

Accepted Manuscript

British Journal of General Practice

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DOI: <https://doi.org/10.3399/BJGP.2022.0394>

To access the most recent version of this article, please click the DOI URL in the line above.

Received 29 July 2022

Revised 25 January 2023

Accepted 27 January 2023

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When citing this article please include the DOI provided above.

Author Accepted Manuscript

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The association of strong opioids and antibiotics prescribing with general practitioner burnout

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Abstract

Background

Prescribing of strong opioids and antibiotics has important implications for patient safety. However, little is known about the effects General Practitioner (GP) wellness can have with overprescribing of both medications in primary care.

Aim

To examine the associations between strong opioid and antibiotic prescribing with practice-weighted GP burnout and other wellness scores.

Design and Setting

A retrospective cross-sectional study using prescription (outcome) data on strong opioids and antibiotics from the Oxford-RCGP Research Surveillance Centre (RSC) whilst linking to a GP wellbeing survey overlaying the same 4-month period December 2019 to April 2020.

Methods

Adult patients prescribed strong opioids and antibiotics were the outcomes of interest. Prescriptions were measured as tablets per-patient. Burnout in GPs (exposure variable) was measured using the shortened versions of the emotional exhaustion and depersonalisation dimensions. Association was examined by fitting a multilevel generalised linear model with negative binomial distribution.

Results

Data for 40,227 patients (13,483 strong opioids and 26,744 antibiotics) were linked to 57 practices and 320 GPs. Greater strong opioid prescribing was associated with increased emotional exhaustion (IRR 1.19, 95%CI 1.10-1.24), depersonalisation (1.10, 1.01-1.16), job dissatisfaction (1.25, 1.19-1.32), diagnostic-uncertainty (1.12, 1.08-1.19) and turnover intention (1.32, 1.27-1.37) in GPs. Greater antibiotic prescribing was associated with increased emotional exhaustion (1.19, 1.05-1.37), depersonalisation (1.24, 1.08-1.49), job dissatisfaction (1.11, 1.04-1.19), sickness-presenteeism (1.18, 1.11-1.25) and turnover intention (1.38, 1.31-1.45) in GPs. Increased strong opioid and antibiotic prescribing was also found in GPs working longer hours (3.95, 3.39-4.61; 5.02, 4.07-6.19, respectively) and in practices in the north of England (1.96, 1.61-2.33; 1.56, 1.12-3.70, respectively).

Conclusion

We found higher rates of prescribing of strong opioids and antibiotics in practices with GPs with more burnout symptoms, job dissatisfaction and turnover intentions, working longer hours and in practices in the north of England serving more deprived populations.

Keywords

Burnout, general practitioner, wellness, opioids, antibiotics, hazardous prescribing, patient safety

How this fits in

Prescribing has important implications for patient safety; this is particularly the case for high-risk medications such as strong opioids, and medications where there may be public health implications such as antibiotics. Physician wellness such as burnout can also have significant impacts on the productivity of healthcare organisations, intentions to leave medical practice and both the quality and safety of patient care. At present, it is unclear the association between the wellness of general practitioners (GPs) within general practices and overprescribing of strong opioids and antibiotics in primary care in England. This first study to assess the association of

prescribing of strong opioids and antibiotics with GP wellness including burnout as a practice-level problem over a four-month period found higher prescribing of strong opioids and antibiotics among GPs with burnout symptoms, job dissatisfaction and turnover intentions, working longer hours and in general practices based in the north of England.

Background

Opioids are commonly used for the treatment of pain, and include medicines such as morphine, fentanyl and tramadol. In England, prescribing of opioids between 2008 and 2018 increased by 34% with more than 231 million prescriptions dispensed in primary care in 2018-19 alone (1). The non-medical use, prolonged use, misuse and use without medical supervision can lead to opioid dependence, other serious health problems and death (2). Worldwide, in 2017, an estimated 53.4 million people were on opioids, with opioids making up two-thirds of deaths related to drug misuse (3).

Antibiotic resistance is also a major challenge to health and care. The era of modern medicine has depended on the effective control of communicable diseases, of which many are bacterial in their origin (4). Faced with a situation where novel antibiotic agents are in short supply, the need to conserve our existing 'supply' of antibiotics becomes ever clearer. Antimicrobial stewardship encompasses a wide range of processes and interventions that are designed to ensure that antibiotics are used in the most effective manner (5, 6). However, the Public Health England's National Infection Service recently found that as many as 23% of all antibiotic prescriptions in general practices may have been inappropriate (7). Optimising opioid and antibiotic prescribing are highly important policy targets globally.

Many medication optimisation strategies focus on identifying and resolving potentially inappropriate prescribing, such as through pharmacist medication reviews and the use of information technology (e.g. PINCER) (8, 9). However, practice characteristics and staff wellness factors might be as equally important in reducing overprescribing and preventing patient safety incidents as patient factors (10). There is increasing evidence internationally that the wellness of physicians including general practitioners (GPs) is associated with poor quality of care outcomes including medication and prescription errors (11). Furthermore, a study among 232 practising GPs suggested that changes at both the practice level and the individual level would help to promote a healthier work environment for staff and patients, and improve patient safety generally (12). However, this evidence has been criticised because it is mostly based on

self-reported quality of care and patient safety data by doctors (13). Moreover, this self-reported evidence has not focused on prescribing specifically.

A key marker of health care staff wellness is *burnout*, which is defined as a work-related syndrome involving three key dimensions i) *emotional exhaustion*; ii) *depersonalisation*; iii) and *personal accomplishment* (14). Closely related characteristics that associate with burnout include turnover intention and job dissatisfaction (15). Importantly, physician wellness has been increasingly seen as an organisational quality indicator. Furthermore, GP wellness has been viewed as an organisational problem, and thus wellness measures could be analysed as a practice-level characteristic rather than an individual-level characteristic of GPs.

Objectives

In this study we aim to assess the association of the volume and potentially hazardous prescribing of strong opioids and antibiotics as the outcome of interest with key characteristics of general practices (with a focus on GP burnout) as the key exposure. Prescription data were obtained from the UK Oxford-Royal College of General Practitioners (RCGP) Research Surveillance Centre (RSC) from December 2019 to April 2020, and the exposure burnout/wellbeing variables were surveyed across the same time period.

Methods

Data source

We conducted a retrospective cross-sectional study involving prescription outcome data that was linked with GP wellbeing responses (exposure) from an online survey from December 2019 to April 2020 using the RSC. The prescription data and survey responses both covered the same 4-month period to ensure consistency when linking the two data in the cross-sectional study. The RSC is an internationally renowned source of information holding pseudo-anonymised individual level GP primary care data (16, 17). It provides patient-level data including prescription records and information about diagnosis, which have been carefully curated into variables historically using the Read terminology and more recently the Systematised Nomenclature of Medicine (SNOMED) Clinical Terms (CT) (18, 19). The RSC sentinel data includes the monitoring of upper and lower respiratory tract infections (URTI and LRTI, respectively) and the careful differentiation of new and ongoing episodes of care (20). RSC data also captures every prescription issued in primary care and has previously conducted research about antibiotic use (21).

We provided the RSC with coded product and medical concepts using similar strategies from our earlier work involving opioids (22) and antibiotics (23). A list of the Read codes, which constitute our inclusion criteria for products and medical conditions, are provided in Table S1.

The GP survey involved 10-items and was intended to reach 350-400 GPs across 70 different practices. The distribution of the survey was done using random sampling in-house and was sent online to participating GP practices through the RCGP RSC using the Survey Monkey platform. Each participating GP received a £20 payment to their GP practice. A copy of the full survey is provided in Figure S1.

Reporting in the study was done in accordance with the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines (24).

Study population(s)

We included patients aged 18 years and over with any indication of chronic pain (including postoperative pain) and prescribed strong opioids, and patients with any RTI and prescribed antibiotics in the four month period. The full medical and product code list is provided in Table S1.

Covariates

Survey and GP wellness scores

GP characteristics collected in the survey included practice identification code (including NHS region), age, sex, full-time equivalence (FTE), and seven key outcomes associated with GP wellness including emotional exhaustion (EE) (25) and depersonalisation (DP) subscales of burnout (25), sickness-presenteeism (26), work-life balance (27), diagnostic uncertainty (28), job satisfaction (29), and intention to leave their job in five years (turnover intention).

The single item measures for GP burnout with the highest factor loading on EE (“feelings of being burnt out”) and DP (“feelings of becoming callous towards people”) were used as the primary measures of burnout. Both items were initially measured on the ordinal scale of 1 (low) to 7 (high), and the other wellness factors were also measured on an ordinal scale (25).

RSC record linked primary care data

GP surveillance data includes all prescriptions issued including the dosage, which was converted to count data based on the total number of tablets per patient. As the data were delivered in various ways (i.e., tablets, capsules, ampoules, and patches), for consistency we standardised each

prescription to the single measure of mgs to allow for adjustment for potency in the modelling. Demographic patient data included baseline characteristics of age, sex, ethnicity (i.e. white, Asian, black, mixed, or other), consultation type (i.e. clinical administration, electronic-consultation, face-to-face, telephone, home visit and unspecified), related comorbidities (i.e. immunocompromised, asthma, chronic respiratory disease), mental health symptoms/episodes (i.e. anxiety, depression, mental health referral, obsessive compulsive disorder, panic attack, post-traumatic stress disorder and stress), smoking (i.e. active, ex-smoker, non-smoker or non-specific), drinking habit (alcoholic, hazardous, safe and non-drinker), history of other available medication use (i.e. hypnotic, antidepressant, anxiolytic), and socioeconomic status measured using the English Index of Multiple Deprivation (IMD) 2015 quintiles (30). The IMD is an aggregate measure of relative deprivation across seven domains, known collectively as the English indices of the Deprivation (income, employment, education and skills, health and disability, crime, barriers to housing and services, and living environment), using an area-based model at a low geography (average of 1500 people) and via practice/patient postcodes. Overall IMD is calculated as a weighted mean across the seven domains, with income and employment deprivation given the largest weight (22.5%), followed by health and education deprivation (13.5%), and the other three domains which are given equal weights (9.3%) (31).

Statistical analysis

As some of the GP wellness scores were missing from the original survey we imputed the missing data using the R package 'MICE: Multivariate Imputation by Chained Equations' (32). Since it was not possible to directly link the individual GP wellness response data from the survey to the main RSC prescription data without attaining consent from the GPs, we had to link the data at the practice level. This meant a *practice-weighted* score for GP wellness was calculated for each practice. The practice-weighted scores were calculated for all of the 9-items in the survey (GP age, FTE, EE, DP, sickness-presenteeism, work-life balance, diagnostic uncertainty, job dissatisfaction and turnover intention) using the average weight function *syby* in the *survey* package of R (33). The variable FTE was used as a predictor to improve approximation of the practice-weighted scores. The GP wellness variable was then included in the multilevel model described below.

Descriptive statistics described the characteristics of the patient population involved, and spearman rank correlations assessed associations across all the practice-weighted GP wellness scores.

The patient-level association of volume of prescribing (response variable) with the practice-weighted wellness scores (EE, DP, job dissatisfaction, sickness-presenteeism, diagnostic uncertainty, turnover intention and work-life balance), practice factors (NHS region, average GP age, FTE) and patient factors (sex, age, ethnicity, IMD, consultation type, comorbidities, symptoms/episodes, history of other medication use related to condition) were examined by fitting a multilevel generalised linear model (GLM) with a negative binomial distribution for each medication independently. A negative binomial model is favoured here because the prescription data were found to be over-dispersed (i.e., the magnitude of the variance exceeds the magnitude of the mean). The Poisson regression model often underestimate the standard errors with the presence of over-dispersion (34). Thus empirically, negative binomial gives more accurate estimates than Poisson regression in most cases (35, 36). Data availability drove the decision as to which variables were to be included in the models. In both models a random effects intercept of practice ID was introduced, and the incidence risk ratio (IRR) and 95% confidence interval (CI) estimates were used to determine the association with increased prescribing. All p-values were two-sided, and we regarded variables with $p\text{-value} < 0.05$ as significant in the model (37). Variance inflation factors (VIF) were examined for multicollinearity, with scores below five considered as moderately correlated, and scores above five considered highly correlated (38). If VIF was violated, a sensitivity analysis removing highly correlated variables from the model will be applied. All analysis was done in R version 4.0.5 (R Foundation for Statistical Computing) (39), and the *MASS* package was used to fit the GLMs (40).

Results

The cross-sectional study of just over four months included 67 practices, of which 57 (85%) of the practices (involving 351 GPs) could be linked to the RSC primary care data for 40,227 patients who met our inclusion criteria. The 10 (15%) practices excluded from the study involved GP trainees consulting at multiple practices at once and therefore could not be consigned to one unique practice ID.

Descriptive patient and service characteristics

The median response rate of the GPs across the practices was 39% (range: 12% to 91%). We identified 13,483 (34%) users of strong opioids and 26,744 (66%) users of antibiotics. The median age of strong opioid users was 65 (range 52-77) years, and for antibiotics it was 50 (24-70) years (See Table 1a & 1b). At least 62% and 57% of users for strong opioids and antibiotics respectively were females. Over 70% of the patients in both treatment groups were of white ethnicity, 67% were based in a city/town and 54% involved patients registered with a NHS

practice in northern England. IMD quintile scores were classified above two in over 60% of patients in both medication groups.

Up to 30% of strong opioid users were classified as 'hazardous' alcohol drinkers and 39% of antibiotic users were ex-smokers. At least 19% and 12% of antibiotic users had asthma and chronic respiratory disease, respectively (Table S2).

Characteristics of the practice-weighted GP wellness scores

The median number of GP respondents per practice was 5 (IQR=4). On average GPs reported EE a few times a week (median=3.3, IQR=1.5), experiences of DP once a week (median=3.7, IQR=1.3), sickness-presenteeism more than five times a year (median=3.3, IQR=0.5), find at least 11% to 15% of patients difficult to diagnose (median=3.0, IQR=0.6) and were dissatisfied with their current work-life balance (median=3.2, IQR=1.2). GPs on average also reported a moderate likelihood of leaving direct patient care within five years (median=2.1, IQR=0.9) and were generally dissatisfied with their job (median=2.5, IQR=0.9).

Figure 1 provides the correlations of the practice-weighted GP burnout scores (EE and DP) against the other practice-weighted GP wellness factors. EE was strongly associated with increased DP ($\rho=0.7$), job dissatisfaction ($\rho=0.7$) and turnover intention ($\rho=0.6$). The correlations between the other factors were low-to-medium ($\rho=0$ to 0.5).

Association of increased prescribing of strong opioids and antibiotics with GP wellness and other patient/practice factors

Strong opioids

Based on 13,483 (34%) users of strong opioids, increased prescribing was significantly associated with a practice-weighted higher risk of EE (IRR 1.19, 95% CI 1.10 to 1.24), DP (1.10, 95% CI 1.01 to 1.16), job dissatisfaction (1.25, 1.19 to 1.32), diagnostic uncertainty (1.12, 95% CI 1.08 to 1.19) and turnover intention (1.32, 1.27 to 1.37) in GPs. Increased opioid prescribing was also found in practices with longer working hours (FTE) (3.95, 95% CI 3.39 to 4.61) and in practices in the north of England (1.96, 95% CI 1.61-2.33) compared to practices in the south (See Table S3 for full results).

In terms of patient factors, strong opioid prescribing was significantly associated with male patients (1.18, 95% CI 1.15 to 1.22) being older (1.01, 95% CI 1.01 to 1.02), more deprived (IMD score of 5) (1.51, 1.22 to 1.89) and with alcoholism (1.13, 95% CI 1.08 to 1.18) or 'hazardous' drinking status (1.09, 95% CI 1.06 to 1.13). Reduced prescribing of strong opioids was found in

black (0.45, 0.24 to 0.82) and mixed (0.45, 0.21 to 0.97) ethnicity patients compared with white patients and in patients with a higher numbers of depression episodes (0.94, 0.91 to 0.96), mental health referrals (0.79, 0.70 to 0.88) and OCD episodes (0.12, 0.02 to 0.64). The VIF scores were all below 5 so no variables were removed.

Antibiotics

Based on 26,744 (66%) users of antibiotics, increased prescribing was significantly associated with a higher practice-weighted risk of EE (1.19, 95% CI 1.05 to 1.37), DP (1.24, 95% CI 1.08 to 1.49), job dissatisfaction (1.11, 95% CI 1.04 to 1.19), sickness-presenteeism (1.18, 95% CI 1.11 to 1.25) and turnover intention (1.38, 1.31 to 1.45) in GPs (Table S4). Increased antibiotics prescribing was also found in practices with longer working hours (5.02, 95% CI 4.07 to 6.19) and in practices in the north of England (1.56, 95% CI 1.12 to 3.70) compared to practices in the South.

With regards to patient factors, increased antibiotic prescribing was significantly associated with male patients (1.18, 95% CI 1.15 to 1.22) being older (1.01, 95% CI 1.01 to 1.02) with higher deprivation (IMD=5, 1.16, 95% CI 1.08 to 1.25). There was a significant reduction in antibiotic prescribing in black patients (0.72, 0.62 to 0.82) diagnosed with asthma (0.86, 95% CI 0.82 to 0.90) or chronic respiratory disease (0.79, 95% CI 0.75 to 0.83) and who active smokers (0.65, 95% CI 0.62 to 0.69) or were ex-smokers (0.79, 95% CI 0.75 to 0.82). No multicollinearity was present in the model.

Discussion

Summary

In this large national cross-sectional study involving 57 practices comprising 351 GPs with 40,227 patients, we found that prescribing of strong opioids over four months in 13,483 patients was greatest in GPs working in practices in the north of England, who worked longer hours, and who showed increased levels of practice-weighted burnout (EE and DP), job dissatisfaction, diagnostic uncertainty and turnover intention. For antibiotic use in 26,744 patients over four months, we found increased prescribing in practices in the north of England, in GPs working longer hours, and those with increased levels of practice-weighted burnout (EE and DP), job dissatisfaction, sickness-presenteeism and turnover intention.

Limitations

The study has several limitations. First, it was not an experimental study design, meaning unmeasurable confounding for prescribing of both drugs is possible. Second, by not being able

to directly link the GP survey responses to the surveillance health records without the GPs consent meant we had to calculate the practice-weighted scores for GP wellness factors. This in turn affected our ability to directly assess for potential clustering factors of the GPs with their prescribing characteristics. Furthermore, the accuracy for estimating the practice-weighted scores may have been impeded by the low response rate, which on average was 39% across practices. This may have led to overestimation or even an underestimation of the average practice burnout/wellbeing scores. However, this is still higher than the 12% response rate attained in the UK's Tenth National GP work-life Survey in 2019 (41). One consideration was to try to account for this low response rate in the study design by using imputation methods (42). However, there are significant complexities surrounding the best ways to impute the missing GP responses and how reliable this would be given we had such limited demographic information about the GPs and practices themselves from our survey. Bayesian models using missing at random and missing not at random algorithms have been proven effective when imputing missing response data (43) but need to be properly tested in this environment. Third, the decision not to apply a form of univariable regressions to observe how each covariate altered the treatment response and establish an order of importance for each of the GP wellbeing factors may have weakened the modelling. However, given the importance of each wellbeing factor we opted to include them all into the final model. In terms of the patient level factors such as patient demographic characteristics and complications/symptoms, these variables were chosen based on input from the clinicians involved in the study. Practice-weighted wellness scores (EE, DP, job dissatisfaction, sickness-presenteeism, diagnostic uncertainty, turnover intention and work-life balance) were selected based on existing frameworks that have studied the relation between occupational distress in physicians and poor quality of patient care outcomes (44, 45). Fourth, the study overlapped with the start of the Covid 19 pandemic March-April 2020 meaning some patients may have been subject to more relaxed medicine management, low morale and predominantly remote care (46) which will have had some impact on antibiotic prescribing (47). We did not adjust for this in the analysis. Fifth, the number of practices recruited in this study was based on available funding for the questionnaire collection, rather than a formal sample size calculation. However, the patient sample was not small, and we did find statistically significant associations between our key variables of interest (GP well-being and over-prescribing) and overprescribing of antibiotics and opioids. However, we strongly encourage larger studies to further investigate these associations, especially in a prospective research design. Sixth as detailed in the methods, dosage data were provided in different forms of delivery. Thus, we had to standardise the data to the unique measure based on mgs. However, as we were unable to

standardise up to 13% of the prescription data to mgs, these data therefore had to be removed from the cohort. We had considered do a sensitivity analysis to adjust for the loss of these data but due to the uncertainty on the dose provided to the patient we decided against this. Finally, due to the relatively low number of general practices (n=57), it was not possible to assess disparities between rural vs. inner city/urban areas, which is important to understand from a UK policy perspective.

Comparisons with existing literature

Our findings are consistent with the fast-growing research evidence which shows that physician burnout may risk the quality of care provided to patients (44, 48). To date, however, most of this evidence has been based on patient safety outcomes, self-reported by physicians. Our findings add to this body of evidence, demonstrating that GP burnout is associated with objectively reported overprescribing of strong opioids and antibiotics, by utilising novel linkages between a GP survey and patient data contained in a large health database. A previous study has shown that primary care providers who overprescribed opioids to treat patients with chronic pain often exhibit signs of burnout and feel unable to help patients overcome their complex challenges (49). However, this study involved a very small sample of only 19 primary care clinicians and 8 nurses, and they used a qualitative ethnographic approach which limited any quantification of the association between prescribing of opioids and burnout. Furthermore, inappropriate antibiotic use has been linked to the emergence of drug resistance and contributes directly to increased medical costs (50). However, the impact of antibiotic overprescribing and GP wellness has not been formally assessed. One such effort (51) had tried to assess the association between physician wellness (burnout and empathy) with antibiotic prescribing for RTIs in 36 primary care practices in the Northeast Ohio region of the United States. They found no association of physician wellness and antibiotic prescribing, but these findings might be more reflective of a lack of statistical power in their study sample.

Implications for Research and/or practice

The findings from our practice-level approach to burnout and quality of patient care, have important policy implications. Policies are urgently needed to mitigate burnout in the UK general practices, commissioned as practice-embedded workforce wellness programmes, rather than external support services made available to individual members of the workforce (e.g. GPs) who may suffer from burnout. Such practice-embedded workforce wellness programmes could produce further improvements to the mainstream category of medication safety improvement strategies, which focus mostly on identifying patients 'at risk' rather than workforce or general practices at risk.

Monitoring and understanding healthcare worker wellness requires conducting health-related surveys and surveillance. But the combining of these data with prescription (surveillance) electronic health records is more challenging as it requires consent to attribute the GPs who are responsible for prescribing the medication (52, 53). Obtaining such consent is considered a controversial area for many physicians, and we are not aware of any such novel and successful efforts to date. If a large enough response rate can be achieved, then the association of wellness factors and prescription characteristics can be assessed with high reliability considering missing responses. We encourage similar innovative efforts to investigate this as a possible model in future research designs.

Acknowledgements

We thank the Oxford-RCGP RSC network member practices for providing the surveillance data and for distributing the GP surveys across English practices. We thank also the RSC team including John Briggs, Filipa Ferreira and Ivelina Yonova for supporting any data and system related queries.

Contributors

AH and MP were the chief investigators. AH, MP, AE, EK and DA had the original research idea for the study, and AH and EK developed the analytical strategy. The study plan was refined with input from all authors. AH analysed the data. Members of the RSC extracted the relevant prescription data and distributed the GP surveys. AH and MP drafted the paper, incorporating comments from all other authors. AH is guarantor.

Funding

This work was funded by the National Institute for Health and Care Research Greater Manchester Patient Safety Translational Research Centre (NIHR GM PSTRC) (award number: PSTRC-2016-003). AH is funded by his NIHR fellowship. CCG is part funded by the NIHR WM ARC. The views expressed are those of the authors and not necessarily those of the NIHR or the Department of Health and Social Care.

Competing interests

All authors with the exception of SdeL declare no competing interest. SdeL has received funding through his University from Astra-Zeneca, Ei-Lilly, GSK, MSD, NovoNordisk, Sanofi, Seqirus and Takeda, and has been a member of advisory boards for Astra-Zeneca, Sanofi and Seqirus.

SdeL is Director of the Oxford-RCGP RSC. DMA reports research grants from AbbVie, Ammirall, Celgene, Eli Lilly, Janssen, Novartis, UCB, and the Leo Foundation.

Ethical Approval

The project was reviewed by the University of Manchester's research ethics committee before approval (IRAS ID: 268533).

Data Sharing

This study used pseudonymised patient-level data from the Oxford-Royal College of General Practitioner Research and Surveillance Centre (RSC). These data can be accessed for ethically approved research by applying via <https://orchid.phc.ox.ac.uk/>

Accepted Manuscript – BJGP – BJGP.2022.0394

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Table 1a: Descriptive characteristics of strong opioid users

Strong opioid prescribing characteristics in patients with chronic pain	Description, n (%) [‡]
<i>Total number of patients:</i>	13483
<i>Age (median [range]):</i>	65 [52 to 77]
<i>Sex:</i>	
- Male	4938 (37)
- Female	8363 (62)
<i>Ethnicity:</i>	
- Asian	171 (0.1)
- Black	59 (<0.1)
- Mixed	46 (<0.1)
- Other	42 (<0.1)
- White	10171 (75)
<i>District:</i>	
- City/Town	9021 (67)
- Conurbation	2275 (17)
- Rural	1281 (10)
<i>IMD patient quintiles:</i>	
- 1	2259 (17)
- 2	2215 (16)
- 3	2697 (20)
- 4	2753 (20)
- 5	2646 (20)
<i>Latest Alcohol:</i>	
- Alcoholism	850 (6)
- Hazardous	3848 (29)
- Non-drinker	3538 (26)
- Safe	4033 (30)
<i>Anxiety episode count*:</i>	
- None	13255 (98)
- More than 1	46 (<0.1)
<i>Depression episode count**:</i>	
- None	13019 (97)
- More than 1	282 (<0.1)
<i>Mental health referral[‡]:</i>	
- None	13183 (98)
- More than 1	118 (<0.1)
<i>Stress episode counts[‡]:</i>	
- None	13295 (99)
- More than 1	9 (<0.1)
<i>One of more hypnotic prescription:</i>	801 (6)
<i>NHS region:</i>	
- London	45 (<0.1)
- Midlands and east	1588 (12)
- North	7246 (54)
- South	4604 (34)
<i>Clinical system:</i>	
- EMIS web TPP	5759 (43)

- SystemOne	7724 (57)
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*Most values do not sum to 100% because their remainder were missing data or not coded.

*Number of Anxiety counts: 0 = 13255; 1 = 39; 2 = 5; 3 = 1; 4 = 1

**Number of depression episode counts: 0 = 13019; 1 = 193; 2 = 47; 3 = 22; 4 = 13; 5 = 2; 6 = 2; 7 = 2; 10 = 1

⁶Mental health referral count: 0 = 13183; 1 = 93; 2 = 22; 3 = 1; 4 = 2

⁵Stress count: 0 = 13295; 1 = 5; 4 = 1

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Table 1b: Descriptive characteristics of antibiotic users

Antibiotic prescribing characteristics in patients with RTIs	Description, n (%) [‡]
<i>Total number of patients:</i>	26744
<i>Age (median [range]):</i>	50 [24 to 70]
<i>Sex:</i>	
- Male	11028 (41)
- Female	15289 (57)
<i>Ethnicity:</i>	
- Asian	794 (3)
- Black	218 (1)
- Mixed	208 (1)
- Other	164 (1)
- White	18788 (70)
<i>District:</i>	
- City/Town	17752 (66)
- Conurbation	4753 (18)
- Rural	2671 (10)
<i>IMD patient quintiles:</i>	
- 1	3970 (15)
- 2	3979 (15)
- 3	5165 (19)
- 4	5308 (20)
- 5	6743 (25)
<i>Asthma:</i>	
- No	21266 (80)
- Yes	5051 (19)
<i>Chronic respiratory disease:</i>	
- No	23094 (86)
- Yes	3223 (12)
<i>Smoking status:</i>	
- Active smoker	4158 (16)
- Ex-smoker	10512 (39)
- Non-smoker	6917 (26)
- Non-specific	74 (0.3)
<i>More than 1 antibiotic prescribed:</i>	16477 (62)
<i>NHS region:</i>	
- London	249 (1)
- Midlands and east	2920 (11)
- North	14466 (54)
- South	9109 (34)
<i>Clinical system:</i>	
- EMIS web TPP	14569 (54)
- SystmOne	12175 (46)

Figure 1: correlation plot of the 57 practice-weighted GP wellness score

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