Abstract

Aims To examine if the introduction of Diabetes Inpatient Specialist Nurses impacted on length of stay and rates of readmission.

Design Knowledge discovery through data mining as part of a larger realist evaluation of the role.

Methods Data from January 2017 to January 2019 was extracted and examined. A subset of performance data from July 2017 -November 2018 was analysed. This consisted of 7320 records for Hospital Episode Statistics and 272 incident reports (Datix). The data were analysed via Generalised Linear Model regression routines in R. Analysis of readmission rates utilised binary logistic regression, while for the Length of Stay a count regression method was employed**.**

Results

Four trusts were found to have complete and rich data sets. All Trusts that returned complete data were found to have varying decreased length of stay and reduced readmission rates. In two trusts there were significant decreases in patient readmissions and length of stay after the introduction of the Diabetes Inpatient Specialist Nurses. A marked decrease (approximately half) in patient length of stay was found in one London trust after the introduction of the post. Issues with data quality were noted.

Conclusion

Reduced patient length of stay and rate of readmission were found since introduction of Diabetes Specialist Nurses. Patient safety data was incomplete and varied significantly between trusts.

Impact

The project sought to understand the impact of employing Diabetes Inpatient Specialist Nurses in hospitals in London**.** Overall, the specialist nurses helped reduce length of stay and the rate of readmissions. The research will have an impact on the workforce in diabetes and also people with diabetes who need hospital care.

Key Words

Diabetes; Clinical Nurse Specialist; Workforce; Safety, Specialist Nursing, Impact

Introduction

NHS England's Diabetes Treatment and Care Transformation Fund invested £44 million in to improving diabetes care in 2016 (NHS England, 2016). NHS Trusts and Clinical Commissioning Groups (CCG) could apply for a share of this sum. One of the fund's priorities was to improve diabetes inpatient care, through improved Diabetes Inpatient Specialist Nursing (DISN) services. As of 2018, 96% of trusts that participated in the National Diabetes Inpatient Audit and received this funding have used it to recruit new diabetes specialist staff, including DISNs (NaDIA, 2018). Prior to receiving transformation funding, a quarter of sites had no Diabetes Inpatient Specialist Nurses (NaDIA, 2018). This evaluation is of nine NHS Trusts in London that received this funding, and as a result deployed new DISNs. This study seeks to assess the impact the introduction of a DISN workforce has on efficiency metrics such as length of stay and rate of readmission. It analyses the ways in which the deployment of these nurses impacted inpatient outcomes over 16 months (to take into account different trusts' DISN start dates).

Background

Almost 4.7 million people are diagnosed with diabetes in the UK 7% of the UK and approximately one million people have undiagnosed type 2 diabetes (Whicher et al 2020).

It has been estimated 1 in 6 United Kingdom hospital inpatients have diabetes (NaDIA 2017) It has been known for a number of years that people with diabetes admitted to hospital (for diabetes or non-diabetes related reasons) appear to have reduced overall control of their condition, with insulin treatment, timing of meals and glucose monitoring affected (National Diabetes Support team 2008). It is widely reported that inpatients who suffer adverse events and medication errors experience an increased length of stay of between 2 to 8 days (Carey et al 2008) and so this is an issue that is not novel.

Diabetes specialist nurses (DSN), among clinical nurse specialists of all specialities are known to improve patient outcomes and increase care efficiency (HSJ Workforce, 2015; RCN, 2009). These expert workforces bring stability to services and are critical to the health economy (Leary, 2014). Whilst specialist nurses' impacts are wide reaching, measures of their value or worth often focus on their impact on patient's length of stay, and rates of readmission, as well as patient safety (Diabetes UK, 2014). There are strong economic cases for specialist nurses (these tend to be speciality-specific) (HSJ Workforce, 2015; Kerr, 2011), and these measures tend to support this case. Despite the large evidence base that supports the value of specialist nursing, the number of DISN is significantly lower than UK recommendations (NaDIA, 2018). Hospitals struggle to recruit into specialist posts and many go unfilled (Diabetes UK, 2014; Diabetes UK, 2018).

That patient education is the cornerstone of diabetes management' has been known for some time (Feddersen and Lockwood 1994). DISNs play a pivotal role in educating patients in hospital and empowering patient self-management of their diabetes (James 2011) . Care and advice given by DSNs in addition to standard care has resulted in increased patient knowledge and confidence (Davies et al 2001). Much of this work laid the ground work for the expansion of specialist diabetes nursing roles leading to positive patient outcomes: patient confidence can delay complications, reduce hospitalisations, facilitate discharge and prevent readmission (Ross et al 2014). More recently Lawler et al (2019) elucidated some of the main mechanisms by which DISNs achieved higher quality and more efficient care including that in international studies, such workers reduce patient length of stay in hospital (Flanagan et al 2008),

To explore patient length of stay and rates of readmission, routinely collected data such as Hospital Episode Statistics (HES) can be analysed. HES is a database containing details of all admissions, accident and emergency (Emergency Department) attendances and outpatient appoints at NHS hospitals in England (Digital NHS Data and Information, 2020). For patient safety, Datix is an incident reporting system used in the majority of NHS Trusts. Data are used to identify hazards and risks in patient care.

Aim: To examine if the introduction of Diabetes Inpatient Specialist Nurses impacted on length of stay and rates of readmission.

Design

The overarching approach utilised knowledge discovery through data mining.

Data were extracted from hospital episode statistics curated at Trust level by the local CCG. Incident reporting data were extracted by the Trust and anonymised. Both datasets were extracted using the ICD-10 codes for diabetes as key.

Data Collection

Data utilised was the routinely collected administrative data from National Health Service Systems from Hospital Episode Statistics, and Incident reporting system called Datix.

The data request can be found in the supplementary file. The data request was co-produced with the real-world expert group (DISNs, endocrinologists, nurse leaders, lived experience experts from Diabetes UK and data scientists). Data was requested from Jan 17-Jan 19 to allow for recruitment and a primary subset of data from July 2017 through November 2018 utilised for most of the analysis as this was consistently available.

Data Quality

After extraction of these data they were examined for volume and completeness. The routinely collected data from hospital administration systems was complete and rich in five hospitals. The reminder returned partial data sets which were utilised with caveats as described in the Analysis and Results sections.

Although the original aim was to include incident reporting data and examine emerging safety issues particularly around delay or readmission, the incident reporting data was of very low volume despite the known issues with diabetes care and previous studies by the research team (Cook et al 2019, Leary et al 2020) and so was excluded from the analysis. This therefore limited the research to impact on efficiency and the lower than expected incident reporting was fed back to the organisations.

Data Analysis

The data were analysed via generalised linear model (GLM) regression routines as implemented in the *stats* (R Core Team R, 2019) and *MASS* (Venables, 2002) package in the R statistical language. Two outcomes were assessed – “readmission within 30 days” which was treated as a binary variable and “Length of Stay” (LOS) as a discrete count of days. In both cases the independent variable set was made up of 4 variables:

• Month of admission
• Diagnosis code (referred to as e-code going forward)
• Description of the specialty of treatment location
• Name of CCG responsible for case.

The “readmission rates” outcome was analyzed via binary logistic regression, and the LoS outcome via a negative binomial regression method after early trials of Poisson regression identified a marked over-dispersion of the model residuals.

Both re-admission and LOS outcomes were analysed for evidence of a step change with respect to month of admission. Unadjusted models for the relationship between month and each outcome were trained via regression – comparing a flat monthly background against step-function changes centred at each month using the

Akaike information criterion (AIC) score. The AIC process determined both if the data demonstrated a step-change in the outcome, and at what time point it occurred.

The unadjusted modelling was performed blind to the date of DISN being employed to avoid bias of the model. The model with the smallest AIC score was selected as the optimal parameterization, setting the month at which the step change occurs, and the coefficients reported as the unadjusted effects. Following characterization of the unadjusted effects, the three confounding parameters (specialty, CCG and e-code) were included in the model, holding the step change at the month found in the unadjusted analysis. Model parameters had significance reported via an omnibus Wald test and 95% confidence intervals were constructed based on the standard normal distribution.

Data governance procedures were completed for each Trust. The HRA algorithm was used to determine if this was a service evaluation of research and each Trusts R&D department was asked to review the evaluation. All trusts agreed to use of the data, via the CCG, on a temporary (six month) basis. Even though this is routinely collected data, the evaluation team agreed to destroy the data six months after analysis in the interests of data security. All data was kept on a secure server. Data used in this study is available from NHS Digital and the individual NHS Trusts.

Ethical Considerations.

This study was subjected to the HRA algorithm and deemed a service evaluation. It was also reviewed by each Trust in terms of research and data governance.

Validity, reliability and rigour

This approach is inductive rather than reductive even though it utilises quantitative data. This allows for a more exploratory paradigm. A standardised data set was utilised and both non linear statistical and modelling methods were applied to check for spurious correlations or fallacious relationships.

Results

Data outline

Data were supplied from nine NHS Trusts across London as part of the evaluation. The analysis here focusses on those Trusts designated as North London, where there was a good quantity of data reported and had both length of stay and readmission status. Five Trusts were found to have a rich data set (Barnet, Royal Free Hopsital (RFH), University College London Hospital (UCLH), Whittington and North Middlesex (North Mids) though North Mids was later excluded as the readmission status was not evident in the data set). The data from four other trusts designated South London, (Epsom & St Hellier (ESH), Croydon, St Georges (SGH) and Kingston) was of poorer quality and although used in the analysis (pattern recognition) are not reported in detail here due to issues around reliability and not being high enough quality to meet the detectable desired outcomes as determined by the commissioners of the evaluation (LoS, rate of readmission and safety features).

The data obtained is shown in the supplementary file.

Data features

The data made available is for the time period July 2017 through November 2018, inclusive, consisting of 7320 records for HES and 272 Datix. This is shown in Table 1.

Insert Table 1 here

From each Trusts data several key variables were extracted per case:
• Month of admission
• LoS (in days)
• Re-admission with 30 days status (True/ False)
• Diagnosis code (referred to as e-code going forward)
• Description of the specialty of treatment location
• Name of CCG responsible for case.

All safety data was of too low volume for analysis, which is unusual compared to Trusts in other evaluations which have been conducted (Leary, 2020). Therefore, this was not progressed.

Re-admission analysis

The reported rate of readmission in the data set varied between Trusts – a brief overview of readmission rates is given in Figure 1. There appears to be a clear decrease in readmissions for the Trust with the highest rate in 2017 (Barnet), commensurate with the date +1-2 months the DISNs went into post.

Insert Figure 1 here

Figure 1: Monthly rate of readmission by Trust from January 2017 till January 2019. A loess-smooth curve has been applied as a guide to the eye.

To quantify this effect, the readmission was modelled via a GLM assuming a binary-logistic model. Both Barnet and RFH demonstrated significant decreases in readmissions centred on time points after the introduction of the DISNs. For Barnet the step change is equivalent to a change in odds of readmission (with 95% CI) of 0.48 [0.35, 0.67] after June 2018 and for RFH of 0.65 [0.42, 0.99] after October 2018. The other two locations showed slight but not significant change in readmission as captured by the proposed models – possibly due to the existing low rate of readmission.

The analysis was repeated for the Barnet and RFH (limiting to the two with most data and highest rate of readmission) adjusting for three key confounding variables:

- Medical specialty e.g. A&E, Geriatrics, Paediatrics
- Second level e-code from the standard NHS coding e.g. E11, E16, E10.
- Service CCG

The adjusted analysis mirrored the unadjusted data, with both showing a significant decrease in readmission in a time period commensurate with the introduction of the DISN staff. For Barnet the step change is equivalent to a change in odds of readmission (with 95% CI) of 0.39 [0.26, 0.59] after June 2018 and for RFH of 0.56 [0.34, 0.92] after October 2018. The omnibus tests for the Specialty, CCG, and E-code for Barnet and RFH are summarized in Tables 2 and 3.

To help contextualize these results – consider Barnet. The Trust reported circa 30 cases per month with an average rate of readmission of 55%, the adjusted analysis predicts that this would reduce to circa 32% (or between [23%, 41%] from the 95% CI) with the addition of the DISN staff. Assuming each readmission cost a single bed day as a lower boundary this would account for a saving of 6.9 [4.2, 9.6] bed days a month. The saving decreases as the rate of diabetes cases and the existing rate of readmission decreases – hence the DISN staff would have the best chance of a good return in Trusts with a high incidence of diabetes and high rate of readmission.

Insert Table 2 here

Insert Table 3 here

Length of Stay analysis

For the unadjusted analysis of the LoS, Barnet and RFH showed only marginal decrease in LoS across the time period of interest in contrast to the readmission analysis. Whittington, however, showed a marked decrease in LoS following June 2018 (in line with the date of DISN start). The unadjusted model suggests that after this date the average LoS at Whittington decreased by a factor of 0.53 [0.36, 0.79] i.e. LoS approximately halved.

The analysis for Whittington was repeated using the optimal step-location adjusting for three key confounding variables:

- Medical specialty e.g. A&E, Geriatrics, Paediatrics
- Second level e-code e.g. E11, E16, E10.
- Service CCG

The adjusted model parameters suggest that the specialty treating the patient has the greatest effect on the LoS, with A&E and General Medicine having the shortest LoS, increasing to Paediatrics and then all other locations (grouped as they each rarely dealt with cases).

Following the introduction of the DISN there was a slight shift to fewer cases being dealt with in the “Other” locations and more within “General medicine” – possibly indicative of improved triage or uncorrelated variations in demand and process.

Summary

Four trusts were found to have complete and rich data sets. All Trusts that returned complete data were found to have varying decreased length of stay and reduced readmission rates. In two trusts there were significant decreases in patient readmissions and length of stay after the introduction of the Diabetes Inpatient Specialist Nurses. More information can be found in the supplementary file.

Discussion

For some time, the primary outcome measures of readmission and patient LoS have been used to evaluate DISNs (Davis, 2000). The direct financial links to these measures are most likely the driver for this (Apollo Nursing Resource, 2013; Joint British Diabetes Society for Inpatient Care, 2019). While these are two highly used measures, there are a multitude of other ways in which diabetes specialist nursing can and should be considered when being evaluated. The diabetes specialist nursing workforce plays a critical role in education of other healthcare professionals, and of patients, including promoting patient self-management. They also improve clinical outcomes such as reducing inpatient complications, providing complex and critical direct care and medicines management, and improve patient experience (Lawler, 2019).

Some trusts did not return any patient safety data, and the data that were received were largely incomplete. Therefore this study was unable to explore the important area of the impact of diabetes specialist nurses on patient harms and safety. One trend that might have been seen had the data been rich enough to explore this area, is an initial increase in reporting patient harms post the introduction of specialist nurses. This increased reporting can be seen when a new role is introduced. This shows the importance of the time scale that evaluations are taken over to be able to explain and account for initial increase or decreases in outcomes. Diabetes UK's report 'Making hospitals safe for people with diabetes' recognises the huge variations in Trusts in this area Diabetes UK 2019). Patient safety is of particular importance for people with diabetes during their hospital stays. The latest national diabetes inpatient audit of 2017 showed that 31% of patients had experienced a diabetes medication error during their hospital stay (NaDIA, 2017). Additionally, 1 in 25 type 1 diabetes inpatients developed diabetic ketoacidosis, a preventable emergency state NaDIA, 2017). This translates to being more likely to experience diabetic ketoacidosis in hospital than out (Joint British Diabetes Society for Inpatient Care, 2020). Diabetes specialist nurses have been shown to reduce inpatient harms and increase patient safety (Carey, 2008; Ross, 2014) as well as Specialist nurses are recognised to reduce both patient length of stay in hospital, and re-admission rates (RCN, 2009; Diabetes UK, 2019; Nuffield Trust, 2015). Therefore, this would have been an important area to explore if data had been of enough quality and volume.

Readmission

Readmission rates within 28 days for people with diabetes are 59% higher than age-matched populations without diabetes (Joint British Diabetes Society for Inpatient Care, 2013). Some of the suggested ways in which specialist nurses reduce and avoid patient readmission rates are through reduced complications, enhanced symptom control and improved patient self-management (Apollo Nursing Resource, 2013). In this study two Trusts demonstrate significant decreases in readmissions centred on time points after the introduction of the DISNs. For the other two Trusts, where a significant decrease was not found, this could have been due to lower initial readmission rates. Differences in patent discharge procedures and follow-up among a number of other compounding factors may have also had different impacts (Joint British Diabetes Society for Inpatient Care, 2017; Vernon, 2019; Smeraglio, 2019; Felix, 2015).

Length of Stay

This study observed a reduced LoS, approximately halved, in one Trust since the introduction of DISNs.

Targeting care by using specialist teams has been shown to reduce patient LoS in hospital (Apollo Nursing Resource, 2013; Nuffield Trust, 2015). Being able to identify people with diabetes on admission to hospital is transformative for diabetes inpatient teams (Diabetes UK, 2019; (Diabetes UK, 2019b). This allows a care plan to be set in place from the start of a patient's hospital stay. Electronic referral pathways to refer to diabetes specialist teams can optimise time and reduce risk for those most in need (Rajendran, 2015). Targeting DISNs time and resources to where it will be most effective will also reduce patient LoS (Diabetes UK, 2019).

The introduction of a DISN workforce appears to have a benefit in terms of efficiency and workforce planners should consider investing in this workforce as this study along with others, suggests they have benefits to people with diabetes and the utilisation of hospital resources.

Additionally, it is important to consider that these measures are all interconnected. Less medication errors may result in a reduced LoS. Longer or shorter LoS may be corelated with readmission avoidance, and further work should be done in this area.

Conclusion

Reduced patient LoS and rate of readmission were found since introduction of DISNs. Patient safety data were incomplete and varied significantly between trusts. However there seems to be an overall benefit in terms of efficiency to patients and hospitals in deploying this workforce. To address issues in planning a safety critical workforce data quality and sensitivity needs to improve.

Limitations

While data was requested from nine NHS trusts, only four trusts' routinely collected data was complete and rich enough to analyse. This shows us a large discrepancy between different trusts' data collection, in particular in safety data, which this study was unable to analyse.

Availability of data and material: Upon reasonable request

Code Availability: Upon reasonable request

Conflict of Interest Statement

No conflict of interest has been declared by the authors.

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Table 1 data provided.

Trust	N HES_SUS episodes (LOS & ERS)	N Datix
Barnet*	747	36
RFH*	731	57
Chase Farm*	12	None supplied
NMid	747	54
Whittington	199	26
UCLH	666	66
SGH	1312	Not known
ESH	873	29 (partial data)
Croydon	1286	22
Kingston	747	11
Total	**7320**	**272**

*are part of one Trust but data was provided by organisation via HES. Hence ten organisations are listed here.

Table 2: Omnibus Wald tests of the adjusted readmission analysis for Barnett.

Parameter	Statistic	Test statistic	Degrees of Freedom	P value
Specialty		173.20	5	<0.0005
CCG		16.71	8	0.033
E code		11.97	3	0.007
Date step		19.29	1	<0.0005

Table 3: Omnibus Wald tests of the adjusted readmission analysis for RFH.

Parameter	Statistic	Test statistic	Degrees of Freedom	P value
Specialty		120.7	5	<0.0005
CCG		28.9	8	<0.0005
E code		3.1	3	0.370
Date step		5.1	1	0.023

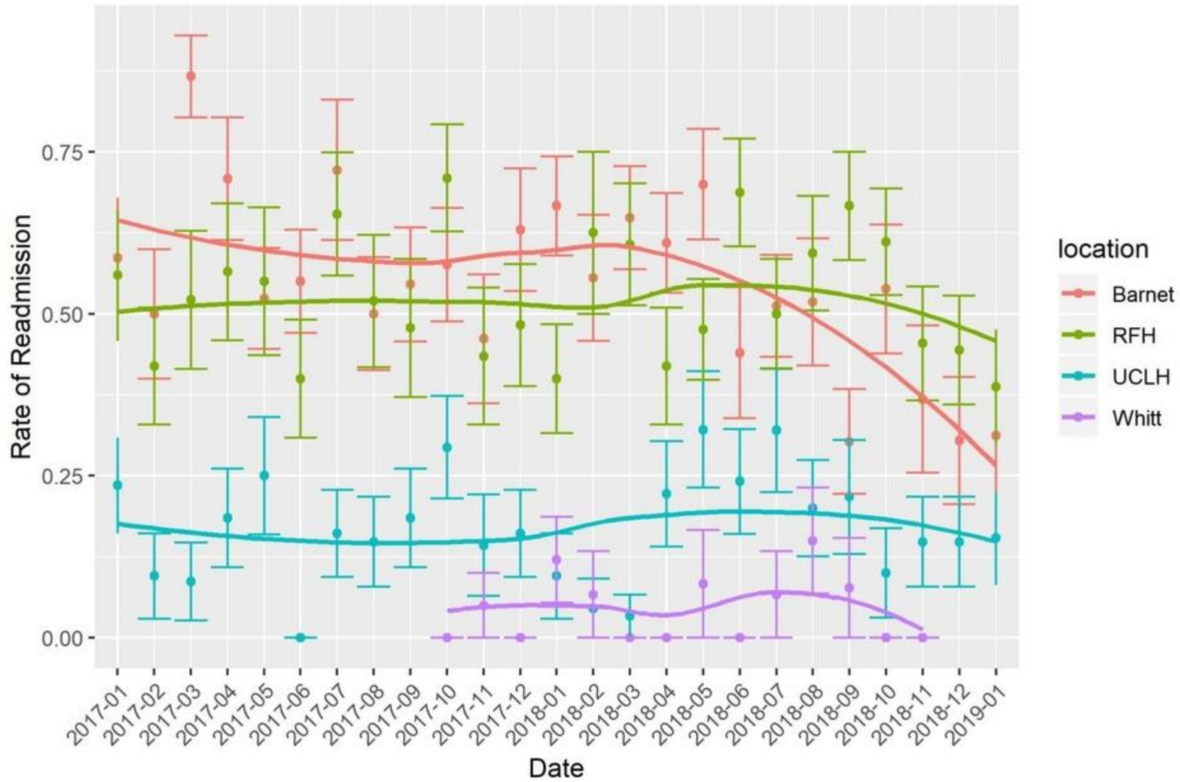

Figure 1

Supplementary information on data acquisition.

Data request for Hospital Episode Statistics (HES)

The data element requested was for Diabetes in the patient diagnosis indicator ICD10 E10.x 11.x. 12.x 13.x 14.x E16.x diabetes and complications. i.e. where x is another number recorded. Any episodes coded under Y40-59 or T36-65 (the mis prescribing/poisoning etc categories).

As well as the ICD10 codes shown in Table 1, the data request included length of stay, rate of re-admission, FCE/FAE, ED, IP, location.

Table 1. Data request for Hospital Episode Statistics

ICD10 code
E10.0 Insulin-dependent diabetes mellitus - With coma
E10.1 Insulin-dependent diabetes mellitus - With ketoacidosis
E10.2 Insulin-dependent diabetes mellitus - With renal complications
E10.3 Insulin-dependent diabetes mellitus - With ophthalmic complications
E10.4 Insulin-dependent diabetes mellitus - With neurological complications
E10.5 Insulin-dependent diabetes mellitus - With peripheral circulatory complications
E10.6 Insulin-dependent diabetes mellitus - With other specified complications
E10.7 Insulin-dependent diabetes mellitus - With multiple complications
E10.8 Insulin-dependent diabetes mellitus - With unspecified complications
E10.9 Insulin-dependent diabetes mellitus - Without complications

E11.0 Non-insulin-dependent diabetes mellitus - With coma
E11.1 Non-insulin-dependent diabetes mellitus - With ketoacidosis
E11.2 Non-insulin-dependent diabetes mellitus - With renal complications
E11.3 Non-insulin-dependent diabetes mellitus - With ophthalmic complications
E11.4 Non-insulin-dependent diabetes mellitus - With neurological complications
E11.5 Non-insulin-dependent diabetes mellitus - With peripheral circulatory complications
E11.6 Non-insulin-dependent diabetes mellitus - With other specified complications
E11.7 Non-insulin-dependent diabetes mellitus - With multiple complications
E11.8 Non-insulin-dependent diabetes mellitus - With unspecified complications
E11.9 Non-insulin-dependent diabetes mellitus - Without complications
E12.0 Malnutrition-related diabetes mellitus - With coma
E12.1 Malnutrition-related diabetes mellitus - With ketoacidosis
E12.2 Malnutrition-related diabetes mellitus - With renal complications
E12.4 Malnutrition-related diabetes mellitus - With neurological complications
E12.6 Malnutrition-related diabetes mellitus - With other specified complications
E12.9 Malnutrition-related diabetes mellitus - Without complications
E13.0 Other specified diabetes mellitus - With coma
E13.1 Other specified diabetes mellitus - With ketoacidosis
E13.2 Other specified diabetes mellitus - With renal complications
E13.3 Other specified diabetes mellitus - With ophthalmic complications
E13.4 Other specified diabetes mellitus - With neurological complications
E13.5 Other specified diabetes mellitus - With peripheral circulatory complications
E13.6 Other specified diabetes mellitus - With other specified complications
E13.8 Other specified diabetes mellitus - With unspecified complications
E13.9 Other specified diabetes mellitus - Without complications
E14.0 Unspecified diabetes mellitus - With coma
E14.1 Unspecified diabetes mellitus - With ketoacidosis
E14.2 Unspecified diabetes mellitus - With renal complications
E14.3 Unspecified diabetes mellitus - With ophthalmic complications
E14.4 Unspecified diabetes mellitus - With neurological complications
E14.5 Unspecified diabetes mellitus - With peripheral circulatory complications
E14.6 Unspecified diabetes mellitus - With other specified complications
E14.8 Unspecified diabetes mellitus - With unspecified complications
E14.9 Unspecified diabetes mellitus - Without complications

Safety Data request

NaDIA harms linked to Hospital Episode Statistics but no Personal Identifiers.

Datix categorical data only i.e. no free text was requested as it has unintentional Personal Identifiers in it (assuming DatixCCS2 is used) tier one: incident affecting patients. Diagnostic process, therapeutic process and subsequent associated tiers. CCF & harm outcomes.

Hypoglycaemic Rescue = Did the patient require injectable rescue treatment for hypoglycaemia more than 6 hours after admission?

Diabetic Ketoacidosis (DKA) = Was the patient diagnosed with new onset DKA more than 24 hours after admission?

Hyperglycaemic Hyperosmolar State (HHS) = Was the patient diagnosed with new onset HHS more than 24 hours after admission?

Diabetic Foot Ulcer = Was the patient diagnosed with a new onset foot ulcer more than 72 hours after admissions?