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Title: Exploring the impact of the discharge medicines review on patient hospital readmissions through national routine data linkage in Wales: a retrospective cohort study

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Abstract

Objectives: To evaluate the effect of the discharge medicines review (DMR) on hospital readmissions through linking national NHS data sets.

Design: Retrospective cohort study.

Setting: All hospitals and 703 community pharmacies across Wales.

Participants: Inpatients meeting the referral criteria for a community pharmacy DMR.

Interventions: Information related to the patient's medication and hospital stay is provided to the community pharmacists, who undertake a two-part service involving medicines reconciliation and a medicine use review. To investigate the impact of the service on hospital readmission, a data linking process was undertaken across six national databases.

Primary and secondary outcome measures: The readmission rates of patients receiving the intervention compared to those that do not and indication of any other patient factors contributing to the likelihood of readmission.

Results: 1923 patients were referred over a 13-month period (February 2017–April 2018). Provision of DMR was found to be the most significantly attributing factor to reducing likelihood of 90-day readmission using chi-squared testing and classification methods. Survival analysis further demonstrated that those receiving the intervention had a lower hospital readmission rate at 30 (22% vs. 36 %), 60 (36% vs. 49%) and 90 (45% vs 56%) days post discharge. Patients aged 50-79 years and male patients appeared to benefit most with a more significant reduction in readmission rate.

Conclusions: DMR after a hospital discharge is correlated with a reduction in risk of hospital readmission. Potentially targeting the 50-79 age bracket or males to offer this service can reduce readmissions even more, however, large patient populations are required to substantiate this. Linking data across disparate national data records is feasible but requires a complex processual architecture. There is a significant value for integrated informatics to improve continuity and coherency of care and also to facilitate service optimisation, evaluation and evidenced-based practice.

Article summary: This study demonstrates the current complexity in assessing the potential of a post-discharge community pharmacy medicines review to reduce hospital readmissions. The linkage of patient data across national databases provides the opportunity to track outcomes of the intervention, investigate for confounding factors and contribute to the optimisation of evidence-based practice. We highlight the significant need for a national integrated technological solution for patient health records to enable the further progress of service design, delivery, research and evaluation towards providing clinically effective patient care.

Strengths and limitations of this study:

- We demonstrate the feasibility to link patient data across numerous databases towards investigating the impact of a post-discharge intervention on hospital readmissions.
- Our analysis explored across demographic factors to investigate for potential confounding effect on risk of readmission.
- Only 1923 records were available for analysis, with only 1844 records for use where deaths were excluded (in chi-squared and conditional inference tree analysis). Therefore, when analysing traits, groups are often relatively small. As more community pharmacists are

completing electronic DMRs using *Choose Pharmacy*, more records will become available for analysis.

- Though we have tried to take into account some socio-economic indicators (i.e. deprivation decile), we have not investigated whether those who have started a DMR are more health conscientious than those who have not, so some of the effect seen here may be indicative of level of patient activation or other related external factors, as yet unmeasured.
- We tested for association of part 1 of the DMR being started and readmission, not accounting for whether part 2 of the DMR had been completed or not. This is because part 2 is essentially an MUR, and such, it was outside of the scope of our study.

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INTRODUCTION

It is widely acknowledged that medicines-related errors and adverse events can occur at points of patients transitioning between healthcare settings.[1-4] Internationally, numerous interventions have been designed and delivered to try and address this eventuality, with the aim to reduce medicines-related, preventable hospital readmissions. A recent systematic review has found that interventions involving a community pharmacist after hospital patients are discharged home, demonstrate capacity to identify and rectify medicine-related problems which could have resulted in avoidable hospital admission.[5] In June 2019, the National Health Service (NHS) in England committed to introduce a post-discharge medicines reconciliation service through CPs by 2024.[6]

Currently in the United Kingdom (UK) there are three main transfer of care technologies or services, whereby community pharmacists contribute to the medicines reconciliation process post hospital discharge: Refer-to-Pharmacy,[7,8] the transfer of care or transfer of care around medicines service using a web-based platform widely used in community pharmacies across England (*PharmOutcomes*),[9,10] and the Discharge Medicines Review (DMR) service.[11]

A service evaluation in 2016, aimed to assess if a new transfer of care service implemented from hospitals in the North East of England that involved patients being referred to a nominated community pharmacy on discharge for follow-up care, led to reduced hospital readmissions.[9] Patient referrals in the hospital were generated using *PharmOutcomes*; hospital pharmacy staff were required to input patient data since there was no interconnectivity with the electronic National Health Service (NHS) patient record at that time. Community pharmacy staff were then completing intervention and outcome data on the *PharmOutcomes* platform. The evaluation showed that this service was associated with significantly reduced patient readmissions to hospital in 30, 60 and 90 days and shorter length of hospital stay if they were readmitted.[9] However, *PharmOutcomes* is not used nationally across England, and outcome data completed by community pharmacists were not networked back to the hospital where the referral was generated. Due to this disjointed information flow, retrieving data about subsequent hospital readmissions and length of hospital stays required access of another database with steps of deanonymisation and reanonymisation to match data in *PharmOutcomes* with data in the hospital admission records.

The DMR service is a two-part community pharmacist-led service introduced in Wales in 2011 to support patients with their transition from one care setting to another. The service has mainly been used for patients recently discharged from hospital and transitioning back into the home environment.[11] The aim, as with the transfer of care service in the North East, is to reduce the risk of preventable medicines-related problems, improve adherence with newly prescribed medicines and improve patient knowledge and use of medicines. This service is operationalised employing electronic platforms and developed interoperability to generate a referral from the hospital to a nominated community pharmacy. Part 1 of the service is a medicines reconciliation between the medications listed in the first prescription from the general practitioner (GP) after discharge and the discharge medication list, including rectifying any unintended discrepancies that have arisen. The rectification of these discrepancies may involve contact with the patient or carer, GP or the hospital to gather the most relevant information. Part 2 is a Medicines Use Review that gives the pharmacist an opportunity to discuss any medicines-related issues with the patients including adherence, dosing and side-effects. Service evaluation of the DMR service has shown positive outcomes including the identification of 1.15-1.3 discrepancies per service completed and an average three-fold return on financial investment. [12,13] After the initial evaluation confirmed the benefits of the service,[12] it was rolled out nationally, currently being available in 703 community pharmacies in Wales. The evaluations focussed on cost benefit and identifying discrepancies in the medicines reconciliation process.

However, to date, there has been no formal process of linking data from the DMR service to hospital data with a subsequent evaluation of the impact of DMR on patient readmission to hospital.

Linking data sets from different divisions in the NHS has been reported to be limited, and it is widely acknowledged that NHS data is not used effectively to guide patient care. [14] The aim of this study was to explore the use of national routine data linkage to investigate the impact of DMR on patient hospital readmission.

METHODS

Intervention description

The independent evaluation undertaken in 2014 provides a description of the DMR service in Wales,[12] however, it is briefly outlined here to provide a contextual background.

Pharmacists in a total of 703 out of 716 community pharmacies in Wales are currently completing DMRs with the support of *Choose Pharmacy*, a national web-based application that supports the delivery of NHS advanced and enhanced community pharmacy services. Accredited community pharmacies and community pharmacists can access via *Choose Pharmacy*, an electronic Discharge Advice Letter (eDAL) generated by the Medicines Transcribing and electronic Discharge (MTeD) functionality in the National Welsh Clinical Portal (WCP), to support an electronic DMR. Patients are linked to the Welsh Demographic Service and matched to existing health records, enabling collection of demographic information such as gender and age. When an eDAL is generated, the patient's nominated community pharmacy receives a notification via the Electronic NHS Alert Service (ENAS) that one of their patients has been discharged from hospital. In the event a patient has been discharged from a non-MTeD ward and has received a paper DAL, a physical copy needs to be taken to the pharmacy for DMR to be initiated. *Choose Pharmacy* is still used to record the DMR undertaken.

Patients are identified and recruited to the DMR service either by referral from a healthcare professional during their hospital stay, or following their discharge by patients self-referring, their nominated carer presenting in the pharmacy, or by the pharmacist when necessary criteria are met.

Patients are eligible for the service where the following criteria are met:

- The patient's medicines have been changed during their hospital stay;
- The patient is taking four or more medicines;
- The patient's medicine requires dispensing into a multi-compartment compliance device;
- The pharmacist has, in their professional opinion, reason to consider that the patient would benefit from the service.

Outcome measures

The primary outcome in this study was to investigate whether there was a reduction of readmissions to hospital for patients who had a DMR. The secondary outcome was to explore the routine service data to investigate if any patient characteristics could be identified which correlated with improved outcomes (reduced hospital readmissions) from DMRs. This information could be used to optimise the patient referral criteria for DMRs.

Routine data collection

Six data sources were used for this study with data obtained via NHS Wales Informatics Service (NWIS) for the period February 2017 – April 2018 (Box 1).

Box 1. A description of the type of data collected and stored in the national databases in Wales that were used in the data linkage in this study.

National data source in Wales	Overview
Choose Pharmacy **(CP)**	A national web-based application that supports the delivery of NHS advanced and enhanced community pharmacy services in Wales. Holds data for all services completed in the pharmacy in the form of clinical information and pre-defined answers, including data for all electronic DMRs that were completed using *Choose Pharmacy*.
Patient Episode Database for Wales (PEDW)	A system that records all episodes of inpatient and day case activity in NHS Wales hospitals, which includes planned and emergency admissions, minor and major operations, and hospital stays for giving birth.
Admitted Patient Care Data set (APCDs)	Captures data for all consultant-led admitted patient activity, regardless of the patient's area of residence. NHS Digital provide data on Welsh resident or registered patients treated in English NHS organisations. Once admitted a patient may have several episodes within a hospital stay. Only once an episode is complete or the hospital spell ends will it be captured in the APC data set.
Office of National Statistics (ONS) Death notifications database	Annual data on deaths registered by age, sex and selected underlying cause of death.
Welsh Demographics Service (WDS)	Provides the demographic characteristics of people registered with GP practices in Wales. The WDS maintains a register of Welsh residents' demographic details, including name, address, date of birth, general practice and NHS number. For any consultations completed via *Choose Pharmacy*, patients are linked to the Welsh Demographic Service and matched to existing health records, enabling collection of demographic information.
National Data Resource (NDR)	A resource currently being developed to better enable NHS Wales to improve patient experience and service outcomes. The NDR aims to deliver a more joined up approach to health and care data, using common language and technical standards and providing improved analytics capability.

Data linkage

The data linkage process was completed in three steps (Figure 1):

- **Step 1:** Extracting data for anonymisation.
  A "referral" for a DMR was defined as the date that an ENAS notification was sent to the pharmacy to flag that a DMR should be completed with the patient. Referrals received by community pharmacy were identified using the NDR audit events system. These referrals were matched with the DAL Information in the *Choose Pharmacy* database, to obtain the patient NHS number and a relevant DAL ID. These pieces of information were used to look up corresponding patients in the *Choose Pharmacy* database and return applicable DMR data.
- **Step 2:** Anonymising patient specific pharmacy data.

The full record was then linked to hospital data with an Anonymous Linking Field (ALF), which allowed individuals to be tracked over time and across datasets, while ensuring researchers had no access to any personal identifiable data.

- **Step 3:** Linking of anonymised pharmacy data to hospital data.
  Once data about the DMR service had been anonymised, it could be linked to data in PEDW. This was done by using the pseudonymised ID provided by NWIS, which is also used within the PEDW dataset. In this way, data from individuals could be linked together to provide a picture of the patient journey without patient identifiable information being shared.

  Information from these datasets was used to create a new dataset for analysis, which included whether the patient had received the DMR service, admission information such as their age, deprivation quintile, diagnosis, length of stay before they were referred into the DMR service, and the same admission information for the first admission occurring after referral to the DMR service.

The full process for the data linkage is included in Supplementary Table 1. The data linkage is consistent with the current roles and responsibilities of NWIS to ensure information is rendered anonymous whilst creating a dataset for the required uses. NWIS Head of Information Governance approved the methodology and helped set the criteria for processing the information to ensure patient privacy was maintained in all circumstances. The model of processing is consistent with NWIS trusted third party responsibilities and is used in many circumstances to ensure confidentiality, integrity and availability of information. No ethics approval was requested for this study given the nature of using routine service activity data and the other official approvals granted. Patients provide informed consent when offered the DMR service as part of routine hospital and community pharmacy care. This consent covers the recording of data for the purpose of service activity, audit and evaluation.

Data analysis

Secondary data analysis was conducted using Microsoft Excel® for descriptive statistics and Stata® and R (using the partykit library) for more complex statistical analyses. In order to ensure that there was sufficient time following referral to capture data about a patient being readmitted, all referrals after 31st December 2017 (which is 90 days prior to the last date in the data extract) were removed from the dataset.

Pearson's chi-squared test, using a significance level of 0.05, was applied to records of all patients offered a DMR who did not die within 90 days of their discharge, to assess whether the DMR changed the probability of readmission and evaluate how likely it is that any observed difference between the sets arose by chance. The chi-squared test has a null hypothesis that there is no association between whether a patient had started a DMR (had completed at least Part 1 of the service) and whether they were readmitted within 90 days. All patients who had died before 90 days after the notification had been sent were removed from this analysis as these deaths could skew the results (for example, if a patient died within 90 days without readmission, they would be recorded as 'no readmission within 90 days', which would be an inappropriate classification).

To better understand the probability of readmission over time, the Kaplan-Meier estimator was used to estimate the likelihood of readmission for a patient who had started a DMR versus a patient who

had not been provided a DMR over specified time intervals. The inverse of the Kaplan-Meier curve was created to describe the likelihood of readmission, based on avoidance of readmission.

All eligibility criteria for the DMR were considered other than medication change during hospital stay to be associated with increasing age; hence, age could be considered as a proxy eligibility criterion. A subgroup analysis by age group (where there was a large enough population to meet the assumptions of the test, n>20) was undertaken to examine the likelihood of readmission for 30, 60 and 90 days after DMR was started.

A classification tree was also produced to look at which patient traits had the strongest association with whether a patient was readmitted within 90 days. A confidence inference tree was used to do this. Confidence inference trees partition cohorts by selecting successive splits in variables with the strongest association to the outcome of interest, as measured by p-values. In this case, the confidence inference tree used gender, deprivation decile, year of birth, diagnosis grouping (e.g. respiratory, circulatory) and whether a DMR had been started, to look at the relationship of these to readmission within 90 days. In the survival analysis, deaths were excluded when they occurred, and patients were removed from the dataset at that point. A significance level of 0.05 was used.

The STROBE checklist for cohort studies was utilised to guide the reporting of this study and is included as Supplementary Table 2.

Patient Involvement

Patients were not involved in the design or conduct of this study.

RESULTS

A total of 1923 records were available within the specified time period (February 2017 – April 2018), up to 90 days prior to the last date in the data extract available.

Only the deprivation quintiles were statistically significantly different between the intervention and non-intervention groups at baseline as shown in Supplementary Table 3. The other demographics did not show a significant difference, which suggests that it is reasonable that any difference in hospital readmissions for these groups was because of random variation. For deprivation quintile, however, these proportions are too different to be random variation according to the test. This indicates that patients with a DMR started and those with no DMR have different deprivation demographics, with those who had a DMR started (intervention group) being of a slightly more deprived population.

Primary outcome

A total of 244 records referred to patients who died within 90 days of a notification being sent; 79 or these patients died prior to any readmission. In order to eliminate any skew caused by patients who were not readmitted but died the 79 records were removed for all chi-squared and conditional inference analysis. Therefore, a total of 1844 records were used, with 673 (36.5%) of those records referring to patients receiving the DMR service, representing the intervention cohort.

A statistically significant difference was identified at the 90 day readmission rate of those patients who had started a DMR and those who had not received a DMR (Pearson chi-squared = 23.0829), $p<0.001$. This means that readmission within 90 days was less likely when a DMR had been started (Table 1). Characteristics and chi-squared analysis of characteristics of the baseline population of the

study (n=1923), split into groups in relation to whether they had received discharge medicines review service (DMR) Part 1 upon discharge from hospital, are presented in Supplementary Tables 3 and 4.

Table 1. The number of patients offered a DMR service who did not die (n=1844) and went on to receive the service by whether there was a hospital readmission within 90 days of discharge.

Patient group	Readmission within 90 days n (%)	No admission within 90 days n (%)	Total n (%)
DMR Started	307 (31.4)	366 (42.2)	**673 (36.5)**
No DMR	670 (68.6)	501 (57.8)	**1171 (63.5)**
Total	**977**	**867**	**1844**

A conditional inference tree was used to identify the variable with the strongest association to readmission within 90 days, using age decile, sex, deprivation decile, diagnostic grouping and DMR type (started or not started) as the possible criteria for classification.

This identified that the variable with the strongest association was whether the patient had started a DMR or not ($p < 0.001$) (Supplementary Figure 1). Just over 40% of those that had started a DMR were readmitted within 90 days, compared to just under 60% of those that did not have a DMR. Amongst those that had started a DMR, the next statistically significant association was age ($p \sim 0.035$). Those in the 20-29, 40-49, 50-59 and 60-69 age brackets had a readmission rate within 90 days of just over 30%, where other ages had a readmission rate within 90 days of around 50%. If a DMR had not been started, gender was the factor with the next strongest association with readmission within 90 days ($p < 0.001$).

To further investigate this, the inverse of the Kaplan-Meier estimator was produced by completing survival analysis (with patients who died acting as censored data) and demonstrated that the patient group who had received a DMR had a lower hospital readmission rate at 30 (22% vs. 36 %), 60 (36% vs. 49%) and 90 (45% vs 56%) days post discharge, as illustrated in the inverse of the Kaplan-Meier curve in Figure 2.

Secondary outcomes

The same analysis was performed for data stratified by the classification criteria highlighted in the conditional inference tree, i.e. age and sex.

Analysis for groups with less than 20 records in either sample set has not been conducted as it is too small a sample to be reliable.

Table 2. The probability of hospital readmission at 30, 60 and 90 days for patients who received a DMR service and for those patients who did not receive the DMR service based on survival analysis. N number of patients changes as deaths were excluded when they occurred, and patients were removed from the dataset at that point.

	Probability of readmission by days after ENAS referral (%)							
	0 days		30 days		60 days		90 days	
Age range (yrs)	DMR started	No DMR	DMR started	No DMR	DMR started	No DMR	DMR started	No DMR
40-49	0% (n=24)	0% (n=33)	21% (n=19)	36% (n=21)	21% (n=19)	39% (n=20)	25% (n=18)	42% (n=19)
50-59	0% (n=53)	0% (n=96)	21% (n=41)	35% (n=62)	34% (n=34)	48% (n=49)	38% (n=32)	58% (n=40)
60-69	0% (n=102)	0% (n=189)	15% (n=87)	31% (n=125)	27% (n=74)	47% (n=96)	34% (n=67)	55% (n=80)
70-79	0% (n=193)	0% (n=351)	27% (n=140)	37% (n=206)	40% (n=112)	52% (n=160)	48% (n=97)	62% (n=128)
80-89	0% (n=231)	0% (n=386)	22% (n=178)	36% (n=233)	41% (n=132)	50% (n=177)	52% (n=106)	57% (n=149)
90+	0% (n=71)	0% (n=133)	23% (n=54)	29% (n=86)	33% (n=46)	40% (n=71)	45% (n=37)	44% (n=62)
Total	**n=674**	**n=1188**	**n=519**	**n=733**	**n=417**	**n=573**	**n=357**	**n=478**

Chi-squared analysis for each age decile for readmission at 90 days showed that of all of these deciles, 50-59 (chi-squared= 5.0785, p=0.024), 60-69 (chi-squared= 12.0663, p=0.001) and 70-79 (chi-squared 9.2981, p=0.002) are significant to a p value of 0.05, so these may be the ages when the DMR was most valuable for preventing readmissions within 90 days. However, there were quite low numbers of patients in the other groupings, so this may not be the case with future studies when larger number of DMRs are considered. Chi-squared analysis for each sex for readmission at 90 days showed that only males (chi-squared= 27.5688, p<0.001) are significant to a p value of 0.05 (Table 3).

Table 3. The probability of hospital readmission at 30, 60 and 90 days for male and female patients who received a DMR service and for those patients who did not receive the DMR service.

	Probability of readmission by days after ENAS referral (%)							
	0 days		30 days		60 days		90 days	
Sex	Patients who started a DMR	Patients without a DMR	Patients who started a DMR	Patients without a DMR	Patients who started a DMR	Patients without a DMR	Patients who started a DMR	Patients without a DMR
Female	0% (n=338)	0% (n=615)	24% (n=252)	31% (n=392)	39% (n=189)	46% (n=275)	47% (n=150)	53% (n=221)
Male	0% (n=350)	0% (n=620)	20% (n=274)	41% (n=336)	34% (n=212)	54% (n=239)	46% (n=170)	65% (n=160)

DISCUSSION

This is the first published study, to our knowledge, utilising a range of national databases to link routine service activity and patient data from community pharmacy and hospital, at a national level to investigate effect on hospital readmissions. The analysis of the linked data has facilitated two methods for checking whether the DMR intervention had an impact on readmission. This process has demonstrated that those patients who had started a DMR were significantly less likely to be

readmitted within 90 days than those who had no DMR provision. The DMR intervention was also found to be the most attributable factor to reduce readmissions when compared to other recorded patient data. The subgroup analysis indicates that those patients aged 50-79 years appeared to benefit most from the DMR intervention, due to a more significant reduction in likelihood of readmission and that gender inequality relating to readmission rate was less prominent amongst those that had started a DMR compared to those who had no DMR. Males also appeared to benefit more from the DMR intervention than their female counterparts in terms of readmission.

The primary outcome data aligns well to that previously published in the North East England transfer of care service,[8, 9] which also demonstrated a significant decrease in readmissions for patients receiving post-discharge community pharmacy care. Both studies share the limitation that the data linkage fails to record patients' access of any other healthcare services, such as the GP, following discharge, which exists as a potential confounder to the results. This means that findings presented here, similar to those of Nazar et al,[8, 9] are that of correlation rather than a direct casual consequence.

Another recent study adopting consensus methodology, aimed to identify appropriate referral criteria of inpatients to be offered this type of follow up care. Age was not a factor rated most highly by expert panel members (i.e. top 3), however, it was recognised as a potential parameter to consider. [13, 15] Our findings infer that patients 50-79 years fare best in terms of reduce hospital readmissions when offered the DMR service, however small numbers of patients across all the age groupings limits the validity of this deduction. The debate around the targeting of these types of post-discharge services is therefore still warranted to understand which patients benefit most significantly towards optimising service efficiency and effectiveness.

The process of data linking depicted here illustrates the complexity in the information technology (IT) healthcare system, which poses challenges for health service providers, commissioners, evaluators and researchers. Work commissioned by the King's Fund, recently reported that key contributing barriers for the provision of clinical services within community pharmacies in the UK are: isolation from the central healthcare system and lack of digital interoperability.[14, 16] The Minister for Health & Social Services in Wales has set the plans to develop a National Data Resource (NDR) as part of a 'Statement of Intent' to better use Health & Care data in October 2017. It aims to deliver linked, longitudinal data for both direct patient care & healthcare analysis & research. NDR will drive forward the interoperability of health and care system, ultimately delivering benefit across the health care economy to patients, clinicians, operational managers and policy makers.

Within England, there has been much attention in the past decade upon shared electronic patient records, the Summary Care Record (SCR). This was introduced in 2009 as part of the National Programme for IT by the Department of Health to provide a mechanism to improve communication and connectedness between many healthcare sectors of the NHS. The sharing of such a record aims to facilitate safe, appropriate and tailored care provision for patients from wherever they may be accessing it. [15, 17] An independent evaluation in 2010, raised a number concerns about complexity, technical challenges, workload and information governance. This has also been accompanied by slower than anticipated uptake and faced controversy, both in the public and professional arenas.[16, 18] Recently, announcements have been made that the SCR will be phased out by 2024, and will be replaced with local health and care records that will combine GP, hospitals, and other health and social care information.[17,19] The data will be anonymised within the NHS and therefore facilitate evaluation and research. This proposal is a development towards improving evidence-based practice, which requires appropriate and supportive informatics infrastructure. Bakken contests that evidence to underpin clinical practice should be broadly conceptualised as a continuum of synthesised

information, ranging from the 'gold standard' of randomised controlled trails, to aggregated data from individual practice of a clinician or experiences of individual patients. In establishing an integrated, longitudinal patient care record, evidence-based practice will be facilitated by the building of evidence from clinical practice and its outcomes.[18,20] However, in the interim, SCR uptake and access has been patchy with little published evidence of facilitating evaluation and research agendas to investigate health outcomes as a consequence of interventions.

CONCLUSION

Evidence supporting systems that identify and enact on unintended discrepancies after patient discharge from hospital, is already widely available; this study demonstrates that the DMR service has a substantial impact on patient readmission rates than reported in previous work. This adds to the body of evidence that continuity of care upon discharge, and transfer of care should be prioritised as a global patient safety challenge, to achieve a 50% reduction in minimising medication safety issues, stated as a target in a recent World Health Organisation report on tackling medication-related harm. [21]

Despite the current challenging nature of linking NHS data collected across a range of organisations, it is possible to utilise linked data effectively to not only improve continuity and coherency of care, but also to facilitate service optimisation, evaluation and evidenced-based practice.

Author contributions:

EM, AE, CW and KH conceptualised the study. EM designed and managed the study, coordinating data collection and linkage. EM and HN were involved in the data interpretation, manuscript preparation and final submission. CP, JP and GJ completed the data analysis and linkage. HT provided guidance on ethical considerations around data linkage and supported data collection across the national databases. All authors were involved in reviewing versions of the manuscript.

Figure 1: Information flow diagram depicting the architecture required to link all required patient data to investigate hospital readmission outcome data for those offered a DMR service.

Figure 2: Survival analysis looking at probability of readmission post-discharge for patients who had started a discharge medicines review service (DMR) compared to those that had not, over time.

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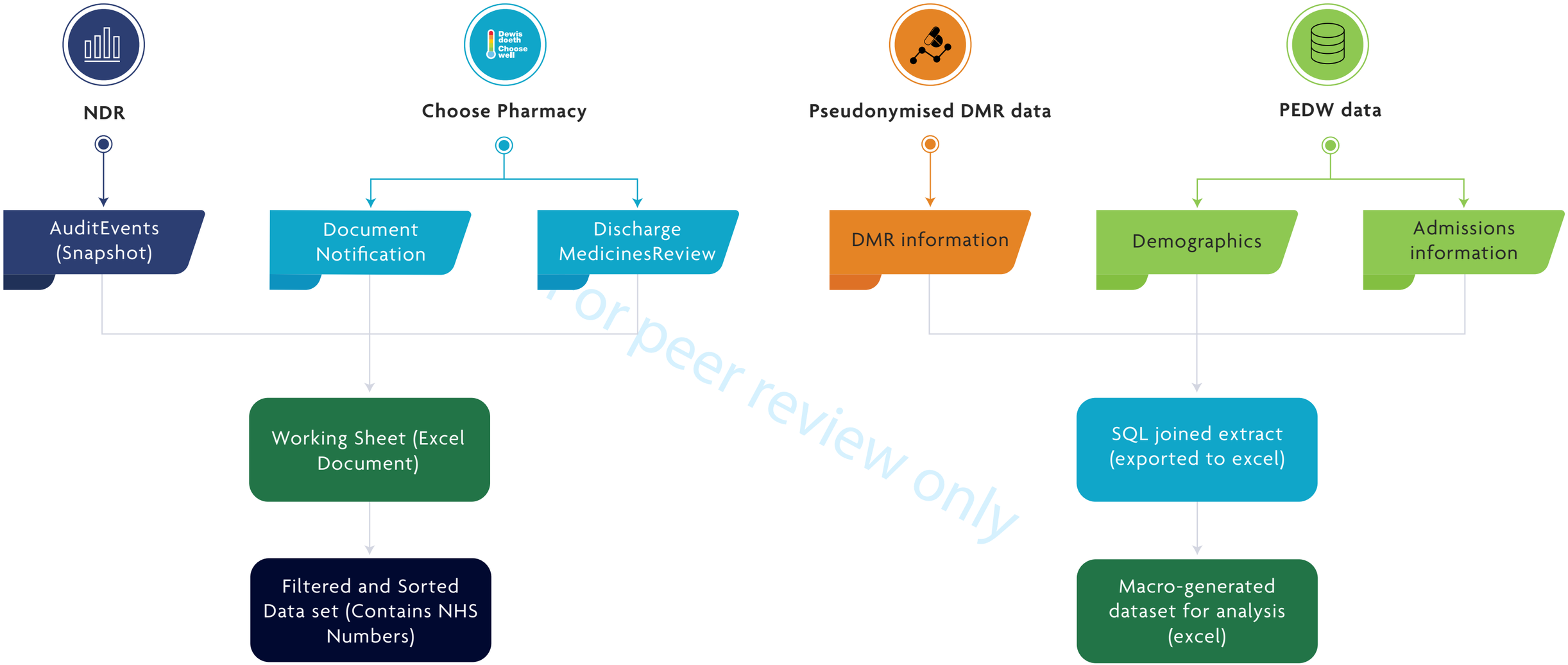


Extracting data for anonymisation 01

Anonymising patient specific pharmacy data 02

Linking of anonymised pharmacy data to hospital data 03

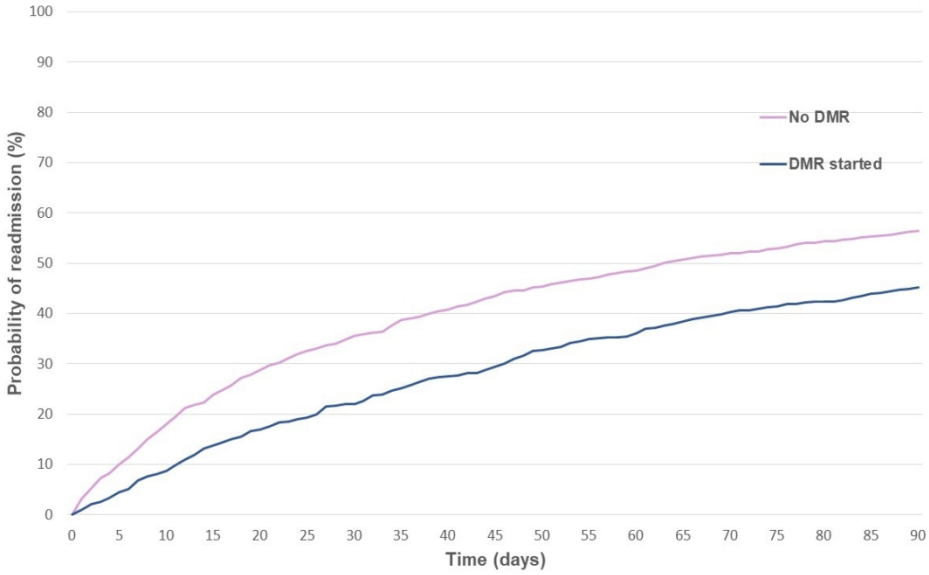
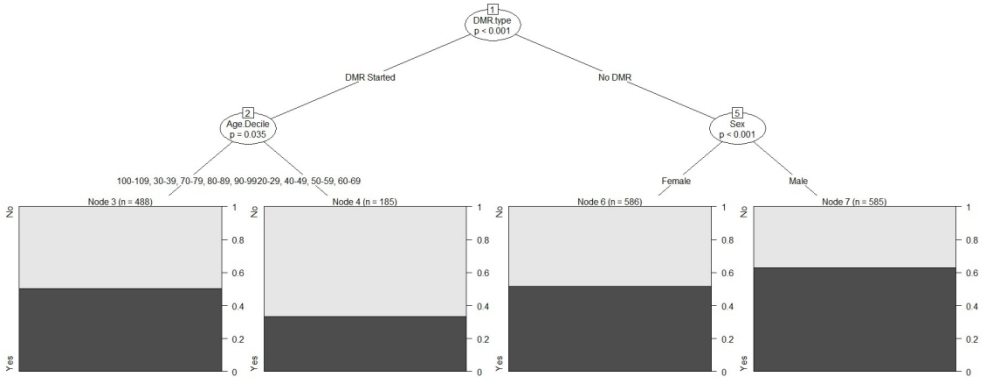


Figure 2: Survival analysis looking at probability of readmission post-discharge for patients who had started a discharge medicines review service (DMR) compared to those that had not, over time.



385x164mm (120 x 120 DPI)

Supplementary Table 1: Full process for data linkage across the national databases used in this study

Steps	Detailed process
Step 1 – Extracting data for anonymisation	A team of information specialists within NHS Wales Informatics Service (NWIS) retrieves data using three sets of queries, to produce 3 tables, as described below. • **Data from National Data Resource (NDR) system**: ○ Date and time whereby the Electronic NHS Alert Service (ENAS) email was sent to the community pharmacy ○ A unique identifier for the Discharge Advice Letter (DAL) document used by the NDR database ○ The email address where the ENAS notification was sent ○ Success or failure status of the community pharmacy picking up the notification • **Information in the DAL**: ○ The unique identifier for the DAL document used by the NDR database ○ The primary key for the Document Notification Table (PK). An integer assigned sequentially. ○ 10-digit identifier for an individual patient ○ The date and time that the DAL is posted to the *Choose Pharmacy* database and hence available to the community pharmacist within the *Choose Pharmacy* application ○ The date and time that the DAL is opened by the community pharmacist within the *Choose Pharmacy* application ○ The type of document made available (currently only DAL) • **Information in *Choose Pharmacy***: ○ The ID of the DAL used in the consultation (FK) ○ The primary key for the Discharge Medicines Review (DMR) table (PK). An integer assigned sequentially. ○ Boolean Flag to denote whether the consultation has been completed and submitted ○ Boolean Flag to denote whether DMR Part 2 was completed ○ If DMR Part 2 was not completed, selection of reason from a drop-down box ○ The date the patient was discharged from hospital, as recorded within the Choose Pharmacy application ○ Date and time the DMR consultation was started within *Choose Pharmacy* application ○ Date and time that part 1 was recorded ○ Date and time that part 2 was recorded A final table combines the tables above to create one dataset, edited to include only the relevant data and then sent for anonymization.

Step 2 – Anonymising patient specific pharmacy data	The audit table, containing the patient's NHS number, is sent through the NWIS pseudonymisation service. This service applies a 64-bit blowfish encryption algorithm to the NHS number, and then this value is mapped to a more readable integer format (Pseudonymised ID). This Pseudonymised ID field is common to all other datasets within NWIS' data warehouse, meaning that records can easily be linked at the level of the individual.
Step 3 – Linking of anonymised pharmacy data to hospital data	Admissions for each indicated patient were joined together from the specially pseudonymised dataset and Patient Episode Database for Wales (PEDW) using Structured Query Language (SQL), a language which is used to build, navigate and manipulate databases. Using the pseudonymised common identifier within both datasets, the data which related to those patients who had a referral to the DMR service (detailed in Table 2) was linked with records of admissions within hospital. This created a database with several rows for each patient, which showed all of the DMR information and all the admissions information for each patient (detailing a portion of information about each admission and providing information about the demographics of the patient at that time). Assuming that the admission which prompted a DMR must be that which immediately preceded the ENAS notification into the Choose Pharmacy system, readmission was determined by checking the linked dataset for any subsequent admission. This was done using the coding language for excel - Visual Basic for Applications - to create a Macro. Macros are used to automate tasks in excel which work by following inputted rules. The anonymised dataset made up of DMR service patients was edited to include columns for information on the admission prior to DMR referral and information on the first subsequent admission (if one occurred). The Macro that was used checked the date of the ENAS and filled in details of the initial admission by looking at the linked dataset and recording the admission immediately before this date. It also looked at any admissions immediately after this date (readmission) and noted them down. In this way, a new dataset for analysis was constructed which contained patient information at their initial admission, patient DMR service information and patient information from their first admission occurring after referral to the DMR service (if applicable).

Supplementary Table 4: STROBE Statement—Checklist of items that should be included in reports of ***cohort studies***

	Item No	Recommendation	Page No.
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1-2
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	1-2
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	3-4
Objectives	3	State specific objectives, including any prespecified hypotheses	4
Methods			
Study design	4	Present key elements of study design early in the paper	5-6
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	4-6
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up	5-6
		(*b*) For matched studies, give matching criteria and number of exposed and unexposed	NA
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	4 and 7
Data sources/ measurement	8	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	*5-6*
Bias	9	Describe any efforts to address potential sources of bias	NA
Study size	10	Explain how the study size was arrived at	NA
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	7
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	7
		(*b*) Describe any methods used to examine subgroups and interactions	7
		(*c*) Explain how missing data were addressed	NA
		(*d*) If applicable, explain how loss to follow-up was addressed	Not included
		(*e*) Describe any sensitivity analyses	NA
Results			
Participants	13	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	7-8
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	Not included
Descriptive data	14	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	8 and supplementary file
		(b) Indicate number of participants with missing data for each variable of interest	Not included
		(c) Summarise follow-up time (eg, average and total amount)	7

Outcome data	15	Report numbers of outcome events or summary measures over time	7-9
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	Not included
		(*b*) Report category boundaries when continuous variables were categorized	Not included
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	Not included
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	9-10
Discussion			
Key results	18	Summarise key results with reference to study objectives	10
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	2
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	10-11
Generalisability	21	Discuss the generalisability (external validity) of the study results	10-11
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	2

Supplementary Table 2: Characteristics of the baseline population of the study (n=1923), split into groups in relation to whether they had received discharge medicines review service (DMR) Part 1 upon discharge from hospital

		DMR started	No DMR
Age	Mean (3sf)	75.1	73.9
	IQR	17 (Q1=68, Q3=85)	16 (Q1=68, Q3= 84)
Sex	Female	338	615
	Male	350	620
Deprivation quintile	1	228	396
	2	257	350
	3	105	217
	4	65	176
	5	33	95
Original admission diagnosis (top 5 BNF chapters)	Respiratory	133	265
	Circulatory	110	157
	Genito-urinary	52	122
	Poisoning	61	96
	Digestive	57	88

Supplementary Table 3: Pearson's chi-squared analysis of the characteristics baseline population of the study (n=1923), when split into groups in relation to whether they had received discharge medicines review service (DMR) Part 1 upon discharge from hospital. The test assumes that the proportions found for each grouping (i.e. each age decile or each deprivation quintile) are the proportions for each of the individual groups.

Demographic comparison analysis	Chi-squared	P-value
Age Deciles	9.2877	0.411
Sex	0.0293	0.864
Deprivation quintile (1-20% of most deprived areas, 5-20% of least deprived areas)	25.2607	<0.001
Diagnosis BNF Chapter (all 19 tested)	28.1993	0.080

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Exploring the association of the discharge medicines review with patient hospital readmissions through national routine data linkage in Wales: a retrospective cohort study

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Title: Exploring the association of the discharge medicines review with patient hospital readmissions through national routine data linkage in Wales: a retrospective cohort study

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Keywords: post-discharge care, hospital readmissions, community pharmacy, discharge medicines review

Abstract

Objectives: To evaluate the association of the discharge medicines review (DMR) community pharmacy service with hospital readmissions through linking national NHS data sets.

Design: Retrospective cohort study.

Setting: All hospitals and 703 community pharmacies across Wales.

Participants: Inpatients meeting the referral criteria for a community pharmacy DMR.

Interventions: Information related to the patient's medication and hospital stay is provided to the community pharmacists upon discharge from hospital, who undertake a two-part service involving medicines reconciliation and a medicine use review. To investigate the association of this DMR service with hospital readmission, a data linking process was undertaken across six national databases.

Primary outcome: rate of hospital readmission within 90 days for patients with and without a DMR Part 1 started. Secondary outcome: strength of association of age decile, sex, deprivation decile, diagnostic grouping and DMR type (started or not started) with reduction in readmission within 90 days.

Results: 1923 patients were referred for a DMR over a 13-month period (February 2017–April 2018). Provision of DMR was found to be the most significant attributing factor to reducing likelihood of 90-day readmission using chi-squared testing and classification methods. Cox's regression survival analysis demonstrated that those receiving the intervention had a lower hospital readmission rate at 40 days ($p<0.000$, hazard ratio:0.59739, CI:0.5043-0.7076).

Conclusions: DMR after a hospital discharge is associated with a reduction in risk of hospital readmission within 40 days. Linking data across disparate national data records is feasible but requires a complex processual architecture. There is a significant value for integrated informatics to improve continuity and coherency of care and also to facilitate service optimisation, evaluation and evidenced-based practice.

Strengths and limitations:

- This is the first study to explore patient data linkage to investigate the association of a post-discharge intervention in community pharmacy with hospital readmissions.
- Pseudonymised data were made identifiable and linked across multiple national databases.
- The data linkage failed to record patients' access of any other healthcare services, such as the GP, following discharge.
- Even though this was a retrospective observational cohort study, we addressed potential for bias by confounder adjusted analysis.
- No investigation was carried out in this study on barriers and facilitators of activation of DMR Part 1, via an implementation science lens.

Word count: 4,217

INTRODUCTION

It is widely acknowledged that medicines-related errors and adverse events can occur at points of patients transitioning between healthcare settings.[1-4] Internationally, numerous interventions have been designed and delivered to try and address this eventuality, with the aim to reduce medicines-related, preventable hospital readmissions. A recent systematic review has found that interventions involving a community pharmacist after hospital patients are discharged home, demonstrate capacity to identify and rectify medicine-related problems which could have resulted in avoidable hospital admission.[5] In June 2019, the National Health Service (NHS) in England committed to introduce a post-discharge medicines reconciliation service through community pharmacies by 2024.[6]

Currently in the United Kingdom (UK) there are three main transfer of care technologies or services, whereby community pharmacists contribute to the medicines reconciliation process post hospital discharge: a) Refer-to-Pharmacy, an online platform adopted in East Lancashire that refers patients along with discharge information from hospital for post-discharge medicines support through the community pharmacy, as judged appropriate by the community pharmacist e.g. targeted medicine use reviews [7,8] b) *PharmOutcomes*, an online portal widely used in community pharmacies across England that allows hospitals to upload discharge information which can then be transmitted and accessed by community pharmacists to provide post-discharge support services [9,10] and c) The Discharge Medicines Review (DMR) service, used across Wales, which integrates the referral of patient hospital discharge information to community pharmacies with a two-stage service including identifying discrepancies between the first prescription post-discharge and the discharge advice letter, followed up by a supportive medication review focussed on adherence.[11]

A service evaluation in 2016, aimed to assess if a new transfer of care service implemented from hospitals in the North East of England that involved patients being referred to a nominated community pharmacy on discharge for follow-up care, led to reduced hospital readmissions.[9] Patient referrals in the hospital were generated using *PharmOutcomes;* hospital pharmacy staff were required to input patient data since there was no interconnectivity with the electronic NHS patient record at that time. Community pharmacy staff were then completing intervention and outcome data on the *PharmOutcomes* platform. The evaluation showed that this service was associated with significantly reduced patient readmissions to hospital in 30, 60 and 90 days and shorter length of hospital stay if they were readmitted.[9] However, *PharmOutcomes* is not used nationally across England, and outcome data completed by community pharmacists were not networked back to the hospital where the referral was generated. Due to this disjointed information flow, retrieving data about subsequent hospital readmissions and length of hospital stays required access of another database with steps of deanonymisation and reanonymisation to match data in *PharmOutcomes* with data in the hospital admission records.

The DMR service is a two-part community pharmacist-led service introduced in Wales in 2011 to support patients with their transition from one care setting to another. The service has mainly been used for patients recently discharged from hospital and transitioning back into the home environment.[11] The aim, as with the transfer of care service in the North East, is to reduce the risk of preventable medicines-related problems, improve adherence with newly prescribed medicines and improve patient knowledge and use of medicines. This service is operationalised employing electronic platforms and developed interoperability to generate a referral from the hospital to a nominated community pharmacy. Part 1 of the service is a medicines reconciliation between the medications listed in the first prescription from the general practitioner (GP) after discharge and the discharge medication list, including rectifying any unintended discrepancies that have arisen. The rectification of these discrepancies may involve contact with the patient or carer, GP or the hospital to gather the

most relevant information. Part 2 is a Medicines Use Review that gives the pharmacist an opportunity to discuss any medicines-related issues with the patients including adherence, dosing and side-effects. Service evaluation of the DMR service has shown positive outcomes including the identification of 1.15-1.3 discrepancies per service completed and an average three-fold return on financial investment. [12,13] After the initial evaluation confirmed the benefits of the service,[12] it was rolled out nationally, currently being available in 703 community pharmacies in Wales. The evaluations focussed on cost benefit and identifying discrepancies in the medicines' reconciliation process. However, to date, there has been no formal process of linking data from the DMR service to hospital data with a subsequent evaluation of the association of DMR with patient readmission to hospital.

Linking data sets from different divisions in the NHS has been reported to be limited, and it is widely acknowledged that NHS data is not used effectively to guide patient care. [14] The aim of this study was to explore the use of national routine data linkage to investigate the association of DMR with patient hospital readmission.

METHODS

Intervention description

The independent evaluation undertaken in 2014 provides a description of the DMR service in Wales,[12] however, it is briefly outlined here to provide a contextual background.

Pharmacists in a total of 703 out of 716 community pharmacies in Wales are currently completing DMRs with the support of *Choose Pharmacy*, a national web-based application that supports the delivery of NHS advanced and enhanced community pharmacy services. Accredited community pharmacies and community pharmacists can access via *Choose Pharmacy*, an electronic Discharge Advice Letter (eDAL) generated by the Medicines Transcribing and electronic Discharge (MTeD) functionality in the National Welsh Clinical Portal (WCP), to support an electronic DMR. Patients are linked to the Welsh Demographic Service and matched to existing health records, enabling collection of demographic information such as gender and age. When an eDAL is generated, the patient's nominated community pharmacy receives a notification via the Electronic NHS Alert Service (ENAS) that one of their patients has been discharged from hospital. In the event a patient has been discharged from a non-MTeD ward and has received a paper DAL, a physical copy needs to be taken to the pharmacy for DMR to be initiated. *Choose Pharmacy* is still used to record the DMR undertaken.

Patients are identified and recruited to the DMR service either by: referral from a healthcare professional during their hospital stay; or following their discharge by patients self-referring; by their nominated carer presenting in the pharmacy, or by the pharmacist when necessary criteria are met.

Patients are eligible for the service where the following criteria are met:

- The patient's medicines have been changed during their hospital stay;
- The patient is taking four or more medicines;
- The patient's medicine requires dispensing into a multi-compartment compliance device;
- The pharmacist has, in their professional opinion, reason to consider that the patient would benefit from the service.

Outcome measures

The primary outcome in this study was the rate of hospital readmission within 90 days for patients with and without a DMR Part 1 started. The secondary outcome was the strength of association of age decile, sex, deprivation decile, diagnostic grouping and DMR type (started or not started) with rate of readmission within 90 days.

Routine data collection

Six data sources were used for this study with data obtained via NHS Wales Informatics Service (NWIS) for the period February 2017 – April 2018 (Box 1).

Box 1. A description of the type of data collected and stored in the national databases in Wales that were used in the data linkage in this study.

National data source in Wales	Overview
Choose Pharmacy **(CP)**	A national web-based application that supports the delivery of NHS advanced and enhanced community pharmacy services in Wales. Holds data for all services completed in the pharmacy in the form of clinical information and pre-defined answers, including data for all electronic DMRs that were completed using *Choose Pharmacy*.
Patient Episode Database for Wales (PEDW)	A system that records all episodes of inpatient and day case activity in NHS Wales hospitals, which includes planned and emergency admissions, minor and major operations, and hospital stays for giving birth.
Admitted Patient Care Data set (APCDs)	Captures data for all consultant-led admitted patient activity, regardless of the patient's area of residence. NHS Digital provide data on Welsh resident or registered patients treated in English NHS organisations. Once admitted a patient may have several episodes within a hospital stay. Only once an episode is complete or the hospital spell ends will it be captured in the APC data set.
Office of National Statistics (ONS) Death notifications database	Annual data on deaths registered by age, sex and selected underlying cause of death.
Welsh Demographics Service (WDS)	Provides the demographic characteristics of people registered with GP practices in Wales. The WDS maintains a register of Welsh residents' demographic details, including name, address, date of birth, general practice and NHS number. For any consultations completed via *Choose Pharmacy*, patients are linked to the Welsh Demographic Service and matched to existing health records, enabling collection of demographic information.
National Data Resource (NDR)	A resource currently being developed to better enable NHS Wales to improve patient experience and service outcomes. The NDR aims to deliver a more joined up approach to health and care data, using common language and technical standards and providing improved analytics capability.

Data linkage

Hospital data was available for all patients who were referred for the service upon hospital discharge, selected by clinical staff based on one or more of the DMR criteria. The data linkage process was completed in three steps and ensured that pseudonymised data from individuals could be linked together to provide a picture of the patient journey without patient identifiable information being shared (Figure 1):

- **Step 1:** Extracting data for pseudonymisation - Records for pseudonymisation were identified when a patient was referred from a hospital to a community pharmacy for a DMR.
- **Step 2:** Pseudonymising patient specific pharmacy data - The pseudonymisation process involved the encryption of the patient's NHS Number to create an Anonymous Linking Field (ALF), which was assigned to each record.
- **Step 3:** Linking of pseudonymised pharmacy data to pseudonymised hospital data - The ALF was used to link these records to the pseudonymised identifiable patient records in hospitals, which have been assigned with the same ALF .

Information from these datasets was used to create a new dataset for analysis, which included whether the pseudonymised patient had received the DMR service, admission information such as their age, deprivation quintile, diagnosis, length of stay before they were referred into the DMR service, and the same admission information for the first admission occurring after referral to the DMR service. The full process for the data linkage is included in Supplementary Table 1.

Ethical considerations

The project was submitted to the Research and Development office of Velindre University NHS Trust as the legal entity responsible for the conduct of studies within NWIS, the organisation that holds all the data we required for this study. It was confirmed that an application to an NHS Research Ethics Committee was not required, and that the study should be conducted ensuring regulatory compliance in line with established NWIS policies and procedures. Throughout the study we liaised with the Head of Information Governance of NWIS to ensure this.

Data collection at the first instance was part of routine collection of information when the patient visits a healthcare setting. Patients provided informed consent when offered the DMR service as part of routine hospital and community pharmacy care. This consent covers the recording of data and any processing or pre-processing to a form (by NWIS), for the purpose of service activity, audit and evaluation, in an identifiable way. Records-based research was then completed that did not involve people directly.

NWIS Head of Information Governance approved the methodology and helped set the criteria for processing the information to ensure patient privacy was maintained in all circumstances. The model of processing and data linkage was consistent with NWIS trusted third party responsibilities and is used in many circumstances to ensure confidentiality, integrity and availability of information, in line with guidance for use of secondary data and criteria set by the General Medical Council in relation to anonymisation and risk of de-identification. [15,16]

Data analysis

Secondary data analysis was conducted using Microsoft Excel® for descriptive statistics and Stata® and R (using the partykit and survival libraries) for more complex statistical analyses. In order to ensure that there was sufficient time following referral to capture data about a patient being readmitted, all referrals after 31st December 2017 (which is 90 days prior to the last date in the data extract) were removed from the dataset. The denominator for the calculations was all inpatients referred for a DMR, the intervention group was those who activated part 1 of the DMR and the comparator was those referred for a DMR but who did not activate it.

Pearson's chi-squared test, using a significance level of 0.05, was applied to records of all patients offered a DMR who did not die within 90 days of their discharge, to assess whether the DMR changed

the probability of readmission and evaluate how likely it is that any observed difference between the sets arose by chance. The chi-squared test has a null hypothesis that there is no association between whether a patient had started a DMR (had completed at least Part 1 of the service) and whether they were readmitted within 90 days. All patients who had died before 90 days after the notification had been sent were removed from this analysis, in line with literature,[17,18] as these deaths could skew the results (for example, if a patient died within 90 days without readmission, they would be recorded as 'no readmission within 90 days', which would be an inappropriate classification).

A conditional inference tree (CTree) was produced to look at which patient traits had the strongest association with whether a patient was readmitted within 90 days. CTrees partition cohorts by selecting successive splits in variables with the strongest association to the outcome of interest, as measured by p-values and have previously been used in health service research.[19,20] CTree is a non-parametric class of regression trees embedding tree-structured regression models into a well-defined theory of conditional inference procedures; it uses a statistical theory (selection by permutation-based significance tests) in order to select variables instead of selecting the variable that maximizes an information measure (Gini coefficient or Information Gain) and thereby removes the potential bias in CART or similar decision trees.[21] In this case, the conditional inference tree used gender, deprivation decile, age decile, diagnosis grouping (e.g. respiratory, circulatory) and whether a DMR had been started, to look at the relationship of these to readmission within 90 days. A significance level of 0.05 was used.

To better understand the probability of readmission over time, the Kaplan-Meier estimator was used to estimate the likelihood of readmission for a patient who had started a DMR versus a patient who had not been provided a DMR over specified time intervals. The inverse of the Kaplan-Meier curve was created to describe the likelihood of readmission, based on avoidance of readmission.

A Schoenfeld residual test for non-proportional hazards was used to test the proportional hazards assumption.[22] To adjust for the findings of this test, we created a time stratified Cox's regression survival analysis using age, sex, diagnosis, deprivation and DMR as variables. We used a step function (time-dependant coefficient) model, using a stratification time we chose based on a plot of the Aalen model.[23] We have looked at the hazard ratio confidence intervals to combat the possible issues with Type 1 error and to better estimate the association between DMR use and readmission.

The STROBE checklist for cohort studies was utilised to guide the reporting of this study and is included as Supplementary Table 2.

Patient Involvement

Patients were not involved in the design or conduct of this study.

RESULTS

A total of 1923 records were available within the specified time period (February 2017 – April 2018), up to 90 days prior to the last date in the data extract available. There was a small number of cases where some data was not recorded in the system (36 patients with blank diagnosis, 1 with missing deprivation quintile). These have been removed for all analysis except the Kaplan Meier.

Primary outcome

A total of 244 records referred to patients who died within 90 days of a notification being sent; 79 or these patients died prior to any readmission. In order to eliminate any skew caused by patients who were not readmitted but died, the 79 records were removed for all chi-squared and conditional inference analysis. Therefore, a total of 1844 records were used, with 673 (36.5%) of those records referring to patients receiving the DMR service, representing the intervention cohort.

A statistically significant difference was identified at the 90-day readmission rate of those patients who had started a DMR and those who had not received a DMR (Pearson chi-squared = 23.0829), $p<0.001$. This implies there was an association between when a DMR had been started and readmission within 90 days, based on the rates of readmission we conclude that readmission was less likely (Table 1). Characteristics of the baseline population of the study (n=1923), split into groups in relation to whether they had received discharge medicines review service (DMR) Part 1 upon discharge from hospital, are presented in Supplementary Table 3.

Table 1. The number of patients offered a DMR service who did not die (n=1844) and went on to receive the service by whether there was a hospital readmission within 90 days of discharge.

Patient group	Readmission within 90 days n (%)	No admission within 90 days n (%)	Total n (%)
DMR Started	307 (31.4)	366 (42.2)	**673 (36.5)**
No DMR	670 (68.6)	501 (57.8)	**1171 (63.5)**
Total	**977**	**867**	**1844**

The conditional inference tree used to identify the variable with the strongest association to readmission within 90 days, used age decile, sex, deprivation decile, diagnostic grouping and DMR type (started or not started) as the possible criteria for classification. This identified that the variable with the strongest association was whether the patient had started a DMR or not ($p<0.001$) (Supplementary Figure 1). Just over 40% of those that had started a DMR were readmitted within 90 days, compared to just under 60% of those that did not have a DMR. Amongst those that had started a DMR, the next statistically significant association was age ($p\sim0.035$). Those in the 20-29, 40-49, 50-59 and 60-69 age brackets had a readmission rate within 90 days of just over 30%, where other ages had a readmission rate within 90 days of around 50%. If a DMR had not been started, gender was the factor with the next strongest association with readmission within 90 days ($p<0.001$).

To further investigate this, the inverse of the Kaplan-Meier estimator was produced by completing survival analysis (with patients who died acting as censored data) and demonstrated that the patient group who had received a DMR had a lower hospital readmission rate at 30 (22% vs. 36 %), 60 (36% vs. 49%) and 90 (45% vs 56%) days post discharge, as illustrated in the inverse of the Kaplan-Meier curve in Figure 2.

To build on this survival analysis, a time stratified Cox's survival analysis was used with a stratification of the DMR variable at 40 days, identified by plotting DMR using the Aalen model. The only variable triggering the significance tests when we ran the Survival Analysis was the stratified DMR variable from 0 to 40 days. This variable had a hazard ratio of 0.59739 with a confidence interval underneath

1 (0.5043-0.7076). This suggests that readmission within 40 days is less likely when a DMR has been started. Supplementary Table 4 presents the full results on p-values for each variable.

Secondary outcomes

The Conditional Inference tree suggested that sex may also be associated with reduction of readmission within 90 days for patients without a DMR. However, the Cox's survival analysis results showed no significant associations other than with DMR, with hazard ratios that do not show any consistent effect from any of the other variables (Supplementary Table 5). This could indicate that further tests should be done to model processes for patients who have started a DMR and those with no DMR separately when more data is available to understand where this discrepancy comes from.

DISCUSSION

This is the first published study, to our knowledge, utilising a range of national databases to link routine service activity and patient data from community pharmacy and hospital, at a national level, to investigate association with hospital readmissions. The analysis of the linked data has facilitated three methods for checking whether the DMR intervention had an association with readmission. This process has demonstrated that those patients who had started a DMR were significantly less likely to be readmitted within 90 days than those who had no DMR provision. The DMR intervention was also found to be the factor most associated with reduced readmissions within 40 days, when conducting multivariate survival analysis to better estimate the independent association between DMR and readmission.

Results from this study support published literature that community pharmacist post-discharge interventions have positive outcomes on patient care. In a recent systematic review looking at pharmacist-led medication reconciliation at patient discharge, only 30% of the studies described a patient discharge plan, and in only 14% of cases information of the patient's medication was shared with community pharmacists.[24]The DMR service provides a structured approach to information sharing, overcoming the major organizational-level and individual-level factors affecting the medication reconciliation process,[25] and an opportunity for a face-to-face discussion and counselling with the patient to account for their changing needs post-discharge. Literature reports that patients' information needs are individual, and even when counselled by hospital pharmacists, only half of the patients could recall information related to medication changes.[26] Unlike other systems in the UK, the DMR service is available nationally across Wales, and from April 2020 a new functionality will become available in the system, so that outcome data completed by community pharmacists will be available to view in the hospital where the referral was generated.

We have found that the DMR service has a more prominent association with patient readmission rates than reported in previous work. This contributes to the body of evidence around community pharmacy services or interventions that may reduce hospital readmissions, thereby supporting delivery of government initiatives to promote the Care Closer to Home agenda.[27] The role of community pharmacists in seamless primary care services has been recognised in the Strategic Programme for Primary Care and, the Welsh Government (WG) having recently announced their support to community pharmacists and committed financially to a sustainable, appropriately trained workforce to deliver extended services.[28-30]

The primary outcome data aligns well to that previously published in the North East England transfer of care service,[8,9] which also demonstrated a significant decrease in readmissions for patients receiving post-discharge community pharmacy care. Both studies share the limitation that the data linkage fails to record patients' access of any other healthcare services, such as the GP, following discharge, which exists as a potential confounder to the results. This means that findings presented here, similar to those of Nazar et al,[8,9] are that of correlation rather than a direct casual consequence.

Another recent study adopting consensus methodology, aimed to identify appropriate referral criteria of inpatients to be offered this type of follow up care. Age was not a factor rated most highly by expert panel members (i.e. top 3), however, it was recognised as a potential parameter to consider.[13,31] Our findings infer that patients 50-79 years fare best in terms of reduced hospital readmissions when offered the DMR service, however small numbers of patients across all the age groupings limits the validity of this deduction. The debate around the targeting of these types of post-discharge services is therefore still warranted to understand which patients benefit most significantly towards optimising service efficiency and effectiveness.

The process of data linking depicted here illustrates the complexity in the information technology (IT) healthcare system, which poses challenges for health service providers, commissioners, evaluators and researchers. Work commissioned by the King's Fund, recently reported that key contributing barriers for the provision of clinical services within community pharmacies in the UK are: isolation from the central healthcare system and lack of digital interoperability.[14,32] The Minister for Health & Social Services in Wales has set the plans to develop a National Data Resource (NDR) as part of a 'Statement of Intent' to better use Health & Care data in October 2017. It aims to deliver linked, longitudinal data for both direct patient care & healthcare analysis & research. NDR will drive forward the interoperability of health and care systems, ultimately delivering benefit across the health care economy to patients, clinicians, operational managers and policy makers.

Within England, there has been much attention in the past decade upon shared electronic patient records, the Summary Care Record (SCR). This was introduced in 2009 as part of the National Programme for IT by the Department of Health to provide a mechanism to improve communication and connectedness between many healthcare sectors of the NHS. The sharing of such a record aims to facilitate safe, appropriate and tailored care provision for patients from wherever they may be accessing it. [31,33] An independent evaluation in 2010, raised a number of concerns about complexity, technical challenges, workload and information governance. This has also been accompanied by slower than anticipated uptake and faced controversy, both in the public and professional arenas.[32,34] Recently, announcements have been made that the SCR will be phased out by 2024, and will be replaced with local health and care records that will combine GP, hospitals, and other health and social care information.[33,35] The data will be anonymised within the NHS and therefore facilitate evaluation and research. This proposal is a development towards improving evidence-based practice, which requires appropriate and supportive informatics infrastructure. Bakken contests that evidence to underpin clinical practice should be broadly conceptualised as a continuum of synthesised information, ranging from the 'gold standard' of randomised controlled trails, to aggregated data from individual practice of a clinician or experiences of individual patients. In establishing an integrated, longitudinal patient care record, evidence-based practice will be facilitated by the building of evidence from clinical practice and its outcomes.[34,36] However, in the interim, SCR uptake and access has been patchy with little published evidence of facilitating evaluation and research agendas to investigate health outcomes as a consequence of interventions.

This was a pragmatic observational cohort study, with enrolment into the DMR based on clinician judgement, and as such, no power calculation could have been performed and there was a large potential for bias. However, we tried to estimate the effect size using hazard ratios in the survival analysis and we addressed this bias as far as possible with confounder adjusted analysis and by exploring the possibility of residual confounding.

Though we have tried to take into account some socio-economic indicators (i.e. deprivation decile), we have not investigated whether those who have started a DMR are more health conscientious than those who are not, so some of the effect seen here may be indicative of some patient activation or other related external factors, as yet unmeasured. Barriers to community pharmacists undertaking follow-up reviews post-discharge have recently been reported in literature. Elson et al. explored patients' knowledge of new medicines after discharge from hospital and identified that fewer than half of the patients who were allocated to receive a community pharmacy medicines review received one.[37] Further work will involve exploring factors that support or inhibit activation of part 1 of the DMR via an implementation science lens.

CONCLUSION

Evidence supporting systems that identify and enact on unintended discrepancies after patient discharge from hospital is already widely available; this study demonstrates that the DMR service has a more prominent association with patient readmission rates than reported in previous work. This adds to the body of evidence that continuity of care upon discharge, and transfer of care should be prioritised as a global patient safety challenge, to achieve a 50% reduction in minimising medication safety issues, stated as a target in a recent World Health Organisation report on tackling medication-related harm.[38]

Despite the current challenging nature of linking NHS data collected across a range of organisations, it is possible to utilise linked data effectively to not only improve continuity and coherency of care, but also to facilitate service optimisation, evaluation and evidenced-based practice.

Figure 1: Information flow diagram depicting the architecture required to link all required patient data to investigate hospital readmission outcome data for those offered a DMR service.

Figure 2: Survival analysis looking at probability of readmission post-discharge for patients who had started a discharge medicines review service (DMR) compared to those that had not, over time.

Author contributions:

EM, AE, CW and KH conceptualised the study. EM designed and managed the study, coordinating data collection and linkage. EM and HN were involved in the data interpretation, manuscript preparation and final submission. CP, JP and GJ completed the data analysis and linkage. HT provided guidance on ethical considerations around data linkage and supported data collection across the national databases. All authors were involved in reviewing versions of the manuscript.

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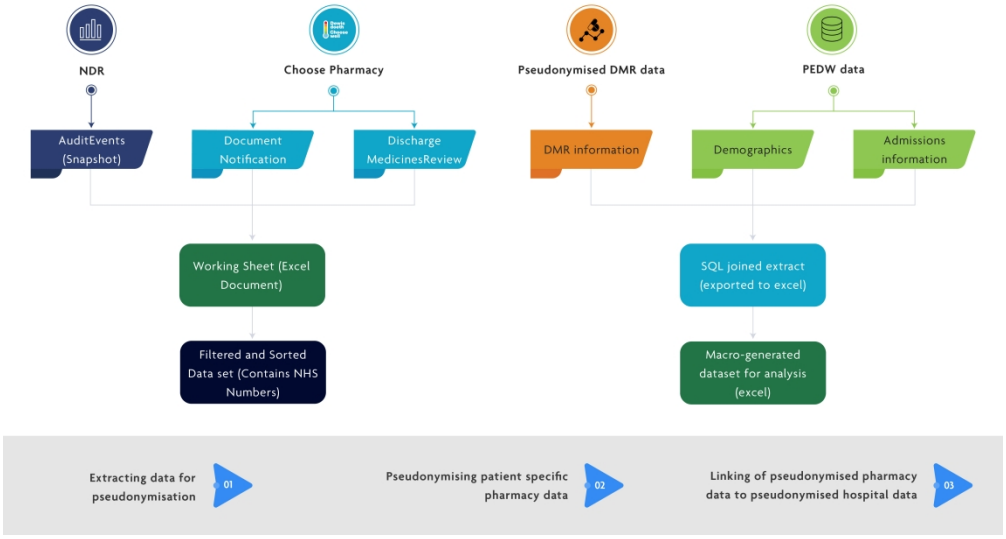


Figure 1: Information flow diagram depicting the architecture required to link all required patient data to investigate hospital readmission outcome data for those offered a DMR service.

451x254mm (300 x 300 DPI)

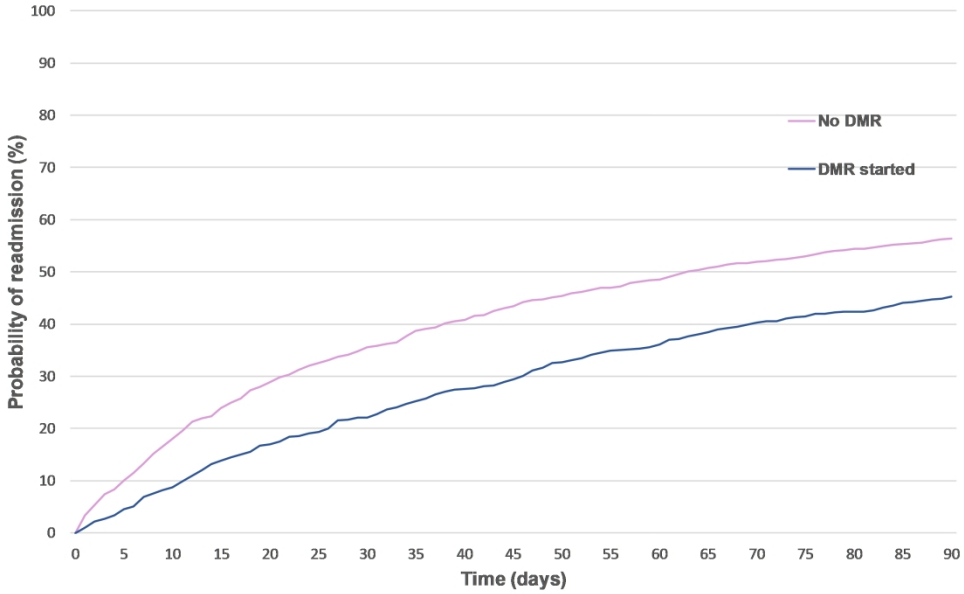
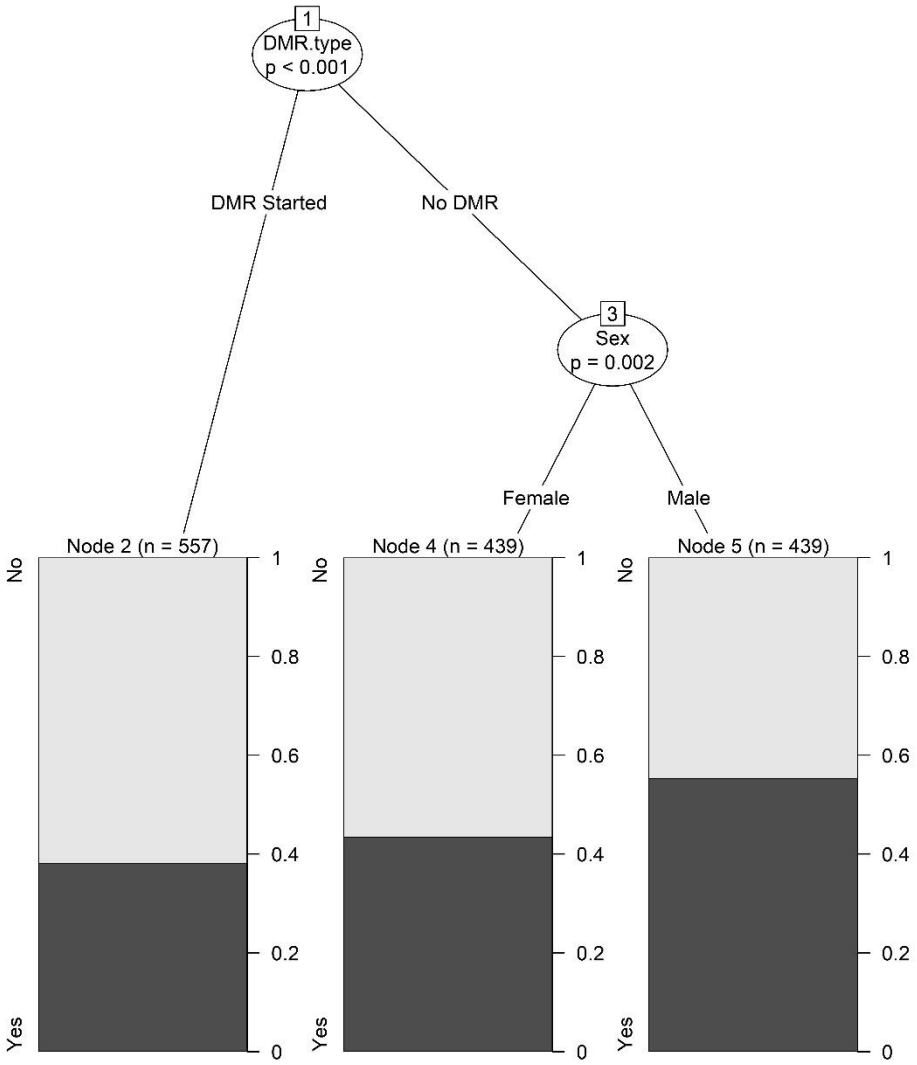


Figure 2: Survival analysis looking at probability of readmission post-discharge for patients who had started a discharge medicines review service (DMR) compared to those that had not, over time.



Supplementary Figure 1: The conditional inference tree (CTree) that was used to identify the variable with the strongest association to readmission within 90 days, using age decile, sex, deprivation decile, diagnostic grouping and DMR type (started or not started) as the possible criteria for classification.

Supplementary Table 1: Full process for data linkage using pseudonymised data across the national databases in this study

Steps	Detailed process
Step 1 – Extracting data for pseudonymisation	A team of information specialists within NHS Wales Informatics Service (NWIS) retrieves data using three sets of queries, to produce 3 tables, as described below. • **Data from National Data Resource (NDR) system**: ○ Date and time whereby the Electronic NHS Alert Service (ENAS) email was sent to the community pharmacy ○ A unique identifier for the Discharge Advice Letter (DAL) document used by the NDR database ○ The email address where the ENAS notification was sent ○ Success or failure status of the community pharmacy picking up the notification • **Information in the DAL**: ○ The unique identifier for the DAL document used by the NDR database ○ The primary key for the Document Notification Table (PK). An integer assigned sequentially. ○ 10-digit identifier for an individual patient ○ The date and time that the DAL is posted to the *Choose Pharmacy* database and hence available to the community pharmacist within the *Choose Pharmacy* application ○ The date and time that the DAL is opened by the community pharmacist within the *Choose Pharmacy* application ○ The type of document made available (currently only DAL) • **Information in *Choose Pharmacy***: ○ The ID of the DAL used in the consultation (FK) ○ The primary key for the Discharge Medicines Review (DMR) table (PK). An integer assigned sequentially. ○ Boolean Flag to denote whether the consultation has been completed and submitted ○ Boolean Flag to denote whether DMR Part 2 was completed ○ If DMR Part 2 was not completed, selection of reason from a drop-down box ○ The date the patient was discharged from hospital, as recorded within the Choose Pharmacy application ○ Date and time the DMR consultation was started within *Choose Pharmacy* application ○ Date and time that part 1 was recorded ○ Date and time that part 2 was recorded A final table combines the tables above to create one dataset, edited to include only the relevant data and then sent for pseudonymization.

Step 2 – Pseudonymising patient specific pharmacy data	The audit table, containing the patient's NHS number, is sent through the NWIS pseudonymisation service. This service applies a 64-bit blowfish encryption algorithm to the NHS number, and then this value is mapped to a more readable integer format (Pseudonymised ID). This Pseudonymised ID field is common to all other datasets within NWIS' data warehouse, meaning that records can easily be linked at the level of the individual.
Step 3 – Linking of pseudonymised pharmacy data to hospital data	Admissions for each indicated patient were joined together from the specially pseudonymised dataset and Patient Episode Database for Wales (PEDW) using Structured Query Language (SQL), a language which is used to build, navigate and manipulate databases. Using the pseudonymised common identifier within both datasets, the pseudonymised identifiable data which related to those patients who had a referral to the DMR service (detailed in Table 2) was linked with records of admissions within hospital. This created a database with several rows for each patient, which showed all of the DMR information and all the admissions information for each patient (detailing a portion of information about each admission and providing information about the demographics of the patient at that time). Assuming that the admission which prompted a DMR must be that which immediately preceded the ENAS notification into the Choose Pharmacy system, readmission was determined by checking the linked dataset for any subsequent admission. This was done using the coding language for excel - Visual Basic for Applications - to create a Macro. Macros are used to automate tasks in excel which work by following inputted rules. The pseudonymised dataset made up of DMR service patients was edited to include columns for information on the admission prior to DMR referral and information on the first subsequent admission (if one occurred). The Macro that was used checked the date of the ENAS and filled in details of the initial admission by looking at the linked dataset and recording the admission immediately before this date. It also looked at any admissions immediately after this date (readmission) and noted them down. In this way, a new dataset for analysis was constructed which contained pseudonymised patient information at their initial admission, patient DMR service information and patient information from their first admission occurring after referral to the DMR service (if applicable).

Supplementary Table 2: STROBE Statement—Checklist of items that should be included in reports of cohort studies

	Item No	Recommendation	Page No.
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1-2
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	2
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	3-4
Objectives	3	State specific objectives, including any prespecified hypotheses	4
Methods			
Study design	4	Present key elements of study design early in the paper	5-7
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	4-7
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up	5-7
		(*b*) For matched studies, give matching criteria and number of exposed and unexposed	NA - 5
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	4 and 7
Data sources/ measurement	8	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	5-7
Bias	9	Describe any efforts to address potential sources of bias	7
Study size	10	Explain how the study size was arrived at	5
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	7
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	7

		(*b*) Describe any methods used to examine subgroups and interactions	7
		(*c*) Explain how missing data were addressed	6-7
		(*d*) If applicable, explain how loss to follow-up was addressed	6-7
		(*e*) Describe any sensitivity analyses	NA
Results			
Participants	13	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	7-8
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	Not included
Descriptive data	14	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	8 and supplementary file
		(b) Indicate number of participants with missing data for each variable of interest	7
		(c) Summarise follow-up time (eg, average and total amount)	7
Outcome data	15	Report numbers of outcome events or summary measures over time	7-9
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	8-9 and supplementary file
		(*b*) Report category boundaries when continuous variables were categorized	Supplementary file
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	NA
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	7-9
Discussion			

Key results	18	Summarise key results with reference to study objectives	9
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	10-11
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	9-10
Generalisability	21	Discuss the generalisability (external validity) of the study results	9-11
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	11

Supplementary Table 3: Characteristics of the baseline population of the study (n=1923), split into groups in relation to whether they had received discharge medicines review service (DMR) Part 1 upon discharge from hospital

		DMR started	No DMR
Age	Mean (3sf)	75.1	73.9
	IQR	17 (Q1=68, Q3=85)	16 (Q1=68, Q3= 84)
Sex	Female	338	615
	Male	350	620
Deprivation quintile	1	228	396
	2	257	350
	3	105	217
	4	65	176
	5	33	95
Original admission diagnosis (top 5 BNF chapters)	Respiratory	133	265
	Circulatory	110	157
	Genito-urinary	52	122
	Poisoning	61	96
	Digestive	57	88
	Unclassified	98	173
Death rate		15 / 688 (2%)	64 / 1235 (5%)

Supplementary Table 4: Coefficients and p-values from the time stratified Cox's survival analysis used with a stratification of the DMR variable at 40 days, identified by plotting DMR using the Aalen model. The only variable triggering the significance tests is the stratified DMR variable from 0 to 40 days. Diagnoses were categorised based on BNF chapters. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

	coef	exp(coef)	se(coef)	z	Pr(>|z|)	
SexMale	0.08574	1.08952	0.04812	1.782	0.0748	.
Quintile1	0.75671	2.13124	1.05655	0.716	0.4739	
Quintile2	0.69989	2.01353	1.05701	0.662	0.5079	
Quintile3	0.68254	1.9789	1.05552	0.647	0.5179	
Quintile4	0.66517	1.94482	1.05795	0.629	0.5295	
Quintile5	0.60378	1.82903	1.06008	0.57	0.569	
AgeDecile100-109	0.2797	1.32273	0.52982	0.528	0.5976	
AgeDecile20-29	0.08408	1.08772	0.47895	0.176	0.8606	
AgeDecile30-39	0.0375	1.03821	0.46302	0.081	0.9355	
AgeDecile40-49	0.01306	1.01314	0.44552	0.029	0.9766	
AgeDecile50-59	0.15763	1.17073	0.4324	0.365	0.7155	
AgeDecile60-69	0.1062	1.11205	0.42818	0.248	0.8041	
AgeDecile70-79	0.24576	1.27859	0.42634	0.576	0.5643	
AgeDecile80-89	0.23562	1.26569	0.42571	0.553	0.5799	
AgeDecile90-99	0.1118	1.11829	0.43128	0.259	0.7955	
BNFChapter 01: Certain infectious and parasitic diseases	-0.04902	0.95216	0.20632	-0.238	0.8122	
BNFChapter 02: Neoplasms	0.31521	1.37054	0.22788	1.383	0.1666	
BNFChapter 03: Diseases of the blood and blood forming organs and certain disorders involving the immune mechanism	0.12141	1.12909	0.27557	0.441	0.6595	
BNFChapter 04: Endocrine, nutritional and metabolic diseases	0.09815	1.10313	0.21346	0.46	0.6457	
BNFChapter 05: Mental and behavioural disorders	0.12945	1.1382	0.24055	0.538	0.5905	
BNFChapter 06: Diseases of the nervous system	0.07728	1.08034	0.23179	0.333	0.7388	
BNFChapter 07: Diseases of the eye and adnexa	-0.0308	0.96967	0.5384	-0.057	0.9544	
BNFChapter 08: Diseases of the ear and mastoid process	0.35829	1.43089	0.60549	0.592	0.554	
BNFChapter 09: Diseases of the circulatory system	-0.03928	0.96148	0.18409	-0.213	0.831	

BNFChapter 10: Diseases of the respiratory system	0.18104	1.19846	0.1808	1.001	0.3167	
BNFChapter 11: Diseases of the digestive system	0.01954	1.01973	0.19288	0.101	0.9193	
BNFChapter 12: Diseases of the skin and subcutaneous tissue	0.01734	1.01749	0.22209	0.078	0.9378	
BNFChapter 13: Diseases of the musculoskeletal system/connective system	-0.24174	0.78526	0.2066	-1.17	0.242	
BNFChapter 14: Diseases of the genitourinary system	0.07846	1.08162	0.19025	0.412	0.6801	
BNFChapter 15: Pregnancy, childbirth and the puerperium	1.79629	6.02727	1.03446	1.736	0.0825	.
BNFChapter 17: Congenital malformations, deformations and chromosomal abnormalities	1.18017	3.25492	0.6058	1.948	0.0514	.
BNFChapter 18: Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified	-0.0463	0.95475	0.18408	-0.252	0.8014	
BNFChapter 19: Injury/poisoning/other consequences of external causes	-0.06103	0.9408	0.19108	-0.319	0.7494	
BNFChapter 21: Factors influencing health and contact with health services	0.23646	1.26675	0.37172	0.636	0.5247	
DMRDMR Started:strata(tgroup)tgroup=1	-0.51519	0.59739	0.08642	-5.962	2.50E-09	***
DMRNo DMR:strata(tgroup)tgroup=1	NA	NA	0	NA	NA	
DMRDMR Started:strata(tgroup)tgroup=2	-0.03336	0.96719	0.06041	-0.552	0.5808	
DMRNo DMR:strata(tgroup)tgroup=2	NA	NA	0	NA	NA	

Supplementary Table 5: Coefficients and confidence intervals from the time stratified Cox's survival analysis for variables other than the stratified DMR. No other significant associations are identified, with hazard ratios that do not show any consistent effect from any of the other variables. Diagnoses were categorised based on BNF chapters.

---	exp(coef)	exp(-coef)	lower .95	upper .95
SexMale	1.0895	0.9178	0.9915	1.1973
Quintile1	2.1312	0.4692	0.2687	16.9033
Quintile2	2.0135	0.4966	0.2536	15.9839
Quintile3	1.9789	0.5053	0.25	15.6632
Quintile4	1.9448	0.5142	0.2445	15.467
Quintile5	1.829	0.5467	0.229	14.6069
AgeDecile100-109	1.3227	0.756	0.4683	3.7364
AgeDecile20-29	1.0877	0.9194	0.4254	2.781
AgeDecile30-39	1.0382	0.9632	0.4189	2.5728
AgeDecile40-49	1.0131	0.987	0.4231	2.4261
AgeDecile50-59	1.1707	0.8542	0.5016	2.7322
AgeDecile60-69	1.112	0.8992	0.4805	2.5739
AgeDecile70-79	1.2786	0.7821	0.5544	2.9487
AgeDecile80-89	1.2657	0.7901	0.5495	2.9154
AgeDecile90-99	1.1183	0.8942	0.4802	2.6041
BNFChapter 01: Certain infectious and parasitic diseases	0.9522	1.0502	0.6355	1.4267
BNFChapter 02: Neoplasms	1.3705	0.7296	0.8768	2.1422
BNFChapter 03: Diseases of the blood and blood forming organs and certain disorders involving the immune mechanism	1.1291	0.8857	0.6579	1.9377
BNFChapter 04: Endocrine, nutritional and metabolic diseases	1.1031	0.9065	0.726	1.6762
BNFChapter 05: Mental and behavioural disorders	1.1382	0.8786	0.7103	1.8238
BNFChapter 06: Diseases of the nervous system	1.0803	0.9256	0.6859	1.7016
BNFChapter 07: Diseases of the eye and adnexa	0.9697	1.0313	0.3376	2.7855
BNFChapter 08: Diseases of the ear and mastoid process	1.4309	0.6989	0.4367	4.6882
BNFChapter 09: Diseases of the circulatory system	0.9615	1.0401	0.6703	1.3792

BNFChapter 10: Diseases of the respiratory system	1.1985	0.8344	0.8409	1.7081
BNFChapter 11: Diseases of the digestive system	1.0197	0.9807	0.6987	1.4882
BNFChapter 12: Diseases of the skin and subcutaneous tissue	1.0175	0.9828	0.6584	1.5724
BNFChapter 13: Diseases of the musculoskeletal system/connective system	0.7853	1.2735	0.5238	1.1773
BNFChapter 14: Diseases of the genitourinary system	1.0816	0.9245	0.745	1.5704
BNFChapter 15: Pregnancy, childbirth and the puerperium	6.0273	0.1659	0.7936	45.7781
BNFChapter 17: Congenital malformations, deformations and chromosomal abnormalities	3.2549	0.3072	0.9928	10.6709
BNFChapter 18: Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified	0.9548	1.0474	0.6656	1.3696
BNFChapter 19: Injury/poisoning/other consequences of external causes	0.9408	1.0629	0.6469	1.3682
BNFChapter 21: Factors influencing health and contact with health services	1.2668	0.7894	0.6113	2.6248
DMRDMR Started:strata(tgroup)tgroup=1	0.5974	1.674	0.5043	0.7076
DMRNo DMR:strata(tgroup)tgroup=1	NA	NA	NA	NA
DMRDMR Started:strata(tgroup)tgroup=2	0.9672	1.0339	0.8592	1.0888
DMRNo DMR:strata(tgroup)tgroup=2	NA	NA	NA	NA