of prescriptions (549.8), followed by oxycodone (364.7). Tramadol (254.7 mean prescriptions) was the third most frequently prescribed opioid type across most categories of specialists, with a few exceptions. These exceptions include specialists of pain medicine, radiology, oncology, and palliative medicine who prescribed morphine, psychiatrists who prescribed methadone, and dentists and obstetricians/gynecologists who prescribed codeine more frequently than tramadol.

The cluster analysis resulted in 35 clusters of prescribers based on the highest average silhouette width (0.71). Every cluster was represented by a single region and specialty (Table 3). Accordingly, for the rest of this study, reference to a specific region or specialty in a cluster is indicative of the representative value. Not all specialties of the high-volume prescribers seen in Table 1 were representative in a cluster. However, of the thirteen representative specialties seen across clusters, all thirteen were found in Southern clusters (compared with only nine in the Midwest, eight in the West, and five in the Northeast), as seen in Table 3. This indicates that Southern clusters had consistently high volumes of opioid prescribing across specialties. The South was the only region with the presence of neurologists, general practitioners, and oncologists as the representing specialty in a cluster (Clusters 8, 9, and 35, respectively). Conversely, several specialties that represented clusters in other regions were missing in Northeastern clusters, including emergency medicine, dentists, surgeons, physician assistants, and nurse practitioners. Regardless of the representative specialty, high volume prescribing was also consistently lower in Western clusters compared to Southern or Midwestern clusters, as evidenced by the median total prescriptions dispensed.

The clusters indicate substantial geographic variation in prescribing patterns by drug type within specialties. For example, pain medicine, family medicine, internal medicine, and orthopedics specialists in Northeastern clusters (Clusters 2, 11, 15, and 25) prescribed less hydrocodone but more oxycodone than their counterparts in Midwestern, Western, and Southern clusters. Physical medicine and rehabilitation specialists in the Northeastern cluster (Cluster 5) likewise prescribed much less hydrocodone, but similar amounts of oxycodone than their counterparts in clusters from other regions. Still, in every cluster represented by Northeastern prescribers, oxycodone prescribing was greater than that of hydrocodone. By specialty, clusters of pain medicine, and physical medicine and rehabilitation providers had the highest median total prescriptions (Clusters 1–7). Clusters represented by emergency medicine specialists had some of the lowest median total prescriptions (Clusters 32–34). Finally, results from the sensitivity analysis obtained from clustering a second random sample were similar to the findings reported in Table 3. Sensitivity analysis also showed that the numbers of clusters identified were robust as well – seven out of the ten random samples resulted in strong cluster structures with between 33 and 35 clusters identified.

4. Discussion

The results from this study indicate that there are specific patterns that define high-volume opioid prescribing in the United States. Opioid prescribing volumes were especially high in Southern clusters, and consistently so across all represented specialties. On the other hand, Northeastern clusters had relatively lower prescribing volume and the least representation of the different specialties amongst high-volume prescribers. Our findings are consistent with prior studies using data from the past decade that have shown overall opioid prescribing rates are the highest in the South (McDonald et al., 2012; Paulozzi et al., 2014). As has been previously hypothesized, one possible contributing factor to persistent regional high-prescribing in the South may be related to prescribing attitudes and norms (McDonald et al., 2012; Olsen et al., 2006). Additionally, factors such as state initiatives to address overprescribing may have a role to play. For example, several North-eastern states, including New York (the most populous state in the Northeast) and Massachusetts have passed legislation to mandate checking of Prescription Drug Monitoring Program (PDMP) databases, as well as set limits on certain (typically first-time) opioid prescriptions (National Conference of State Legislatures, 2018).

The five most common specialties of high-volume prescribers were family medicine, internal medicine, orthopedics, emergency medicine, and pain medicine. Moreover, the specialties of family medicine, orthopedics, and pain medicine were over-represented in the high-volume prescribing group, when compared with all opioid prescribers. The cluster analysis identified the additional specialties of physical medicine and rehabilitation, neurology, and general practice as high-volume prescribers, in spite of these specialties being less common. Clusters represented by emergency medicine specialists had some of the lowest median total prescriptions when compared to those of other specialties. Notably, emergency medicine physicians had the largest drop in opioid prescribing rates between 2007 and 2012 (Levy et al., 2015). Some of this could stem from the early adoption of guidelines to address inappropriate prescribing of opioids in emergency medicine (Weiner et al., 2017). Recent research has also shown that opioid prescriptions in emergency department settings were shorter and for lower daily doses (Jeffery et al., 2018).

Our findings underscore the variability in opioid prescribing within specialties. With respect to prescribing practices associated with specific opioid types, our results show specialties in Northeastern clusters consistently prescribe more oxycodone than hydrocodone. Oxycodone was found to have some of the greatest increases in prescriptions between 2000 and 2010 (Kenan et al., 2012). A previous study found that oxycodone (followed by hydrocodone) had the highest rate of emergency department-related visits per 100,000 population for misuse or abuse of drugs, as well as the greatest percent increase in visits in 2011 compared to 2004 (Substance Abuse and Mental Health Services Administration, 2013). However, our study was not able to answer why specialties in Northeastern clusters consistently prescribed more oxycodone, nor whether this pattern existed prior to our study period. Future research should explore the causes and impacts of such patterns. Past studies indicate that not only are there vast differences in the amounts of opioids prescribed overall (Guy et al., 2017) and within specialties (Guy and Zhang, 2018; Heins et al., 2006), as previously described, but also considerable variation in opioid prescribing even within identical patient case scenarios containing the same clinical and contextual information (Tamayo-Sarver et al., 2004).

The findings of this study are subject to some limitations. As with any clustering application, results are dependent on the selected variables, clustering method, and choice of distance metric. We were limited to using a representative sample of high-volume prescribers in order to keep the cluster analysis tractable. Finally, the scope of our study was limited by the lack of data on dosage, duration, or indication (e.g., acute or chronic pain) for prescriptions as well as number of patients seen by the prescribers. Additional research and data are required to study the role of opioid dosage and days' supply on opioid prescribing patterns, along with changes in prescribing by specialty over time.

Our results provide an improved understanding of current high-volume prescribers and their prescribing patterns. In light of the ongoing opioid overdose epidemic, this knowledge is critical for opioid misuse, opioid use disorder, and overdose prevention activities given the substantial volume of opioids prescribed by the top 10% of prescribers. Additionally, insight into high-volume prescribing patterns can help develop and target public health intervention efforts for improving opioid prescribing. The clusters highlight the role that specialties, region, and opioid type play in understanding high-volume prescribing. Provider education focused on these specialties and regions identified by the clusters may be beneficial.

Notably, three of the top five high-prescribing groups identified in our study (family medicine, internal medicine, and pain medicine) are specialties more likely to treat chronic pain (Guy and Zhang, 2018). It is also noteworthy that high-volume prescribing in these specialty groups was wide-spread across all geographical regions. For these specialties, provider education can incorporate the CDC *Guideline for Prescribing Opioids for Chronic Pain,* released in March 2016, which offers specific recommendations on opioid prescribing in primary-care settings for chronic pain (outside of cancer pain, palliative care, and end-of-life settings) as well as non-pharmacologic and non-opioid pharmacologic alternatives to pain management (Dowell et al., 2016). In addition, prescribing volume was greatest in the South. This region also saw the largest representation of a range of specialties, including those with particularly high-volume prescribing that were not represented in other regions such as neurologists and general practitioners. For those specialties and others as well, that are not the targeted audience of any prescribing guideline, review of PDMP data before prescribing opioids may help inform prescribing practices for safer pain management (Dowell et al., 2016; Rasubala et al., 2015). At an individual-level, academic detailing can serve as a valuable tool to help educate providers about existing guidelines, prescribing practice compared with peers, and evidence-based approaches to patient care (Cochella and Bateman, 2011; Davis et al., 2017). In addition, insurer interventions may include policies or interventions encouraging providers to prescribe non-opioid pain medication and covering non-pharmacologic therapies for pain management in alignment with guideline recommendations.

Given the multi-faceted and complex nature of the overdose epidemic, supply-side interventions as described above need to be carried out in conjunction with other strategies such as harm reduction and access to substance abuse treatment (Dasgupta et al., 2018; Saloner et al., 2018). Nonetheless, improving opioid overprescribing practices is critical to preventing opioid use disorder, non-fatal overdoses, and deaths associated with the current opioid overdose crisis in the US (Pacula and Powell, 2018; Saloner, 2019). This epidemic of opioid overdose deaths requires coordinated responses across a variety of federal, state, and local agencies spanning the public health, public safety, and healthcare sectors.

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Table 1

Characteristics of opioid prescribes between July 2016 and June 2017.

Variable		Analytic sample (N = 10,000)	High-volume prescribers (N = 79,014)	All opioid prescribers (N = 665,337)
Age		52.8 (10.77)	52.7 (10.78)	49.6 (12.76)
Mean (SD)				
Specialty (N)	Family Medicine	3,222 (32.2%)	25,609 (32.4%)	99,576 (15.0%)
N (%)	Internal Medicine	2,291 (22.9%)	18,136 (23.0%)	158,500 (23.8%)
	Orthopedics	1,138 (11.4%)	8,624 (10.9%)	27,739 (4.2%)
	Emergency Medicine	679 (6.8%)	5,151 (6.5%)	44,440 (6.7%)
	Pain Medicine	580 (5.8%)	4,443 (5.6%)	13,934 (2.1%)
	Surgery	384 (3.8%)	3,282 (4.2%)	69,885 (10.5%)
	Physical Medicine/Rehabilitation	319 (3.2%)	2,429 (3.1%)	7,597 (1.1%)
	Physician Assistant	297 (3.0%)	2,404 (3.0%)	19,259 (2.9%)
	Dentist	283 (2.8%)	2,265 (2.9%)	26,346 (4.0%)
	Nurse Practitioner	245 (2.5%)	2,062 (2.6%)	29,549 (4.4%)
	General Practice	125 (1.3%)	873 (1.1%)	5,303 (0.8%)
	Oncology	118 (1.2%)	1,095 (1.4%)	19,020 (2.9%)
	Neurology	117 (1.2%)	967 (1.2%)	10,853 (1.6%)
	Obstetrics/Gynecology	79 (0.7%)	686 (0.9%)	37,681 (5.7%)
	Other	66 (0.7%)	528 (0.7%)	33,957 (5.1%)
	Pediatrics	20 (0.2%)	106 (0.1%)	31,442 (4.7%)
	Psychiatry	13 (0.1%)	116 (0.1%)	17,222 (2.6%)
	Hospitalist	10 (0.1%)	107 (0.1%)	4,691 (0.7%)
	Palliative Medicine	9 (0.1%)	95 (0.1%)	850 (0.1%)
	Radiology	5 (0.05%)	36 (0.05%)	7,493 (1.1%)
Region	South	4,641 (46.4%)	36,679 (46.4%)	252,856 (38.0%)
N(%)	Midwest	2,328 (23.3%)	19,081 (24.1%)	155,782 (23.4%)
	West	1,875 (18.8%)	14,047 (17.8%)	138,055 (20.8%)
	Northeast	1,156 (11.6%)	9,207 (11.7%)	118,644 (17.8%)

Table 2

Distribution of prescriptions by opioid type in the analytic sample of high-volume prescribers (N = 10,000).

Opioid Type	Mean	SD	Range	25th Percentile	Median	75th Percentile
Hydrocodone	549.8	748.0	11,496.9	205.3	361.7	611.7
Oxycodone	364.7	694.0	16,429.5	64.9	176.2	376.3
Tramadol	254.7	250.0	5,880.8	96.4	191.6	334.9
Total[a]	1,412.2	1,730.8	32,715.3	653.8	893.5	1,421.6

[a]Total prescriptions include other opioids in addition to the prescriptions for hydrocodone, oxycodone, and tramadol shown in this table.

Table 3

Summaries of prescriber clusters obtained from the PAM clustering algorithm.

Cluster	Representative[a] Specialty (%)	Representative[a] Region (%)	Median age	Median Hydrocodone Rx	Median Oxycodone Rx	Median Tramadol Rx	Median Totals Rx	N
Sample	–	–	***53***	***362***	***176***	***191***	***894***	***10,000***
1	Pain Medicine (82.4)	MW (100)	52	879	622	260	2,850	142
2	Pain Medicine (96.8)	NE (100)	47	241	1,069	178	1,996	94
3	Pain Medicine (98.5)	S (100)	52	1,034	1,008	287	3,656	270
4	Pain Medicine (92.2)	W (100)	46	536	649	148	2,049	115
5	Physical Med/Rehab (80.9)	NE (100)	46	190	531	184	1,165	89
6	Physical Med/Rehab (97.2)	S (97.2)	47	749	555	263	2,313	144
7	Physical Med/Rehab (84.1)	W (92.7)	53	650	682	183	2,170	82
8	Neurology (97)	S (95.5)	54	407	235	218	1,210	67
9	General Practice (78.1)	S (73.4)	69	410	160	159	1,062	128
10	Family Medicine (99.3)	MW (100)	55	405	137	238	930	884
11	Family Medicine (97.2)	NE (100)	56	222	275	182	864	359
12	Family Medicine (99.9)	S (100)	53	413	114	294	1,006	1,350
13	Family Medicine (98)	W (100)	52	378	179	158	869	659
14	Internal Medicine (99.8)	MW (100)	52	377	116	236	890	516
15	Internal Medicine (100)	NE (100)	58	161	315	172	838	449
16	Internal Medicine (97.8)	S (100)	57	336	123	297	961	944
17	Internal Medicine (98)	W (100)	54	362	160	166	845	454
18	Dentist (91.4)	MW (97.5)	54	685	32	16	952	81
19	Dentist (95.9)	S (93.8)	48	490	12	26	841	146
20	Dentist (84.4)	W (90.9)	49	537	65	8	693	77
21	Nurse Practitioner (84.3)	MW (99)	46	322	171	195	836	102
22	Nurse Practitioner (97)	S (100)	47	285	70	258	783	99
23	Nurse Practitioner (54.9)	W (98.2)	62	309	172	131	745	113
24	Orthopedics (99.2)	MW (100)	51	374	205	145	848	260
25	Orthopedics (92)	NE (100)	52	120	368	115	695	113
26	Orthopedics (99.5)	S (100)	52	358	271	177	901	586

Cluster	Representative[a] Specialty (%)	Representative[a] Region (%)	Median age	Median Hydrocodone Rx	Median Oxycodone Rx	Median Tramadol Rx	Median Totals Rx	N
Sample	–	–	***53***	***362***	***176***	***191***	***894***	***10,000***
27	Orthopedics (92.3)	W (100)	56	301	232	104	704	209
28	Physician Assistant (89.8)	MW (88.2)	39	290	219	121	718	127
29	Physician Assistant (91.7)	S (96.2)	43	236	121	172	720	156
30	Surgery (69.6)	MW (88.4)	59	411	135	64	773	112
31	Surgery (95.5)	S (98.1)	52	348	155	43	657	266
32	Emergency Medicine (97.2)	MW (99.1)	52	414	89	71	682	107
33	Emergency Medicine (96.6)	S (98.7)	44	354	100	133	727	472
34	Emergency Medicine (77.9)	W (98.6)	46	363	105	48	632	140
35	Oncology (87.5)	S (90.9)	50	167	318	35	701	88

Dentists include oral surgeons. Abbreviations: Prescriptions (Rx), Physical Medicine and Rehabilitation (Physical Med/Rehab), Midwest (MW), Northeast (NE), South (S), West (W).

[a] Indicates the majority category that appeared in more than half the prescribers within a given cluster. The corresponding percent is reported in parentheses.