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Defining "Doctor Shopping" with Dispensing Data: A Scoping Review

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Abstract

Background. "Doctor shopping" typically refers to patients that seek controlled substance prescriptions from multiple providers with the *presumed* intent to obtain these medications for non-medical use and/or diversion. The purpose of this scoping review is to document and examine the criteria used to identify "doctor shopping" from dispensing data in the United States. **Methods.** A scoping review was conducted on "doctor shopping" or analogous terminology from January 1, 2000, through December 31, 2020, using the Web of Science Core Collection (seven citation indexes). Our search was limited to the United States only, English-language, peer-reviewed and US federal government studies. Studies without explicit "doctor shopping" criteria were excluded. Key components of these criteria included the number of prescribers and dispensers, dispensing period, and drug class (e.g., opioids). **Results.** Of 9,845 records identified, 95 articles met the inclusion criteria and our pool of studies ranged from years 2003 to 2020. The most common threshold-based or count definition was ($\geq$4 Prescribers [P] AND $\geq$4 Dispensers [D]) (n = 12). Thirty-three studies used a 365-day detection window. Opioids alone were studied most commonly (n = 69), followed by benzodiazepines and stimulants (n = 5 and n = 2, respectively). Only 39 (41%) studies provided specific drug lists with active ingredients. **Conclusion.** Relatively simple *P x D* criteria for identifying "doctor shopping" are still the dominant paradigm with the need for ongoing validation. The value of *P x D* criteria may change through time with more diverse methods applied to dispensing data emerging.

Introduction

The drug-related mortality rate has increased exponentially in the United States since the 1980s: from about 6,100 deaths in 1980 to 70,630 in 2019 [1, 2]. Among fatal drug poisonings in 2019, nearly 49,860 involved an opioid (70.5%) with 14,139 (20%) involving a prescription opioid [2]. According to the National Survey on Drug Use and Health (NSDUH), among people aged 12 years and older reporting pain reliever misuse in 2020, 1.0% (90,000 people) obtained those prescriptions from more than one doctor [3]. Patients are known to have multiple opioid prescribing physicians providing appropriate care. For example, approximately 12% of Medicare beneficiaries, 2.7% of Medicaid enrollees, and

1.3% of privately insured beneficiaries had four or more opioid prescribers in 2010 [4, 5]. However, at some point, the use of multiple prescribers and/or dispensers is deemed extreme and inappropriate especially when it involves addictive medications like opioids. For example, the US Department of Health and Human Services reported that 22,308 Medicare Part D beneficiaries had such extreme use in 2016 on the basis of an average daily MED greater than 120 mg for 3 months and had four or more prescribers and four or more pharmacies [6]. This behavior, known as "doctor shopping", has been associated with an increased risk of opioid use disorder and fatal overdose [7–9]. Furthermore, patients involved in "doctor shopping" for opioids are at-risk of having co-occurring mental health disorders, alcohol dependence, and low socioeconomic status [10].

Accurately identifying patients as "doctor shoppers" has important medical and legal implications. State prescription drug monitoring programs (PDMPs), national insurers, health plans and other entities commonly use controlled substance dispensing data to identify and (sometimes) proactively report on patients [11]. In a therapeutic medical context, this information gives healthcare providers an opportunity to intervene on unrecognized problematic opioid use and address gaps in continuity of care thus improving health outcomes for their patients. Although there is a high degree of confidence among healthcare providers that these administrative reports are effective [12], the ability of prescribers and dispensers to accurately identify patients with an opioid use disorder (OUD) and differentiate patients with OUD from patients with other complex medical needs is unclear. Even routine healthcare utilization like use of different prescribers in the same medical practice can increase risk scores using administrative data [13]. Unfortunately, negative outcomes can include patient dismissal from practice or refusal to prescribe when "doctor shopping" is suspected [14, 15]. In many states, patients designated as potential "doctor shoppers" can be questioned by law enforcement for breaking laws "to obtain a narcotic drug, or procure or attempt to procure the administration of a narcotic drug . . by fraud, deceit, misrepresentation, or subterfuge." [16] Yet, despite the widespread use of dispensing data as a proxy signal for emerging or existent opioid use disorder and the clear medical and legal ramifications [17], it is unclear whether there is consistency in the criteria used to identify "doctor shopping" in the United States.

The goal of the current study was therefore to: (1) synthesize the available definitions of "doctor shopping" previously used within the United States; and (2) building upon this literature, to identify and catalog important components of "doctor shopping" definitions in support of future efforts to identify problematic prescription drug patterns in administrative records. To these ends, we conducted a scoping review of the literature on "doctor shopping."

Methods

Data Sources and Literature Search

This scoping review was reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR). We conducted the review to systematically document the criteria used to define "doctor shopping" using dispensing data as the primary data source in the published study. The following research question guided this review: Do the definitions of "doctor shopping" suggest scientific consensus? Are components of the definitions well-documented and replicable? To be included in our review, studies needed to have at least the following components in their definitions: use of dispensing data, a patient's distinct count of prescribers and/or pharmacies (e.g., 5 or more prescribers AND 5 or more dispensers [written in notation as $P \geq 5 \wedge D_{\geq 5}$]), drug class specifications (e.g., opioids), and a measurement time frame over which the behavior is screened (e.g., 90 days). Prescriber and dispenser counts with a Boolean relationship were standardized to facilitate direct comparisons (i.e., greater than four prescribers ($P > 4$) became five or more prescribers ($P \geq 5$)). Descriptive statistics are provided at both the study and criteria levels (i.e., multiple criteria are sometimes found in a single study). Studies were primarily limited to English-language, peer-reviewed literature conducted in the United States. We chose to include documents published by key US federal agencies that promulgate "doctor shopping" definitions in national reports (e.g., the US Government Accountability Office). State managed PDMPs routinely use "doctor shopping" algorithms, but there is no central repository of their definitions [18]; therefore, we only included PDMP definitions if they were referenced in a peer-reviewed publication.

We searched the Web of Science Core Collection for titles and abstracts of relevant articles published from January 1, 2000, through December 31, 2020. Web of Science Core Collection includes seven major indexes [19]. An initial search was conducted on September 30, 2020, and a follow-up search was made on June 25, 2021. Our search strategy (developed by C.D./J.B.) used search terms from a published review on prescription drug misuse (2000–2013) that used 46 different terms describing people who may be misusing prescription drugs including multiple variants of "doctor shopper." We do note that many of these terms can be stigmatizing [20]. We modified by adding studies of patients multiple provider episodes known as high- or super-utilizers [17, 21] This strategy cast a wide net to avoid missing definitions when papers used colloquial variants of the term "doctor shopping" or otherwise included comparable populations. Likewise, we included opioids, benzodiazepines, stimulants and other controlled substances in our search to identify "doctor shopping" even when it involved drug classes other than opioids. The final search results were imported into Zotero and duplicates were removed by

JB. Our search terms are presented in Supplementary Data Table 1. JB/MD reviewed abstracts and CD resolved questions of eligibility and data extraction. CD/JB developed and iteratively modified the data charting tool using Microsoft Excel spreadsheet. JB/MD independently extracted study information, resolved any disagreement through discussion and confirmed the accuracy of the final data set. "Doctor shopping" parameters and studies are summarized in Supplementary Data Table 2.

We supplemented our scoping review with national trends that are directly or indirectly associated with "doctor shopping" to provide additional context. Opioid dispensing rates per 1,000 population were obtained from the US Centers for Disease Control and Prevention [22]. The source where pain relievers were obtained for most recent misuse among past year misusers aged by age group was obtained from the Substance Abuse and Mental Health Services Administration [3]. "Doctor shopping" rates per 100,000 state population were obtained from the Prescription Behavioral Surveillance System [23].

Results

The flowchart of our literature review is shown in Figure 1. Of 9,845 studies identified, 95 met the inclusion criteria with publication years ranging from 2003 to 2020. Figure 2 shows the count of studies per year from 2008 (n = 1) to 2019 (n = 19) with overlaid contextual data (see figure note). A single study can apply multiple "doctor shopping" definitions to the same study population and we found 173 instances where these definitions were used of which 72 were distinct on just the number prescribers, dispensers and time frames before even taking drug types and other parameters into consideration.

Most studies used a priori criteria while others used empirical methods to identify "doctor shopping" [24–29]. For example, McDonald (2013) used a finite mixture model to estimate that 10 or more prescribers were likely associated with "doctor shopping" [28]. One study hybridized a priori (a range and combination of thresholds from $P \geq 4 \wedge D_{\geq 4}$ to $P \geq 6 \wedge D_{\geq 6}$ within 3 months) and empirical thresholds (i.e., patients exceeding an average patient-to-prescriber travel distance and being in the top 1% of recipients for the number of times that they geographically "hopped" prescribers) to identify "doctor shopping" [30]. Figure 3 shows the threshold counts of prescribers, dispensers and their Boolean relationships found in our review. Of 148 a priori and hybrid thresholds, the most prevalent (18) definition of "doctor shopping" included ≥4 prescribers AND ≥4 dispensers. Among those 18 instances, a 1-year time frame was the most common (n = 10), followed by 6 months (n = 3) and 3 months (n = 5).

Of the 95 studies, 40 studies (42%) defined "doctor shopping" with thresholds of at least ≥2 prescribers AND ≥3 dispensers [6, 8, 23, 30–66], 26 studies (27%) did not restrict the number of prescribers (i.e., ≥1) [8, 33, 52, 55, 63, 67–87], and 43 studies (45%) did not restrict the number of dispensers [4, 5, 7, 8, 32, 33, 41, 52, 55, 63, 69–71, 74, 76, 77, 79–105].

Of historical note, the earliest study identified by our search examined "pharmacy shopping" for benzodiazepines defined as "filling a prescription for the same benzodiazepine from two different pharmacies within seven days" which was a definition associated with a dose escalation [75]. The first study to publish a definition for opioids used an "overlap" approach: ≥2 different sustained-release or long-acting opioids for ≥90 consecutive days. According to the study's authors, this criteria would have identified 5 enrollees out of hypothetical healthcare plan with 500,000 members [74].

One year was the most commonly used time period to determine "doctor shopping" (n = 33; range: 1 week [67, 68, 75, 78] to 48 months [4–7, 27–29, 33, 34, 43, 45, 49, 50, 52, 55, 56, 58, 60, 63, 71, 72, 74, 80, 82, 88, 89, 91, 93, 94, 98, 101, 102, 105, 106]. There were 39 definitions applied to populations at the national-level [4–6, 25, 26, 28, 29, 32–38, 42, 43, 46, 47, 50, 54, 64, 65, 71–74, 77, 83, 87, 93, 95, 98, 101, 105, 107–111] with 26 distinct state populations found. The most frequently studied states included California (n = 11) [23, 51, 57, 60, 61, 88, 90, 91, 103, 112, 113], Oregon (n = 7) [27, 70, 82, 84, 85, 99, 100], New York (n = 6) [41, 67, 68, 78, 90, 96], and Massachusetts (n = 6) [48, 49, 76, 86, 89, 96]. Eight studies made state by state comparison available [23, 25, 40, 51, 53, 57, 67, 68]. There were three studies that conducted spatial analyses of "doctor shopping" rates at the zip code level in Arkansas [30], Massachusetts [76], and Texas [45]. Only one study (2008) made all county-level "doctor shopping" rates per 1,000 residents available [25]. Most studies (n = 55; 58%) used all payer insurance populations [7, 8, 23, 25, 27–32, 34, 35, 37, 38, 40–42, 45–49, 51–54, 57–62, 64, 70, 76, 79–81, 84, 86–89, 91, 92, 97, 99, 100, 103, 107–109, 111–113], followed by Medicaid (n = 21; 22%) [5, 24, 39, 50, 55, 56, 63, 65, 67, 68, 72, 75, 78, 82, 84, 85, 90, 94, 96, 101, 102], Medicare (n = 10; 11%) [4, 6, 43, 71, 77, 83, 87, 93, 95, 104], private (n = 11; 12%) [5, 26, 33, 36, 50, 69, 74, 95, 98, 101, 105, 110], Veteran Affairs (n = 1; 1%) [73] and Workers Compensation (n = 1; 1%) [44].

Sixty-nine studies focused on opioids-only to define doctor shopping [4–6, 23, 25–31, 33–35, 37, 39–44, 47–50, 53–57, 61, 63–66, 69–73, 76, 77, 80, 82–89, 91, 92, 94–99, 101–104, 107–111, 113]. Chilcoat (2016) provides estimates that examine changes in "doctor shopping" rates pre-post reformulation of Oxycontin to its abuse deterrent version in 2010 [36]. We did not classify this study as "opioid-only," for example, since the study also involved benzodiazepines.

We reiterate that "doctor shopping" criteria was not limited to opioids and studies frequently examined opioids combined with other medications such as:

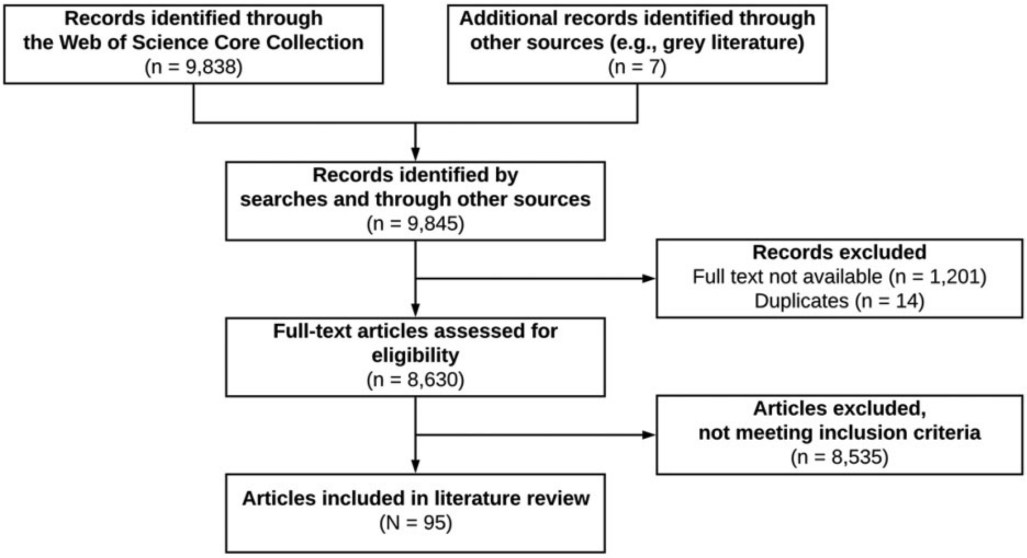

Figure 1. Flowchart of our literature review. Note: "full text not available" includes abstracts, letters, book chapters and reviews, editorial materials, and so forth.

		Dispensers (No.)							
Boolean	Prescribers (No.)	D≥1	D≥2	D≥3	D≥4	D≥5	D≥6	D≥8	Total
∧ (AND)	P≥1		8	7	12	6		1	34
	P≥2	10	3	18					31
	P≥3	8		4					12
	P≥4	14			18				32
	P≥5	8		1	1	14			24
	P≥6	4					2		6
	P≥8	1							1
	P2	1							1
	P3	1							1
∨ (OR)	P≥3			1					1
	P≥4				1				1
	P≥5					2			2
	P≥6				1		1		2
Total		47	11	31	33	22	3	1	148

Figure 2. Heatmap of count of prescriber and dispenser a priori thresholds used to define "doctor shopping." Time frames, drug types and other features vary across the thresholds.

benzodiazepines only (n = 4; 4%) [8, 32, 36, 74]; benzodiazepines and stimulants only (n = 4; 4%) [59, 81, 100, 112], and other medications such as muscle relaxants [62]. Of those studies not including opioids, five studies identified doctor shopping using benzodiazepines only [67, 68, 75, 78, 105] and 2 studies used stimulants for ADHD medications only [38, 46]. High dosage (n = 4; 4%) [6, 43, 50, 65] and overlapping prescriptions (n = 16; 17%) [29, 32, 34–39, 42, 46, 47, 50, 64, 83, 105, 109] were used to define thresholds across multiple drug classes. Other drug schedules used were: schedule II only (n = 12; 13%) [34, 35, 39, 46–49, 52, 73, 91, 107, 113], schedule IV only (n = 5; 5%) [67, 68, 75, 78, 105], schedule II-III (n = 6; 6%) [6, 71, 82, 87, 88, 103], schedule II-IV (n = 38; 40%) [4, 5, 7, 8, 23, 25, 28, 29, 31, 36, 40–42, 44, 45, 50, 51, 56, 59–62, 64, 72, 81, 83–86, 90, 93, 94, 96, 100, 101, 109, 111, 112] and schedule II-V (n = 4; 4%) [66, 80, 89, 102]. Thirty studies did not include drug schedules with the manuscript [24, 26, 27, 30, 32, 33, 37, 38, 43, 53–55, 57, 58, 63, 65, 69, 70, 74, 76, 77, 79, 92, 95, 97–99, 104, 108, 110]. Only 39 (41%) studies provided drug lists with active ingredients [4, 5, 7, 25, 28, 29, 33, 34, 36, 38, 39, 46, 47, 49–51, 56, 60, 61, 73, 75, 81–86, 88, 90, 91, 93, 94, 101, 102, 105, 106, 109, 112, 113]. We did not reach out to authors to obtain this information.

Of 87 studies of opioids or multiple drug classes, 22 excluded cancer diagnoses [5, 6, 26, 33, 39, 43, 56, 65, 72, 74, 76, 77, 82, 92–96, 101, 103, 107, 111], 30 excluded buprenorphine [5, 7, 23, 27, 31, 33, 34, 36, 39, 40, 42–44, 50, 60, 62, 70, 73, 82, 84–86, 88, 90, 91, 93, 96, 106, 112, 113], and 9 excluded methadone [33, 34, 36, 42, 47, 73, 93, 96, 106]. Eighty-seven studies had information to provide direct or indirect prevalence

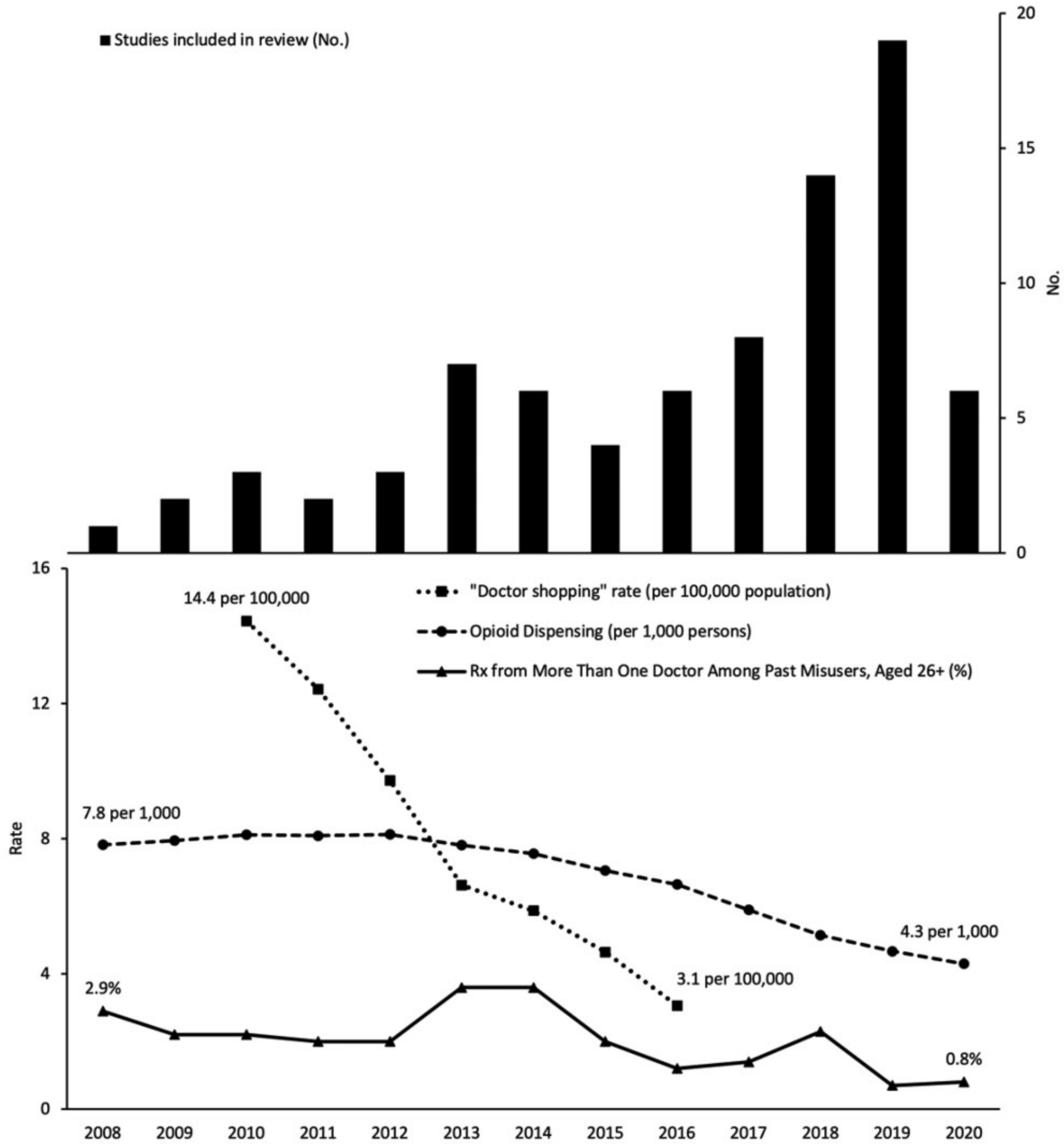

Figure 3. Count of "doctor shopping" studies (top) and select national epidemiologic indicators associated with opioid prescribing and "doctor shopping" (bottom).

estimates [4–8, 23, 25, 28–58, 60–64, 66–102, 104, 105, 108–110, 112, 113].

Discussion

There is no consensus in the criteria used to identify "doctor shopping". We demonstrated this by scoping 20 years of research that uses such criteria with dispensing data. Opioids tended to be the focus of this literature yet even opioids were frequently described in vague terms such as "high-dose" or "opioids used to treat opioid use disorder" without further specifying dose cut-offs or specific formularies. Studies using drug schedules to define "doctor shopping" often did not include specific drug lists which is problematic for replication. Furthermore, drug schedules even for the same medication can change through time (e.g., hydrocodone changed from III to II) [114]. At a minimum, drug lists should be provided and standardized notation (akin to what we have introduced here) should be considered by future researchers.

Even the relatively simple prescriber and dispenser threshold criteria resulted in many variants in the literature. A one-increment change in this threshold (e.g., four instead of five prescribers) can have large relative impacts at the population-level. For example, in California, Katz (2016) showed that modifying the criteria from the four to five level identified nearly 2.5 times more "doctor shopping" patients (2,748 and 1,149, respectively) [49]. Using administrative data to characterize patient motivations and the veracity of painful conditions is challenging, and we found that validation is still needed [115]. We did find three studies that attempted to validate "doctor shopping" in some manner. One study trained a model to match pharmacists recommendations ("lock-in," "prescriber alert," or "no action") to "shopping behavior" scores [24]. Two papers from the Opioid Post-Marketing Research Consortium showed little association between doctor shopping and opioid abuse/misuse in both a claims-based study and survey [108, 110]. Furthermore, we identified no papers on outcomes for patients dismissed from practice as a result of being identified as a "doctor shopper." This should be an area of priority research. Still, it is encouraging to see that a diverse set of algorithms are emerging that move beyond simple threshold counts but must be critically evaluated (e.g., composite risk scoring using overlapping drug utilization windows, dosage considerations, spatial analysis, vulnerable population exclusions, multiple drug classes and prescriber network analysis).

For example, Young et al. (2019) recommend a measure that they term "doctor hopping" into PDMPs. The method involves top-percentile ranking of patients in the same zip code based on the number of times they geographically bypass nearer opioid prescribers for more distant ones (using zip code center points) in Arkansas [30]. We assume that this study excludes buprenorphine prescriptions (authors not explicit) because patients with "doctor hopping" flags are compared against their high MME calculations from CDC's MME conversion table which excludes buprenorphine. If PDMPs adopt this measure and do not carefully consider patients with OUD, they risk identifying legitimate patients known to travel long distances to find a buprenorphine prescriber especially in rural areas with limited accessibility and/or provider willingness to treat [116, 117].

With respect to PDMPs, research and anecdotal discussions with healthcare providers show that there is widespread belief among PDMP users that their PDMPs reduce "doctor shopping" and effectively facilitate communication about "doctor shopping" [12, 118, 119]. However, two recent papers found that requiring providers to access their PDMPs was only modestly or not associated with "doctor shopping" [120, 121]. It is clear that "doctor shopping" is declining in prevalence to the point of being a relatively rare behavior; as we and others have reported [4, 101, 121–123]. Formally estimating the prevalence of "doctor shopping" was beyond the scope of this review but all-payer data from Strickler et al. (2019) identified a combined estimate of 9,544 patients (2017) from Kentucky, Ohio, and West Virginia, putting the prevalence in these high-risk states at approximately 0.55% of the general population [40, 124].

We did not find any research suggesting that "doctor shopping" criteria are adjusted through time to account for declining prevalence akin to modifying a diagnostic test to avoid false positives. Indeed, there is some publicly reported evidence that high false positive rates are occurring. Approximately, 9% (63/684) of patients' identified as a "doctor shopper" in Florida had a physician or law enforcement officer receive a "proactive report" to this effect [125]. In other words, 91% of patients identified by the PDMP's screening criteria did not warrant a final report (likely at the expense of extensive and costly manual record review by PDMP staff). This high apparent "false positive" rate suggests that while the existing criteria are relatively easy for PDMP's to apply to dispensing data, there is significant room for improvement and refinement of these criteria.

Our review shows that *P x D* thresholds are commonly used to identify "doctor shopping" in research but some argue that they are "obsolete" as stand-alone data points in real-world clinical practice [122, 123]. There are calls for the creation and triangulation of multiple administrative measures to better characterize this complex behavior in practice [126].

Limitations

Our scoping reviewed relied on the Web of Science Core Collection which identified all papers from two other reviews of this topic that used MedLine and additional papers not found by the other researchers. We did not examine health or legal outcomes (if reported) associated with "doctor shopping" nor could we include the criteria that state PDMPs use to identify "doctor shopping" in practice which likely change through time. A central repository of state PDMP criteria would be very helpful for future research on opioid policy. Our scoping review did not include studies from other countries and our conclusions on the effectiveness of identifying "doctor shopping" may vary depending on the country setting.

Conclusion

"Doctor shopping" identification using dispensing data varies and currently relies heavily on simplistic prescriber and dispenser utilization counts. These criteria, found in the research and used every day in practice to complement medical judgement need validation, on-going evaluation and triangulation with additional signals of problematic opioid use.

Supplementary Data

Supplementary data are available at *Pain Medicine* online.

References

1. Jalal H, Buchanich JM, Roberts MS, Balmert LC, Zhang K, Burke DS. Changing dynamics of the drug overdose epidemic in the United States from 1979 through 2016. Science 2018;361 (6408):eaau1184.
2. Overdose Death Rates. National Institute on Drug Abuse. Published January 29, 2021. Available at: https://www.drugabuse.gov/drug-topics/trends-statistics/overdose-death-rates (accessed May 14, 2021).

3. 2019 National Survey on Drug Use and Health: Detailed Tables. Substance Abuse and Mental Health Services Administration; 2020:2472. Available at: https://www.samhsa.gov/data/report/2019-nsduh-detailed-tables (accessed June 15, 2021).
4. Jena AB, Goldman D, Weaver L, Karaca-Mandic P. Opioid prescribing by multiple providers in Medicare: Retrospective observational study of insurance claims. BMJ-Br Med J 2014;348 (1):g1393.
5. Ali MM, Tehrani AB, Mutter R, et al. Potentially problematic opioid prescriptions among individuals with private insurance and Medicaid. Psychiatr Serv 2019;70(8):681–8.
6. US Department of Health and Human Services. Opioids in Medicare Part D: Concerns About Extreme Use and Questionable Prescribing. US Department of Health and Human Services; 2017:16.
7. Hall AJ, Logan JE, Toblin RL, et al. Patterns of abuse among unintentional pharmaceutical overdose fatalities. JAMA J Am Med Assoc 2008;300(22):2613–20.
8. Peirce GL, Smith MJ, Abate MA, Halverson J. Doctor and pharmacy shopping for controlled substances. Med Care 2012; 50(6):494–500.
9. Dhalla IA, Mamdani MM, Sivilotti MLA, Kopp A, Qureshi O, Juurlink DN. Prescribing of opioid analgesics and related mortality before and after the introduction of long-acting oxycodone. Can Med Assoc J 2009;181(12):891–6.
10. Biernikiewicz M, Taieb V, Toumi M. Characteristics of doctor-shoppers: A systematic literature review. J Mark Access Health Policy 2019;7(1):1595953.
11. Use of Opioids from Multiple Providers. NCQA. Available at: https://www.ncqa.org/hedis/measures/use-of-opioids-from-multiple-providers/ (accessed April 26, 2021).
12. Gershman JA, Gershman JA, Fass AD, Popovici I. Evaluation of Florida physicians' knowledge and attitudes toward accessing the state prescription drug monitoring program as a prescribing tool. Pain Med Malden Mass 2014;15(12):2013–9.
13. Shonesy BC, Williams D, Simmons D, Dorval E, Gitlow S, Gustin RM. Screening, brief intervention, and referral to treatment in a retail pharmacy setting: The pharmacist's role in identifying and addressing risk of substance use disorder. J Addict Med 2019;13(5):403–7.
14. Thomas CP, Kim M, Nikitin RV, Kreiner P, Clark TW, Carrow GM. Prescriber response to unsolicited prescription drug monitoring program reports in Massachusetts: State prescription monitoring reports. Pharmacoepidemiol Drug Saf 2014;23 (9):950–7.
15. Irvine JM, Hallvik SE, Hildebran C, Marino M, Beran T, Deyo RA. Who uses a prescription drug monitoring program and how? Insights from a statewide survey of Oregon clinicians. J Pain 2014;15(7):747–55.
16. Centers for Disease Control and Prevention, Public Health Law. Doctor Shopping Laws; 2012. Available at: https://www.cdc.gov/phlp/docs/menu-shoppinglaws.pdf (accessed December 29, 2021).
17. Blanch B, Buckley NA, Mellish L, Dawson AH, Haber PS, Pearson SA. Harmonizing post-market surveillance of prescription drug misuse: A systematic review of observational studies using routinely collected data (2000-2013). Drug Saf 2015;38 (6):553–64.
18. The Prescription Drug Monitoring Program Training and Technical Assistance Center (PDMP TTAC). Personal Communication; 2021.
19. Clarivate. Web of Science Core Collection. Web of Science Group; 2021. Available at: https://clarivate.com/webofsciencegroup/solutions/web-of-science-core-collection/ (accessed July 24, 2021).
20. Health in Justice Action Lab. They're Just Doctor Shopping Until They Find Someone to Supply Their Pill Addiction. Changing the Narrative. Available at: https://www.changingthenarrative.news/multiple-providers (accessed November 22, 2021).
21. Delcher C, Yang C, Ranka S, Tyndall JA, Vogel B, Shenkman E. Variation in outpatient emergency department utilization in Texas Medicaid: A state-level framework for finding "superutilizers." Int J Emerg Med 2017;10(1):31.
22. US Opioid Prescribing Rate Maps | Drug Overdose | CDC Injury Center; 2019. Available at: https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html (accessed September 12, 2019).
23. Strickler GK, Kreiner PW, Halpin JF, Doyle E, Paulozzi LJ. Opioid prescribing behaviors — prescription behavior surveillance system, 11 states, 2010–2016. MMWR Surveill Summ 2020;69(1):1–14.
24. Mailloux AT, Cummings SW, Mugdh M. A Decision support tool for identifying abuse of controlled substances by ForwardHealth Medicaid Members. J Hosp Mark Public Relat 2010;20(1):34–55.
25. McDonald DC, Carlson KE. The ecology of prescription opioid abuse in the USA: Geographic variation in patients' use of multiple prescribers ("doctor shopping"). Pharmacoepidemiol DRUG Saf 2014;23(12):1258–67.
26. Perry BL, Yang KC, Kaminski P, et al. Co-prescription network reveals social dynamics of opioid doctor shopping. McCollister KE, ed. Plos ONE 2019;14(10):e0223849.
27. Geissert P, Hallvik S, Van Otterloo J, et al. High-risk prescribing and opioid overdose: Prospects for prescription drug monitoring program–based proactive alerts. Pain 2018;159 (1):150–6.
28. McDonald DC, Carlson KE. Estimating the prevalence of opioid diversion by "doctor shoppers" in the United States. PLoS One 2013;8(7):e69241.
29. Simeone R. Doctor shopping behavior and the diversion of prescription opioids. Subst Abuse Res Treat 2017;11 :117822181769607.
30. Young SG, Hayes CJ, Aram J, Tait MA. Doctor hopping and doctor shopping for prescription opioids associated with increased odds of high-risk use. Pharmacoepidemiol Drug Saf 2019;28(8):1117–24.
31. McDonald DC, Carlson KE, Jalbert SK. An experimental test of the effectiveness of unsolicited reporting by a prescription drug monitoring program in reducing inappropriate acquisition of opioids. Pain Med 2019;20(5):944–54.
32. Cepeda MS, Fife D, Chow W, Mastrogiovanni G, Henderson SC. Assessing opioid shopping behaviour a large cohort study from a medication dispensing database in the US. Drug Saf 2012;35(4):325–34.
33. Chua KP, Brummett CM, Conti RM, Haffajee RL, Prosser LA, Bohnert ASB. Assessment of prescriber and pharmacy shopping among the family members of patients prescribed opioids. JAMA Netw Open 2019;2(5):e193673.
34. Cepeda MS, Fife D, Vo L, Mastrogiovanni G, Yuan Y. Comparison of opioid doctor shopping for tapentadol and oxycodone: A cohort study. J Pain 2013;14(2):158–64.
35. Cepeda MS, Fife D, Kihm MA, Mastrogiovanni G, Yuan Y. Comparison of the risks of shopping behavior and opioid abuse between tapentadol and oxycodone and association of shopping behavior and opioid abuse. Clin J Pain 2014;30 (12):1051–6.

36. Chilcoat HD, Coplan PM, Harikrishnan V, Alexander L. Decreased diversion by doctor-shopping for a reformulated extended release oxycodone product (OxyContin). Drug Alcohol Depend 2016;165:221–8.
37. Cepeda MS, Fife D, Yuan Y, Mastrogiovanni G. Distance traveled and frequency of interstate opioid dispensing in opioid shoppers and nonshoppers. J Pain 2013;14(10):1158–61.
38. Cepeda MS, Fife D, Berwaerts J, Friedman A, Yuan Y, Mastrogiovanni G. Doctor shopping for medications used in the treatment of attention deficit hyperactivity disorder: Shoppers often pay in cash and cross state lines. Am J Drug Alcohol Abuse 2015;41(3):226–9.
39. Sun BC, Lupulescu-Mann N, Charlesworth CJ, et al. Does prescription opioid shopping increase overdose rates in Medicaid beneficiaries? Ann Emerg Med 2018;71(6):679–87.
40. Strickler GK, Zhang K, Halpin JF, Bohnert ASB, Baldwin GT, Kreiner PW. Effects of mandatory prescription drug monitoring program (PDMP) use laws on prescriber registration and use and on risky prescribing. Drug Alcohol Depend 2019;199:1–9.
41. Bachhuber MA, Tuazon E, Nolan ML, Kunins HV, Paone D. Impact of a prescription drug monitoring program use mandate on potentially problematic patterns of opioid analgesic prescriptions in New York City. Pharmacoepidemiol Drug Saf 2019;28(5):734–9.
42. Cepeda MS, Fife D, Chow W, Mastrogiovanni G, Henderson SC. Opioid shopping behavior: How often, how soon, which drugs, and what payment method. J Clin Pharmacol 2013;53(1):112–7.
43. US Department of Health and Human Services, Office of Inspector General. Opioid Use in Medicare Part D Remains Concerning; 2018:23. Available at: https://oig.hhs.gov/oei/reports/oei-02-18-00220.pdf (accessed December 29, 2021).
44. Durand Z, Nechuta S, Krishnaswami S, Hurwitz EL, McPheeters M. Prescription opioid use by injured workers in Tennessee: A descriptive study using linked statewide databases. Ann Epidemiol 2019;32:7–13.
45. Ferries EA, Gilson AM, Aparasu RR, Chen H, Johnson ML, Fleming ML. Prevalence and factors associated with multiple provider episodes in Texas: An epidemiological analysis of prescription drug monitoring program data. Pain Med 2017;18(10):1941–51.
46. Cepeda MS, Fife D, Berwaerts J, Yuan Y, Mastrogiovanni G. Shopping behavior for ADHD drugs: Results of a cohort study in a pharmacy database. Drugs RD 2014;14(3):205–11.
47. Coplan P, Chilcoat H, Butler S, et al. The effect of an abuse-deterrent opioid formulation (OxyContin) on opioid abuse-related outcomes in the postmarketing setting. Clin Pharmacol Ther 2016;100(3):275–86.
48. Young LD, Kreiner PW, Panas L. Unsolicited reporting to prescribers of opioid analgesics by a state prescription drug monitoring program: An observational study with matched comparison group. Pain Med 2018;19(7):1396–407.
49. Katz N, Panas L, Kim M, et al. Usefulness of prescription monitoring programs for surveillance-analysis of Schedule II opioid prescription data in Massachusetts, 1996–2006. Pharmacoepidemiol Drug Saf 2010;19(2):115–23.
50. Rough K, Huybrechts KF, Hernandez-Diaz S, Desai RJ, Patorno E, Bateman BT. Using prescription claims to detect aberrant behaviors with opioids: Comparison and validation of 5 algorithms. Pharmacoepidemiol Drug Saf 2019;28(1):62–9.
51. Paulozzi LJ, Strickler GK, Kreiner PW, Koris CM; Centers for Disease Control and Prevention (CDC). Controlled substance prescribing patterns - prescription behavior surveillance system, eight states, 2013. MMWR Surveill Summ 2015;64(9):1–14.
52. McCall KL, III, Tu C, Lacroix M, Holt C, Wallace KL, Balk J. Controlled substance prescribing trends and physician and pharmacy utilization patterns: Epidemiological analysis of the Maine Prescription Monitoring Program from 2006 to 2010. J Subst Use 2013;18(6):467–75.
53. Chang HY, Murimi I, Faul M, Rutkow L, Alexander GC. Impact of Florida's prescription drug monitoring program and pill mill law on high-risk patients: A comparative interrupted time series analysis. Pharmacoepidemiol Drug Saf 2018;27(4):422–9.
54. Esposito DB, Cepeda MS, Lyons JG, Yin R, Lanes S; Members of the Opioid Post-Marketing Consortium Observational Studies Working Group. Medical record-based ascertainment of behaviors suggestive of opioid misuse, diversion, abuse, and/or addiction among individuals showing evidence of doctor/pharmacy shopping. J Pain Res 2019;12:2291–303.
55. Moyo P, Gellad WF, Sabik LM, et al. Opioid prescribing safety measures in Medicaid enrollees with and without cancer. Am J Prev Med 2019;57(4):540–4.
56. Cochran G, Lo-Ciganic WH, Gellad WF, et al. Prescription opioid quality measures applied among Pennsylvania Medicaid enrollees. J Manag Care Spec Pharm 2018;24(9):875–85.
57. Chang HY, Murimi IB, Jones CM, Alexander GC. Relationship between high-risk patients receiving prescription opioids and high-volume opioid prescribers. Addiction 2018;113(4):677–86.
58. Ferries EA, Gilson AM, Aparasu RR, Chen H, Johnson ML, Fleming ML. The prevalence of and factors associated with receiving concurrent controlled substance prescriptions. Subst Use Misuse 2017;52(12):1639–45.
59. Kreiner PW, Strickler GK, Undurraga EA, Torres ME, Nikitin RV, Rogers A. Validation of prescriber risk indicators obtained from prescription drug monitoring program data. Drug Alcohol Depend 2017;173:S31–S38.
60. Lev R, Lee O, Petro S, et al. Who is prescribing controlled medications to patients who die of prescription drug abuse? Am J Emerg Med 2016;34(1):30–5.
61. Schneberk T, Raffetto B, Friedman J, Wilson A, Kim D, Schriger DL. Opioid prescription patterns among patients who doctor shop: Implications for providers. PLoS ONE 2020;15(5):e0232533.
62. Wang Y, Delcher C, Li Y, Goldberger BA, Reisfield GM. Overlapping prescriptions of opioids, benzodiazepines, and carisoprodol: "Holy Trinity" prescribing in the state of Florida. Drug Alcohol Depend 2019;205:107693.
63. Hung A, Bush C, Greiner M, et al. Risk factors and outcomes of opioid users with and without concurrent benzodiazepine use in the North Carolina Medicaid population. J Manag Care Spec Pharm 2020;26(2):169–75.
64. Cepeda MS, Fife D, Berlin JA, Mastrogiovanni G, Yuan Y. Characteristics of prescribers whose patients shop for opioids: Results from a cohort study. J Opioid Manag 2012;8(5):285–91.
65. US Department of Health and Human Services. Medicare Part D Overutilization Monitoring System; 2013:5.
66. Buchmueller TC, Carey CM, Meille G. How well do doctors know their patients? Evidence from a mandatory access prescription drug monitoring program. Health Econ 2020;29(9):957–74.
67. Ross-Degnan D, Simoni-Wastila L, Brown JS, et al. A controlled study of the effects of state surveillance on indicators of problematic and non-problematic benzodiazepine use in a Medicaid population. Int J Psychiatry Med 2004;34(2):103–23.

68. Simoni-Wastila L, Ross-Degnan D, Mah C, et al. A retrospective data analysis of the impact of the New York triplicate prescription program on benzodiazepine use in Medicaid patients with chronic psychiatric and neurologic disorders. Clin Ther 2004;26(2):322–36.
69. White AG, Birnbaum HG, Schiller M, Tang J, Katz NP. Analytic models to identify patients at risk for prescription opioid abuse. Am J Manag Care 2009;15(12):897–906.
70. Deyo RA, Hallvik SE, Hildebran C, et al. Association of prescription drug monitoring program use with opioid prescribing and health outcomes: A comparison of program users and non-users. J Pain 2018;19(2):166–77.
71. Raman SR, Bush C, Karmali RN, Greenblatt LH, Roberts AW, Skinner AC. Characteristics of new opioid use among Medicare beneficiaries: Identifying high-risk patterns. J Manag Care Spec Pharm 2019;25(9):966–72.
72. Yang Z, Wilsey B, Bohm M, et al. Defining risk of prescription opioid overdose: Pharmacy shopping and overlapping prescriptions among long-term opioid users in Medicaid. J Pain 2015; 16(5):445–53.
73. Goodman F, Glassman P. Evaluating potentially aberrant outpatient prescriptions for extended-release oxycodone. Am J Health Syst Pharm 2005;62(24):2604–8.
74. Parente ST, Kim SS, Finch MD, et al. Identifying controlled substance patterns of utilization requiring evaluation using administrative claims data. Am J Manag Care 2004;10(11 Pt 1):783–90.
75. Soumerai SB, Simoni-Wastila L, Singer C, et al. Lack of relationship between long-term use of benzodiazepines and escalation to high dosages. Psychiatr Serv 2003;54(7):1006–11.
76. Stopka TJ, Amaravadi H, Kaplan AR, et al. Opioid overdose deaths and potentially inappropriate opioid prescribing practices (PIP): A spatial epidemiological study. Int J Drug Policy 2019;68:37–45.
77. Carey CM, Jena AB, Barnett ML. Patterns of potential opioid misuse and subsequent adverse outcomes in Medicare, 2008 to 2012. Ann Intern Med 2018;168(12):837–45.
78. Pearson SA, Soumerai S, Mah C, et al. Racial disparities in access after regulatory surveillance of benzodiazepines. Arch Intern Med 2006;166(5):572–9.
79. Hunt AW, Clegg K, Reyes CD, Riley-Behringer M, Zyzanski S, Werner J. Characteristics and red flag correlates of psychiatric outpatients in a mandated-use prescription drug monitoring program state: A PBRN card study. Addict Disord Their Treat 2019;18(1):36–43.
80. Gwira Baumblatt JA, Wiedeman C, Dunn JR, Schaffner W, Paulozzi LJ, Jones TF. High-risk use by patients prescribed opioids for pain and its role in overdose deaths. JAMA Intern Med 2014;174(5):796–801.
81. McCall K, Nichols SD, Holt C, Ochs L, Cattabriga G, Tu C. Prescription monitoring program trends among individuals arrested in Maine for trafficking prescription drugs in 2014. Pharmacother J Hum Pharmacol Drug Ther 2016;36(6):585–9.
82. Kim H, Hartung DM, Jacob RL, McCarty D, McConnell KJ. The concentration of opioid prescriptions by providers and among patients in the Oregon Medicaid program. Psychiatr Serv 2016;67(4):397–404.
83. Axeen S. Trends in opioid use and prescribing in Medicare, 2006–2012. Health Serv Res 2018;53(5):3309–28.
84. Hartung DM, Ahmed SM, Middleton L, et al. Using prescription monitoring program data to characterize out-of-pocket payments for opioid prescriptions in a state Medicaid program. Pharmacoepidemiol Drug Saf 2017;26(9):1053–60.
85. Hartung DM, Johnston KA, Hallvik S, et al. Prescription opioid dispensing patterns prior to heroin overdose in a state Medicaid program: A case-control study. J Gen Intern Med 2020;35 (11):3188–96.
86. Larochelle MR, Bernstein R, Bernson D, et al. Touchpoints – opportunities to predict and prevent opioid overdose: A cohort study. Drug Alcohol Depend 2019;204:107537.
87. Buchmueller TC, Carey C. The effect of prescription drug monitoring programs on opioid utilization in Medicare. Am Econ J Econ Policy 2018;10(1):77–112.
88. Wilsey BL, Fishman SM, Gilson AM, et al. An analysis of the number of multiple prescribers for opioids utilizing data from the California Prescription Monitoring Program: Number of multiple prescribers of opioids. Pharmacoepidemiol Drug Saf 2011;20(12):1262–8.
89. Weiner SG, Griggs CA, Langlois BK, et al. Characteristics of emergency department "doctor shoppers." J Emerg Med 2015; 48(4):424–31.
90. US Government Accountability Offices. Fraud and Abuse Related to Controlled Substances Identified in Selected States; 2009:18. Available at: https://www.gao.gov/new.items/d091004t.pdf. Accessed October 28, 2019.
91. Han H, Kass PH, Wilsey BL, Li CS. Increasing trends in Schedule II opioid use and doctor shopping during 1999-2007 in California. Pharmacoepidemiol Drug Saf 2014;23(1):26–35.
92. Kappa SF, Green EA, Miller NL, et al. Narcotic use and postoperative doctor shopping by patients with nephrolithiasis requiring operative intervention: Implications for patient safety. J Urol 2016;196(3):763–8.
93. US Government Accountability Office. Instances of Questionable Access to Prescription Drugs; 2011:32. Available at: https://www.gao.gov/new.items/d11699.pdf (accessed October 28, 2019).
94. Sun BC, Charlesworth CJ, Lupulescu-Mann N, et al. Effect of automated prescription drug monitoring program queries on emergency department opioid prescribing. Ann Emerg Med 2018;71(3):337–47.
95. Zhang Y, Johnson P, Jeng PJ, et al. First opioid prescription and subsequent high-risk opioid use: A national study of privately insured and medicare advantage adults. J Gen Intern Med 2018;33(12):2156–62.
96. Canan CE, Chander G, Monroe AK, et al.; HIV Research Network. High-risk prescription opioid use among people living with HIV. J Acquir Immune Defic Syndr 2018;78 (3):283–90.
97. Morris BJ, Zumsteg JW, Archer KR, Cash B, Mir HR. Narcotic use and postoperative doctor shopping in the orthopaedic trauma population. J Bone Jt Surg 2014;96(15):1257–62.
98. Tkacz J, Pesa J, Vo L, et al. Opioid analgesic-treated chronic pain patients at risk for problematic use. Am J Manag Care 2013;19(11):871–80.
99. Fink PB, Deyo RA, Hallvik SE, Hildebran C. Opioid prescribing patterns and patient outcomes by prescriber type in the Oregon Prescription Drug Monitoring program. Pain Med 2018;19(12):2481–6.
100. Hallvik SE, Geissert P, Wakeland W, et al. Opioid-prescribing continuity and risky opioid prescriptions. Ann Fam Med 2018; 16(5):440–2.
101. Ali MM, Tehrani AB, Mutter R, et al. Factors associated with potentially problematic opioid prescriptions among individuals with private insurance and Medicaid. Addict Behav 2019;98 :106016.
102. Obadan-Udoh E, Lupulescu-Mann N, Charlesworth CJ, et al. Opioid prescribing patterns after dental visits among beneficiaries of Medicaid in Washington state in 2014 and 2015. J Am Dent Assoc 2019;150(4):259–268.e1.

103. Wilson MP, Cucciare MA, Porter A, et al. The utility of a statewide prescription drug-monitoring database vs the Current Opioid Misuse Measure for identifying drug-aberrant behaviors in emergency department patients already on opioids. Am J Emerg Med 2020;38(3):503–7.
104. Delaney LD, Gunaseelan V, Rieck H, Dupree JM, Hallstrom BR, Waljee JF. High-risk prescribing increases rates of new persistent opioid use in total hip arthroplasty patients. J Arthroplasty 2020;35(9):2472–9.e2.
105. Ong MS, Olson KL, Cami A, et al. Provider patient-sharing networks and multiple-provider prescribing of benzodiazepines. J Gen Intern Med 2016;31(2):164–71.
106. Cepeda MS, Fife D, Ma Q, Ryan PB. Comparison of the risks of opioid abuse or dependence between tapentadol and oxycodone: Results from a cohort study. J Pain 2013;14(10):1227–41.
107. Sullivan MD, Edlund MJ, Fan MY, DeVries A, Braden JB, Martin BC. Risks for possible and probable opioid misuse among recipients of chronic opioid therapy in commercial and Medicaid insurance plans: The TROUP Study. Pain 2010;150(2):332–9.
108. Walker AM, Weatherby LB, Cepeda MS, Bradford DC. Information on doctor and pharmacy shopping for opioids adds little to the identification of presumptive opioid abuse disorders in health insurance claims data. Subst Abuse Rehabil 2019;10:47–55.
109. Walker AM, Weatherby LB, Cepeda MS, Bradford D, Yuan Y. Possible opioid shopping and its correlates. Clin J Pain 2017;33(11):976–82.
110. Stephenson JJ, Cepeda MS, Zhang J, et al. The association between doctor and pharmacy shopping and self-reported misuse and abuse of prescription opioids: A survey study. J Pain Res 2020;13:689–701.
111. Martin BC, Fan MY, Edlund MJ, DeVries A, Braden JB, Sullivan MD. Long-term chronic opioid therapy discontinuation rates from the TROUP study. J Gen Intern Med 2011;26(12):1450–7.
112. Wilsey BL, Fishman SM, Gilson AM, et al. Profiling multiple provider prescribing of opioids, benzodiazepines, stimulants, and anorectics. Drug Alcohol Depend 2010;112(1-2):99–106.
113. Gilson AM, Fishman SM, Wilsey BL, Casamalhuapa C, Baxi H. Time series analysis of California's prescription monitoring program: Impact on prescribing and multiple provider episodes. J Pain 2012;13(2):103–11.
114. Drug Enforcement Administration, Department of Justice. Schedules of controlled substances: Rescheduling of hydrocodone combination products from schedule III to schedule II. Final rule. Fed Regist 2014;79(163):49661–82.
115. Cochran G, Woo B, Lo-Ciganic WH, Gordon AJ, Donohue JM, Gellad WF. Defining nonmedical use of prescription opioids within health care claims: A systematic review. Subst Abuse 2015;36(2):192–202.
116. Andrilla CHA, Moore TE, Patterson DG, Larson EH. Geographic distribution of providers with a DEA Waiver to prescribe buprenorphine for the treatment of opioid use disorder: A 5-year update. J Rural Health 2019;35(1):108–12.
117. Cole ES, DiDomenico E, Cochran G, et al. The role of primary care in improving access to medication-assisted treatment for rural Medicaid enrollees with opioid use disorder. J Gen Intern Med 2019;34(6):936–43.
118. Delcher C, Wang Y, Goodin A, Freeman PR, Reisfield GM. Rapid expansion of the opioid ecosystem: National implications for prescriber-pharmacist communication. Am J Prev Med 2018;55(5):656–61.
119. Freeman PR, Goodin A, Troske S, Talbert J. Kentucky House Bill 1 Impact Evaluation. University of Kentucky; 2015:88. Available at: http://www.khpi.org/dwnlds/2015/KentuckyHB1ImpactStudyReport03262015.pdf (accessed February 4, 2016).
120. Lee B, Zhao W, Yang KC, Ahn YY, Perry BL. Systematic evaluation of state policy interventions targeting the US opioid epidemic, 2007–2018. JAMA Netw Open 2021;4(2):e2036687.
121. Sacks DW, Hollingsworth A, Nguyen T, Simon K. Can policy affect initiation of addictive substance use? Evidence from opioid prescribing. J Health Econ 2021;76:102397.
122. Delcher C, Harris DR, Park C, Strickler G, Talbert J, Freeman PR. "Doctor and Pharmacy Shopping": A fading signal for prescription opioid use monitoring? Drug Alcohol Depend 2021;221:108618.
123. Perry BL, Odabaş M, Yang KC, et al. New means, new measures: Assessing prescription drug-seeking indicators over 10 years of the opioid epidemic. Addict Abingdon Engl 2022;117(1):195–204.
124. Strickler GK. Personal Communication; 2021.
125. Florida Department of Health. 2017–2018 Prescription Drug Monitoring Program Annual Report; 2018. Available at: http://www.floridahealth.gov/statistics-and-data/e-forcse/health_care_practitioners/_documents/2018-pdmp-annual-report.pdf (accessed October 28, 2019).
126. Soeiro T, Micallef J. Commentary on Perry et al.: New means, new measures-without discarding all the previous ones! Addict Abingdon Engl 2022;117(1):205–6.