Methodological paper

Hospital Readmission Ratio

Methodological report of the 2018 model

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1. Introduction

1.1 Indicators of quality of hospital care

Overall quality of hospital care can be estimated using several types of quality indicators based on hospital admission data. Such indicators for identifying potentially suboptimal quality of hospital care might focus for example on unexpected in-hospital or post-discharge mortality, potentially preventable hospital readmissions or unexpected long duration of admissions. In the Netherlands, hospital admission and discharge data is registered in the LBZ, a national hospital discharge register covering all general, university and a few specialised hospitals. Other specialised clinics, independent treatment centres and private clinics are not included. Inpatients as well as day cases and prolonged observations without overnight stay are registered. For each hospital discharge administrative data of the admission are registered, as well as diagnoses and procedures.

In the Netherlands, hospitals participating in the LBZ registration are annually provided by Dutch Hospital Data (DHD) with a set of indicators based on their performance in the previous year. Up to 2016 this set included the (unadjusted) hospital readmission rate, which is the ratio of the number of observed readmissions to the total number of hospital admissions. However, since this ratio does not correct for case mix differences, it might be less indicative of differences in the true number of potentially preventable readmissions. Therefore, in 2017 DHD has asked Statistics Netherlands to develop a model to estimate the expected readmission risks adjusted for relevant covariates, in a fashion similar to the estimation of the hospital standardized mortality rates (HSMR). From 2017 onwards, Statistics Netherlands produces Hospital Readmission ratio models on a yearly basis.

1.2 Predictive value of the hospital readmission model

Internationally, models for estimating hospital readmission rates are used for the purpose of risk stratification but also as a quality indicator. From previous studies it is known that several patient characteristics can contribute to the risk to be readmitted to the hospital. In a systematic review by Kansagara *et al.* (2011), an overview is presented of the various validated models that have been used internationally, the covariates included in those models and their overall predictive value. Common covariates include comorbidity indexes, age, sex and/or prior use of medical services (hospitalizations). Regardless of the number of included covariates, the results of only a small fraction of the models are moderately discriminative (AUC/C-statistic>0.70). The model developed by Statistics Netherlands includes additional covariates such as severity of the main diagnosis, urgency of the admission and socio-economic status. However, the overall predictive value of the model did not exceed previously published values (AUC=0.69). It was demonstrated though, that the level of case mix correction applied by the model significantly improved comparability of the outcomes of the individual hospitals. So, although the case mix correction is probably incomplete, it does, to some extent, reduce effects due to differences in patient populations. As such, applying the model to calculate adjusted readmission ratios for individual hospitals is an improvement over calculating crude rates (Van der Laan *et al.* 2017).

1.3 Development of the hospital readmission model in the Netherlands

The initial hospital readmission model, developed by Statistics Netherlands in 2017, was based on the linkage of admissions and readmissions that occurred within the same hospital (intra-hospital readmissions).

In 2018 Statistics Netherlands improved this intra-hospital readmissions model by excluding planned transfers to and from neighbouring or specialized hospitals ('2016 model'; this model was based on LBZ data of 2015 and 2016 and was named after the most recent year of included data). It is common practice for hospitals to refer inpatients to other hospitals for specific procedures, such as coronary interventions. Such planned transfers should not be labelled as readmissions.

The results of this improved intra-hospital model were compared to that of a newly developed inter-hospital model, that also took into account readmissions in other hospitals, while excluding planned transfers. Since readmissions can also take place in other hospitals, including inter-hospital readmissions in the model might improve its predictive value.

The predictive value of both models was however largely comparable, and it was concluded that apart from views regarding the relevance of inter-hospital readmissions for measuring quality of care, practical considerations might determine which of both models will be used for calculating the readmission ratios of the individual hospitals (Van der Laan *et al.* 2018). A practical disadvantage of the inter-hospital ratio is that hospitals need patient information from other hospitals to calculate the ratios and to study the files of the patients with readmissions. For this reason, DHD decided to use the intra-hospital model (excluding planned transfers) in their regular hospital indicators reports.

From 2019 onwards, Statistics Netherlands yearly produces updated versions of this intra-hospital model, using the latest available hospital admissions data.

1.4 Aim of the current project

In the current 2020 project we produced an updated version ('2018 model') of the intra-hospital model, excluding planned transfers, based on LBZ data of 2017 and 2018. The outcome is described in chapter 3.

1.5 Output

Statistics Netherlands has only calculated the model for the hospital readmission risks based on LBZ data of 2017-2018, not the outcomes for the individual hospitals. For their regular hospital indicators reports, DHD will use this model to estimate the expected readmission risk, adjusted for relevant covariates, for each individual primary (index) hospital admission in 2019. For each hospital, the standardized (adjusted) readmission ratio can be calculated as the observed number of readmissions (x 100) divided by the sum of the expected readmission risks of the index admissions of that hospital.

2. Methods

2.1 Changes compared to the previous intra-hospital model

Like previous year we used the methods of the intra-hospital model which excludes transfers (admissions starting on the same day as the discharge date of the preceding admission) as readmissions (Van der Laan *et al.* 2018).
However, compared to previous year ('2017 model'), all one-day inpatient admissions with residential environment, rehabilitation facilities or nursing homes as destination after discharge were removed from the dataset of the present '2018 model'. The methods used are described in more detail in the next paragraphs.

2.2 Readmission ratio

The (hospital) readmission ratio is calculated using the expected (hospital) readmission risk as the denominator and observed readmission as the numerator. The expected readmission risk is predicted for each individual admission within a given period, adjusted for patient and admission characteristics of that admission as covariates. Readmission risk was predicted for all (index) admissions that potentially could be followed by a readmission, excluding admissions for diagnoses with complex care paths where planned readmissions are often involved.
Readmissions are defined as those admissions that occurred within 30 days of the discharge date of the preceding index admission. Detailed information on the characteristics and criteria of index admissions and readmissions is given in paragraphs 2.3.5 and 2.3.6 respectively.
Expected readmission risk is determined for each of the included diagnosis groups, which are based on the CCS *(Clinical Classifications Software*), which clusters ICD codes of the main diagnoses of the admissions into 259 clinically meaningful categories[1]. In accordance with the HSMR, we further clustered these groups into 157 diagnosis groups, which are partly the same clusters used for the SHMI (Summary Hospital-level Mortality Indicator) in the UK (HSCIC, 2016).
To determine readmission risk we used logistic regression models, with an observed readmission as the target (dependent) variable and various variables available in the LBZ as covariates.

The methodology for estimating the expected readmission risk is very similar to that used for estimating expected mortality rates applied for calculating the HSMR rates, described in detail elsewhere (Van der Laan *et al.* 2019b). In the following section, we therefore briefly describe the applied methods, while deviations from the HSMR methodology or other methods specific to the current project are described in more detail.

2.3 Target population and data set

2.3.1 Patient identifier

Statistics Netherlands has linked the LBZ data to the Dutch national population register, using a pseudonym of the national personal identification number, and the combination of date of birth, sex and postal code as linkage keys. Through this linkage, a unique pseudonymised person ID could be added to the LBZ dataset. With this linkage >99% of all admissions could be uniquely linked to a person in the population register; thus the loss of data was minimal (<1%). Using this

[1] *See https://www.cbs.nl/-/media/_excel/2019/40/classification%20of%20variables%20hsmr%202018.xlsx*

identifier not only allows identification of transfers to other hospitals, it also eliminates bias due to administrative errors in hospital-specific patient numbers.

2.3.2 Admissions – general criteria

We consider both the population of hospitals and the population of admissions. Our population of (re)admissions consists of "all hospital stays (inpatient admissions) of Dutch residents in Dutch short-stay hospitals within the study period". In the LBZ, the date of discharge, and not the day of admission, determines the LBZ year a record is assigned to. Therefore, the registered hospital stays of year *t* comprise all inpatient admissions that ended in year *t*. Day cases and prolonged observations were excluded, since subsequent readmissions might be elective, for example, for prolonged treatment. In addition, incomplete admissions without a registered main diagnosis are also excluded, but this normally does not occur as hospitals have to register the inpatient admissions completely.

For the 2018 model, we additionally excluded (elective and acute) one-day inpatient admissions with residential environment, rehabilitation facilities or nursing homes as destination after discharge. These inpatient admissions are characterized by a discharge on the day of admission or a discharge before 7 a.m. on the day following the day of admission. Since these admissions do not meet the (financial) registration rules of the Dutch Healthcare Authority for inpatient admissions and since part of the elective one-day inpatient admissions cannot be distinguished from day cases, DHD has decided to exclude the above-mentioned one-day inpatient admissions from all LBZ indicators that will be calculated using the LBZ 2019 data. Since DHD will use the model parameters of the 2018 model to calculate the 2019 readmission ratio, DHD has asked CBS to remove those admissions from all LBZ data included in the 2018 model. In addition, admissions of foreigners were excluded from the model, since readmissions might have also taken place in a hospital in their residential country. Furthermore, foreigners cannot be linked to the Dutch population register. The number of admissions of foreigners is relatively small.

Lastly, duplicate admissions with identical values for date and time of admission and of discharge in combination with identical values for either (1) hospital ID and hospital-specific patient ID or (2) the pseudonymised person ID, were removed. In case of duplicate admissions, the admission with the lowest LBZ registration number was removed and the one with the highest number was kept, since we assumed that the latter admission might have been registered as a corrected version of the first. Duplicate admissions rarely occur in the LBZ.

2.3.3 Hospitals

Hospitals report admission data (hospital stay data) in the LBZ. However, not all hospitals participate in the LBZ. In principle, the hospital readmission risk model includes all general hospitals, all university hospitals and short-stay specialised hospitals with inpatient admissions participating in the LBZ in the study period.

One of the short-stay specialised hospitals was excluded since it mostly treats patients with oncological diseases, which are excluded from the data (see paragraph 2.3.5). The new children's hospital for pediatric oncology, that had started registering admissions in the LBZ mid-2018, was excluded for the same reason.

In 2017 one of the general hospitals stopped operating on October 1st. Therefore, in the dataset of study period 2017 (see paragraph 2.3.4), admissions with a discharge date in August

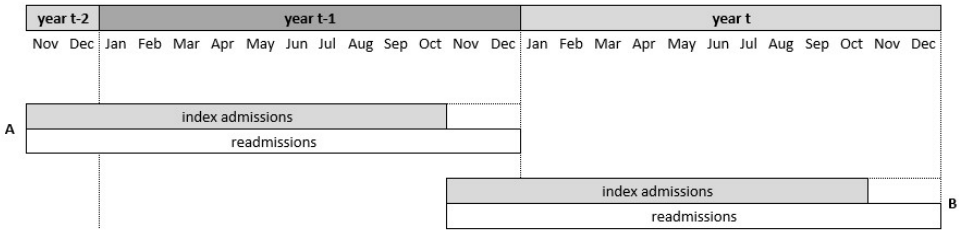
and September 2017 in that hospital were only considered as potential readmissions and not as index admissions, since those admissions could not logically be followed by readmissions in the same hospital after October 1st.
Finally, in 2018 two general hospitals had closed and their admission data registered before closing had not been validated. Therefore, these two hospitals were excluded from the dataset of study period 2018.

The readmission ratio is calculated using LBZ data on admissions, using the pseudonymised personal ID as the unique key for identifying (re)admissions. The combination of the person ID (for identifying patients) and the hospital ID number (for identifying the same hospital) was used for linking admissions. In case of merging hospitals, the hospital ID number that the hospital used in the LBZ registration year, was used for the associated study period in the models. For example, two hospitals that had merged in study period *t* were analysed as separate units for study period *t-1* and as a single unit for study period *t*. Otherwise, if the merged hospital (C) ID was also used for study period *t-1*, the year in which the unmerged hospitals (A and B) were still operating separately, an admission in hospital A followed by an admission in hospital B, could then potentially be identified as an index admission - readmission combination in hospital C. This would result in the identification of readmissions that in reality were admissions in another hospital.

2.3.4 Study periods

For the calculation of the current model, LBZ data of 2017 and 2018 was used. Previously we have shown that to identify the highest percentage of readmissions ending in year *t*, using index admissions with a discharge date from November 1st of year *t-1* up to October 31st of year *t* (study period) is optimal (Van der Laan *et al.* 2017). Thus, for study period 2017 ('year'=2017 in the model) we selected index admissions with a discharge date from November 1st 2016 up to October 31st 2017 and for study period 2018 we selected index admissions with a discharge date from November 1st 2017 up to October 31st 2018 ('year'= 2018 in the model). The occurrence of readmissions was analysed in the period between November 1st 2016 up to December 31st 2018. If hospitals had merged in study period *t*, the hospital ID of the merged hospital was also used for the data of November and December of year *t-1*.

2.3.4.1 Study periods used for identifying index admissions and readmissions.



A=study period *t-1* using hospital IDs from year *t-1* for all admissions; B=study period *t* using hospital IDs from year *t* for all admissions

Figure 2.3.4.1 shows which LBZ data is included in both study periods. For the processing of index admissions, transfers and readmissions, the optimal approach was to construct two separate datasets (A and B in figure 2.3.4.1) each containing data of one of the study periods, rather than constructing a single dataset containing data from both study periods. Below we explain why this was necessary.

If the data of both study periods were combined into a single dataset, for each LBZ year we would use the hospital ID that the hospital had used in that year for registering their data. If none of the hospitals would have merged during the entire period, there would be no issues and a single dataset would be possible. However, if hospitals X and Y in year *t-1* would merge into hospital Z in year *t*, the LBZ data from November and December of year *t-1* would be registered under different hospital IDs (X and Y) and could therefore not be linked to the data of hospital Z in year *t*. Since data from that two-month period is also part of study period *t-1*, it should therefore be possible to link that part of the data to two different study periods. In case of mergers, it is not possible to do so in a single dataset.

To avoid this issue, data from both study periods were processed separately for the identification of index admissions, transfers and readmissions (see figure 2.3.4.1). After processing, all index admissions of both study periods were combined into a single dataset that was entered into the model.

The approach of two separate datasets however causes another issue, since the period of November and December of year *t-1* is part of both datasets. This means that theoretically, some of the admissions in that period can be identified as readmissions to index admissions in study period *t-1*, while the same admissions can also be labelled as readmissions to index admissions in study period t. However, it was estimated that this will only occur in a few cases and that its effect will be negligible.

2.3.5 Criteria for index admissions

Expected readmission risk was only calculated for those inpatient admissions (meeting the general criteria for admissions, see 2.3.2) for which readmission was possible (i.e. patient did not die during the index admission), and excluding some specific diagnosis groups. These admissions are referred to as index admissions. Thus, in summary, the index admissions had to meet the following criteria:

- The patient did not die during the admission.
- The main diagnosis of the admission was not related to oncology (CCS groups 11-45) or psychiatry (CCS groups 65-75) since hospital care for these diagnoses is usually complex and follow-up care might be required. In addition the main diagnosis was not related to obstetrics (CCS groups 176-196; 218), since most deliveries do not take place during inpatient admissions, so it cannot be determined whether an admission for this purpose is the 'true' index admission.
- The date of discharge was from November 1st 2016 up to October 31st 2017 ('year *t-1*'= 2017) or from November 1st 2017 up to October 31st 2018 ('year *t*'= 2018).

2.3.6 Criteria for potential readmissions

Inpatient admissions only qualified as potential readmissions (meeting the general criteria for admissions, see 2.3.2) if the following criteria were matched:

- The main diagnosis of the admission was not related to oncology (CCS groups 11-45) or psychiatry (CCS groups 65-75) since hospital care for these diagnoses is usually complex and follow-up care might be required. In addition the main diagnosis was not related to obstetrics (CCS groups 176-196; 218), since most deliveries do not take place during inpatient admissions, so it cannot be determined whether an admission for this purpose is a "true" readmission.

- The main diagnosis of the admission was not related to social, socio-economic or psychosocial circumstances or administrative purposes (ICD10: Z55-Z65), other circumstances (ICD10: Z70-Z76) or screening, follow-up care or rehabilitation (CCS groups 254-258), since admissions for these purposes are usually planned.
- The discharge date of the admission was before or on December 31st of year *t*.
- The maximal time lapse between the admission date of the readmission and the discharge date of the index admission is 30 days (29 days interval at maximum). For example, when an index admission has a discharge date of January 1st, a subsequent admission on January 30th is classified as a readmission, while a subsequent admission on January 31st is not.
- If a readmission in the same hospital started on the same day as the discharge date of the index admission, the minimal time lapse between both admissions is one hour. If the hour of discharge of the index admission or the hour of admission of the readmission is unknown in this specific situation, the subsequent admission is not identified as a readmission.

Note that the main diagnosis of the readmission does not have to be related to the main diagnosis of the index admission.

2.3.7 Transfers

Transfers were not labelled as readmissions. Transfers are defined as admissions with a date of admission that was identical to the date of discharge of the previous admission in another hospital. In case of 'overlapping admissions' in two different hospitals (i.e. the start date of the second admission preceded the date of discharge in the first hospital) the second admission was also labelled as a transfer. Transfers affect the identification of readmissions in two ways:

First, <u>when index admissions are followed by a transfer, these index admissions (by definition) cannot have a readmission</u>. Although index admissions that are followed by a transfer cannot have readmissions, these index admissions were not removed from the model.

Second, <u>transfers cannot be readmissions</u>. In case of 'to and fro' transfers from hospital A to hospital B and back to hospital A, the latter admission in hospital A is *not* a readmission of the first admission in hospital A. In fact, an admission in hospital A that is a transfer from hospital B can (by definition) never be a readmission of any other previous admission.

The general criteria for admissions, the additional criteria for index admissions and readmissions and the role of transfers are summarised in table 2.3.7.1.

2.4 Target variable

The target variable for the regression analysis of the model is the occurrence of a readmission within 30 days of the discharge date of the preceding index admission.

The pseudonymised person ID (resulting after linkage of the LBZ to the national population register) was used as the unique key for identifying admissions of the same patient in a single hospital and for the identification of transfers to other hospitals.

The dataset was composed based on the criteria presented in section 2.3. According to the criteria for index admissions and readmissions, two variables were added to the dataset to mark both types of admissions. Readmissions can also count as index admissions in case they are followed by another readmission.

2.3.7.1 General criteria, additional criteria for index admissions and readmissions and the influence of transfers.

	Criteria for index admissions	Criteria for potential readmissions
General	- Inpatient admissions registered in the LBZ - Completely registered admissions with a registered main diagnosis - Admissions of Dutch residents	- Inpatient admissions registered in the LBZ - Completely registered admissions with a registered main diagnosis - Admissions of Dutch residents
Follow-up	The patient did not die during the admission.	
Diagnosis	The main diagnosis of the admission was not related to oncology (CCS groups 11-45), psychiatry (CCS groups 65-75) or obstetrics (CCS groups 176-196; 218).	The main diagnosis of the admission was not related to oncology (CCS groups 11-45), psychiatry (CCS groups 65-75), obstetrics (CCS groups 176-196; 218), social, socio-economic or psychosocial circumstances or administrative purposes (ICD10: Z55-Z65), other circumstances (ICD10: Z70-Z76) or screening, follow-up care or rehabilitation (CCS groups 254-258).
Period	For year t in the model the date of discharge was from November 1st year t-1 up to October 31st year t ('year'= t).	The discharge date of the admission was before or on December 31st of year *t*.
Maximal time lapse		The maximal time lapse between the admission date of the readmission and the discharge date of the index admission is 30 days (29 days interval at maximum)
Minimal time lapse		If the readmission started on the same day as the discharge date of the index admission, the minimal time lapse between both admissions is one hour
Influence of transfers[1]	Index admissions followed by a transfer cannot have a readmission.	Transfers cannot be readmissions.

[1] A transfer is an admission in hospital B with a date of admission that is identical to the date of discharge of a previous admission in hospital A.

After that, the dataset was processed to allocate readmissions to index admissions: index admissions and potential readmissions of the same patient (person ID) are identified within the same hospital only. As was explained in section 2.3.4, this allocation is done for each year separately. Within the set of admissions per patient, for each index admission the presence of a readmission within 30 days is determined. Each index admission can only be followed by a single subsequent readmission, and a single readmission can also be only allocated to a single index admission. If an index admission is followed by multiple potential readmissions within 30 days, only the first occurring readmission is marked as such. Based on this algorithm, for each index admission the presence of a readmission is marked.

Transfers are identified according to the method presented in section 2.3.7. After that, the previously described rules are applied ('an admission followed by a transfer cannot have a readmission' and 'a transfer cannot be a readmission'), with the result that some of the admissions are no longer regarded as readmissions. The index admissions associated with those readmissions were initially marked as having a readmission, but since these readmissions are no longer categorized as such after applying the transfer rules, the presence of a readmission is cleared from the respective index admissions.

Subsequently, all index admissions and the corresponding covariates are selected, plus the target variable (whether the primary admission was followed by a readmission or not) and these were entered into the model.

To illustrate the implementation of excluding transfers from the model, an example is given in table 2.4.1.

2.5 Stratification

Instead of performing one logistic regression for all admissions, we performed a separate logistic regression for each main diagnosis group. These sub-populations of index admissions are more homogeneous than the entire population. Hence, this stratification may improve the precision of the estimated readmission probabilities. As a result of the stratification, covariates are allowed to have different regression coefficients across diagnosis groups. Due to the exclusions of specific CCS groups for the index admissions, 35 of the 157 diagnosis groups (as used for the HSMR) are fully excluded. Therefore, the model included 122 separate logistic regressions, one for each diagnosis group selected (see Appendix II for the diagnosis groups included).

2.6 Covariates (explanatory variables or predictors of readmission risk)

By including covariates of patient and admission characteristics of the index admissions in the model, the hospital readmission risk is adjusted for these characteristics. For this purpose we selected the same covariates that are also regularly used in the (H)SMR model estimations, which are variables (available in the LBZ) known to be associated with in-hospital mortality. During the development of the readmission model, it was demonstrated that these covariates indeed contributed to the predictive value of the model (Van der Laan *et al.* 2017).

2.4.1 Example of the identification of readmissions after excluding transfers.

		Step 1	Step 2		Step 3
Admission	**Hospital**	**Is the admission followed by a readmission?**	**Is the admission followed by a transfer?**	**Is the admission a transfer?**	**Is the admission followed by a readmission (after correction for transfers)?**
A1	A	Yes (A2)	No	No	No, A2 is a transfer
<patient is home>					
B1	B	Yes (B2)	Yes (A2)	No	No, B2 is a transfer
A2	A	Yes (A3)	Yes (B2)	Yes (of B1)	No, A2 is followed by a transfer (B2)
B2	B	No	No	Yes (of A2)	No
<patient is home>					
A3	A	No	No	No	No

In this example a patient is admitted five times to two different hospitals within a period of 30 days. All admissions are index admissions, and admissions B1, A2 and B2 are consecutive admissions (date of admission of A2 is equal to date of discharge of B1; and date of admission of B2 is equal to date of discharge of A2). According to the criteria for readmissions, in step 1 the presence of readmissions is determined. After that, the presence of transfers is determined in step 2. Finally, the information of steps 1 and 2 is combined into step 3: the presence of readmissions corrected for transfers, where we apply the rules 'an index admission followed by a transfer cannot have a readmission' and 'a transfer cannot be a readmission'.

For example, A2 is a possible readmission to A1, but since A2 is a transfer, it cannot be a readmission. As a result, A1 is not followed by a readmission. In addition, A3 is not a readmission of A2, since A2 is followed by a transfer (B2) and thus cannot have a readmission.

The LBZ variables that are included in the model as covariates are age, sex, socio-economic status, severity of main diagnosis (based on mortality risk categories), urgency of admission, Charlson comorbidities, source of admission, month of admission and year. These variables are described below. Detailed information on these variables and their content is available in the HSMR methodology report (Van der Laan *et al.* 2019b). For the variables socio-economic status, severity of main diagnosis and source of admission the detailed classifications are presented in the file 'Classification of variables', published together with the methodology report of the HSMR (Van der Laan *et al.* 2019b). The variable 'year' is different from the variable used for the HSMR model, since it reflects the study period the index admission belongs to, rather than year of discharge. The specific (modified) definitions of 'year' for the readmission model are described in 2.3.4.

For the regressions, all categorical covariates are transformed into dummy variables (indicator variables), having scores 0 and 1. A patient scores 1 on a dummy variable if he/she belongs to the corresponding category, and 0 otherwise. As the dummy variables for a covariate are linearly dependent, one dummy variable is left out for each categorical covariate. The corresponding category is the so-called reference category. We used the first category of each covariate as the reference category.

Covariates:

- **Age at admission** (in years): *0, 1-4, 5-9, 10-14, …, 90-94, 95+*.
- **Sex** of the patient: *male, female.*
- **SES (socio-economic status)** of the postal area of patient's address: *lowest, below average, average, above average, highest, unknown.*
- **Severity of main diagnosis** groups: *[0-0.01), [0.01-0.02), [0.02-0.05), [0.05-0.1), [0.1-0.2), [0.2-0.3), [0.3-0.4), [0.4-1], Other*.
- **Urgency** of the admission: *elective, acute.*
- **Comorbidity_1 – Comorbidity_17**. All 17 covariates are dummy variables, having categories: *0* (*no*) and *1* (*yes*).
- **Source of admission**: *home, nursing home or other institution, hospital.*
- **Month of admission.** Six 2-month periods: *January/February, …, November/December.*
- **Year.** Year of the study period (generally for index admissions year t is defined by a discharge date from November 1st of year t-1 up to October 31st): *2017, 2018*.

2.7 Estimation of the model

Logistic regression models were estimated for each of the 122 diagnosis groups using the variables of the index admissions mentioned in the previous paragraph and the dichotomous variable indicating whether an admission was followed by a readmission as the target variable. Computations were performed using the glm function in R (R Core Team, 2015). Categories, including the reference category, are collapsed if the number of index admissions is smaller than 50 or when there are no readmissions in the category. For more information on this see the aforementioned methodology report for the HSMR.

The results of the model are described in chapter 3.

3. Outcome of the 2018 model

3.1 Dataset

Table 3.1.1 shows the number of hospitals that were included in the model. All general and university hospitals could be included in both study periods (2017 and 2018). Specialised hospitals where patients are mostly treated for oncological disease (one in 2017 and two in 2018) were excluded. The number of general hospitals was lower in study period 2018 compared to 2017, because one hospital closed mid-2017 and two other general hospitals closed in 2018. The 2018 data of the latter two were excluded since the data had not been validated.

3.1.1 Number of hospitals in the 2018 model.

Study period		General hospitals[a)]	University hospitals	Selected specialised hospitals[b)]	Total hospitals
2017	Total number	67	8	2	77
	Used in model	67	8	1	76
2018	Total number	64	8	3	75
	Used in model	64	8	1	73

a) Excluding military hospital
b) One eye hospital, one cancer hospital in 2017 and two in 2018

The number of index admissions included in the model, the total number of identified readmissions and the unadjusted readmission rate for both study periods are listed in Table 3.1.2.

3.1.2 Admissions and readmissions in 2018 model.

	2017	2018
Total number of index admissions included in model	1 276 522	1 223 296
Number of identified readmissions	114 755	108 902
Unadjusted readmission rate	9.0%	8.9%

3.2 Impact of the covariates on readmission rate

Appendix I shows which covariates have a statistically significant (95 percent confidence) impact on readmission rate for each of the 122 regression models (one for each diagnosis group). Tables 3.2.1 and 3.2.2 show the total number of significant covariates and the total Wald statistics for the 122 regression models. The tables are sorted in descending order (most important variables at the top). The first table shows the number of diagnosis groups in which a variable is significant in the model. The effect of variables on the predicted probabilities, and, therefore, the importance of the variables for the case mix correction performed by the models, is better measured with the Wald-statistics (shown in the second table).

The order of the variables differs somewhat in both tables, but in both tables age, urgency and severity are in the top 5 of the most important variables for model estimation. For the HSMR 2018 model (Van der Laan *et al.* 2019b) this is also the case, indicating that these variables are relevant for both predicting readmissions and in-hospital mortality.

For the 2018 readmission model, sex and Charlson comorbidity 10 (Diabetes) are more important compared to the 2018 HSMR model, while for the 2018 HSMR model the Charlson comorbidities 16 (metastatic cancer) and 17 (severe liver disease) are more important than for the 2018 readmission model. Apparently severe liver disease has a higher influence on estimating in-hospital mortality, while diabetes has a higher influence on estimating readmissions. The difference in importance of Charlson group 16 in both models can be explained by the fact that cancer-related main diagnoses are excluded from the readmission model, since planned readmissions for those diagnoses are frequent.

3.2.1 Statistical significance of the covariates for the 122 logistic regressions (summary), model 2018.

Covariate	No. of significant results	Covariate	No. of significant results
Age	106	Source of admission	39
Comorbidity 13	82	Comorbidity 5	30
Urgency	77	Comorbidity 7	26
Comorbidity 3	75	SES	18
Severity	70	Year	17
Comorbidity 10	64	Comorbidity 16	14
Sex	63	Comorbidity 4	14
Comorbidity 2	56	Month of admission	13
Comorbidity 6	56	Comorbidity 12	12
Comorbidity 1	54	Comorbidity 17	11
Comorbidity 14	51	Comorbidity 8	1
Comorbidity 11	49	Comorbidity 15	0
Comorbidity 9	39		

3.2.2 Wald chi-square statistics for the 122 logistic regressions, model 2018.

Covariate	Sum of Wald statistics	Sum of df	Covariate	Sum of Wald statistics	Sum of df
Age	15 811	2 002	Month of admission	814	610
Urgency	9 407	121	Comorbidity 11	773	85
Severity	4 487	296	SES	740	550
Source of admission	2 284	215	Comorbidity 9	658	93
Comorbidity 13	2 068	112	Comorbidity 5	358	91
Sex	1 958	120	Comorbidity 7	257	89
Comorbidity 3	1 217	109	Comorbidity 16	232	95
Comorbidity 6	1 128	116	Year	226	122
Comorbidity 2	1 018	96	Comorbidity 12	158	60
Comorbidity 1	992	112	Comorbidity 17	109	26
Comorbidity 10	989	118	Comorbidity 8	11	8
Comorbidity 14	987	106	Comorbidity 15	0	2
Comorbidity 4	900	91			

Compared to the 2017 intra-hospital readmission model (Van der Laan *et al.* 2019a), the current model was based on less data since no data for 2018 was included in the model for three

hospitals that had registered data in 2017 (one only partially). As a result, the number of significant covariates and the Wald statistics were slightly lower in the current model compared to the 2017 model. Nevertheless, the order of the variables remained largely comparable.

3.3 Model evaluation for the 122 regression analyses

Appendix II shows the Areas Under the Curve (AUCs; also known as C-statistics) for each of the 122 regression models. From these AUCs it can be concluded that most models have weak predictive power (this was also the case in the 2016 intra-hospital model and the 2017 model). Of the 122 diagnosis groups, only 20 have an AUC of 0.70 or above:

- Shock (diagnosis nr. 151): AUC = 0.78
- Joint disorders and dislocations; trauma-related; sprains and strains (diagnosis nr. 132): AUC = 0.77
- Other connective tissue disease (diagnosis nr. 126): AUC = 0.75
- Disorders of mouth, teeth, and jaw (diagnosis nr. 91): AUC = 0.75
- Open wounds of extremities (diagnosis nr. 141): AUC = 0.74
- Superficial injury; contusion (diagnosis nr. 144): AUC = 0.74
- Fracture of upper limb (diagnosis nr. 135): AUC = 0.73
- Other non-traumatic joint disorders (diagnosis no. 123): AUC = 0.73
- HIV infection (diagnosis nr. 5): AUC = 0.73
- Other and ill-defined heart disease (diagnosis nr. 66): AUC = 0.73
- Residual codes; unclassified (diagnosis nr. 157): AUC = 0.73
- Tuberculosis (diagnosis nr. 1): AUC = 0.73
- Open wounds of head; neck; and trunk (diagnosis nr. 140): AUC = 0.72
- Lymphadenitis and gangrene (diagnosis nr. 150): AUC = 0.72
- Other upper respiratory disease (diagnosis nr. 89): AUC = 0.72
- Multiple sclerosis and other degenerative nervous system conditions (diagnosis nr. 53): AUC = 0.71
- Other skin disorders, chronic ulcer of skin (diagnosis no. 120): AUC = 0.70
- Intracranial injury (diagnosis nr. 138): AUC = 0.70
- Burns (diagnosis nr. 145): AUC=0.70
- Fracture of lower limb (diagnosis nr. 136): AUC=0.70

Most (14/20) of these diagnosis groups also had AUCs above 0.70 in the 2017 model. In the 2017 model, however, only 14 diagnosis groups had an AUC of 0.70 or above.

3.4 Regression coefficients

The file “coefficients intra-hospital readmission index 2018.xslx” contains the estimated regression coefficients (columns ‘Estimate’) for each of the 122 logistic regressions as well as their standard errors (columns ‘Std. Err.’). For the sake of clarity, the reference categories are given in the first row of the corresponding covariates, and by definition have zero coefficient for each regression. In many cases categories are collapsed. This results in equal coefficients for the collapsed categories. If all categories were collapsed into one category for a certain variable and for a certain diagnosis group (i.e. if there was only one category with ≥50 admissions and ≥1 readmission), the variable was dropped from the model and all associated coefficients were set to zero. The significance of each of the coefficients is shown in Appendix I.

3.5 Limitations

The readmission indicator has largely the same limitations as the HSMR. Below we will address some issues that are specific to the readmission indicator.

- In principle all readmissions are included in the model: planned and unplanned; related and not related to the index admission. Ideally only unplanned readmissions should be included. However, these are not registered as such in the LBZ. The LBZ contains the variable urgency (acute versus not acute). An admission is registered 'acute' if care is needed within 24 hours and therefore does not seem to reflect the difference between planned and unplanned readmissions. To avoid the inclusion of planned readmissions, some diagnosis groups where planned readmissions are likely (for example the various groups concerning cancer) are excluded as index and readmissions. Also diagnoses that are likely planned readmissions (for example follow-up care and rehabilitation) are excluded as potential readmissions. Furthermore, in the present model (planned) transfers are excluded as readmissions. However, there will still be planned readmissions remaining in the dataset.
- Unlike with the HSMR, Statistics Netherlands does not provide readmission ratios for 2018, based on the model of 2018. DHD will use the estimated models to calculate the ratios using hospital data from 2019. This means that the models are applied to a different year than that on which they were estimated. As was shown for the readmission model 2015 (Van der Laan *et al.* 2017), this results in a bias and extra variance. Fortunately, the bias can be estimated and the overall average of the ratio can be presented to the hospitals.
- It is difficult to predict readmissions using the variables present in the models: the models explain only a small part of the observed variation. This makes it more likely that there are unobserved population differences that are not corrected for, that influence the readmission probability. This means that some of the differences in the current readmission ratio can be caused by unobserved population differences.
- The model described identifies intra-hospital readmissions only and readmissions that occur in another hospital are not identified. As a result, for hospitals where patients are often readmitted in another hospital, the indicator could underestimate the readmission ratio and vice versa.

4. Conclusion

The outcome of the 2018 readmission model is largely comparable to that of the models of the previous two years (the 2016 intra-hospital model and the 2017 model).

Like in the above-mentioned previous two models, ‘to and fro’ transfers are excluded as readmissions. This removes some of the noise from the model, as these transfers can be considered as planned readmissions, which are not of interest when the readmission ratio is used as an indicator of quality of care. Although several diagnosis groups consisting of diseases that require treatment during multiple, consecutive admissions have been excluded from the model, it is possible that the data still contains planned readmissions, resulting in a less reliable outcome. Although the predictive power of the model is generally low, the case mix correction performed by the model does remove some of the differences between the hospitals caused by population differences. However, because of the weak predictive power of the models, it is likely that there are still population differences remaining for which the model does not correct. Nevertheless, applying the model for calculating readmission ratios for individual hospitals is preferable to calculating crude rates.

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Appendix I: Results of the logistic regressions

Statistical significance (95% confidence) of the covariates for the 122 logistic regressions (1=significant; 0=non-significant; "-"=variable dropped because all categories are collapsed, due to < 50 admissions or no readmissions in all but one category).

Diagnosis group	Sex	Age	Urgency	Severity	Comorbidity_1	Comorbidity_2	Comorbidity_3	Comorbidity_4	Comorbidity_5	Comorbidity_6	Comorbidity_7	Comorbidity_8	Comorbidity_9	Comorbidity_10	Comorbidity_11	Comorbidity_12	Comorbidity_13	Comorbidity_14	Comorbidity_15	Comorbidity_16	Comorbidity_17	SES	Month admission	Source admission	Year
1	0	1	0	0	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	0	0	0	1
2	0	1	1	1	0	0	1	0	1	0	1	-	1	0	1	0	1	0	-	0	0	0	0	1	0
3	1	1	0	0	1	0	0	0	0	0	0	-	0	1	0	-	1	0	-	0	-	0	0	0	0
4	0	0	0	0	0	-	-	-	-	0	-	-	-	0	-	-	1	0	-	0	-	0	0	0	0
5	0	0	1	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	-	-	0	0	0	0
6	0	1	1	1	1	0	1	0	1	0	0	-	1	1	1	1	1	1	-	0	1	0	0	0	1
37	1	1	1	1	1	1	1	0	0	1	0	-	0	1	0	0	1	0	-	0	-	1	0	0	0
38	1	1	1	0	1	1	0	0	0	1	0	-	0	0	1	-	1	1	-	0	-	0	0	0	0
39	0	1	1	1	0	1	1	0	0	1	1	-	0	0	1	-	0	0	-	0	-	0	0	0	0
40	1	1	0	1	1	1	1	0	0	0	0	-	0	1	1	0	1	0	-	0	-	0	0	0	0
41	1	1	1	1	1	0	0	1	0	0	0	-	0	1	0	0	1	1	-	0	-	1	0	0	0
42	1	1	1	1	1	1	1	0	1	1	0	-	1	1	0	1	1	1	-	0	0	0	0	1	0
43	0	0	0	0	-	-	-	-	-	0	-	-	0	0	-	-	-	-	-	-	-	0	0	-	0
44	1	1	1	1	0	0	1	0	0	0	0	-	0	1	-	-	1	0	-	0	-	0	0	0	0
45	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	0	1	1	-	1	1	0	0	0	0
46	0	1	1	-	0	-	0	-	-	0	1	-	0	0	-	-	0	0	-	1	-	1	0	0	0
51	0	1	1	1	0	-	1	0	-	0	-	-	0	0	-	0	0	0	-	-	-	1	0	1	0
52	0	0	0	0	1	-	-	-	0	0	-	-	-	0	-	-	0	-	-	-	-	0	0	0	0
53	1	1	1	1	0	-	0	0	1	0	-	-	-	0	-	0	0	0	-	1	-	1	0	1	0
54	0	1	0	0	0	-	0	0	-	1	-	-	-	0	-	0	0	0	-	0	-	0	0	0	0
55	0	1	0	1	0	0	0	0	0	0	0	-	0	1	0	0	1	0	-	0	-	0	0	1	0
56	0	0	1	0	1	-	0	0	1	0	-	-	-	0	-	-	0	0	-	-	-	0	0	0	0
57	0	1	1	0	1	1	1	1	0	1	1	-	0	1	1	0	1	1	-	0	-	0	0	0	1
58	1	1	1	1	1	1	1	0	0	1	0	-	1	1	1	0	1	1	-	0	0	1	1	1	0
59	0	1	1	0	0	1	0	0	0	0	1	-	0	0	1	-	1	0	-	0	-	0	0	1	1
60	0	1	1	1	0	1	0	0	-	0	0	-	0	1	0	-	1	1	-	0	-	0	0	1	0
61	0	1	0	1	0	1	1	0	0	0	0	-	-	0	1	-	1	0	-	-	-	0	0	0	0
62	1	1	1	1	1	1	1	0	0	1	0	-	0	1	1	0	1	1	-	1	-	0	0	1	1
63	1	1	1	0	0	1	1	0	0	1	0	-	0	1	1	0	1	0	-	0	-	0	0	1	0
64	1	1	0	-	1	1	1	1	1	1	1	-	1	1	1	0	1	1	-	1	-	1	0	1	1
65	0	1	1	1	0	1	1	0	0	1	1	-	0	1	1	0	1	1	-	1	-	0	0	1	0
66	0	0	1	1	0	0	0	-	-	0	-	-	-	1	-	-	1	-	-	-	-	0	0	1	0
67	0	1	1	0	1	0	1	0	0	1	0	-	1	0	0	-	1	1	-	0	-	0	0	0	0
68	1	1	1	1	1	1	1	0	1	1	1	-	1	1	1	0	1	1	-	0	-	0	0	0	0
69	0	0	0	0	0	1	0	0	-	0	-	-	0	0	-	-	1	0	-	-	-	0	0	0	0
70	1	1	1	1	1	1	1	0	1	1	1	-	0	1	1	0	1	0	-	0	0	0	0	1	1
71	1	1	0	1	1	1	1	1	1	1	1	-	0	1	1	0	1	1	-	0	1	0	0	1	0

Diagnosis group	Sex	Age	Urgency	Severity	Comorbidity_1	Comorbidity_2	Comorbidity_3	Comorbidity_4	Comorbidity_5	Comorbidity_6	Comorbidity_7	Comorbidity_8	Comorbidity_9	Comorbidity_10	Comorbidity_11	Comorbidity_12	Comorbidity_13	Comorbidity_14	Comorbidity_15	Comorbidity_16	Comorbidity_17	SES	Month admission	Source admission	Year
72	1	1	0	1	1	1	1	1	0	1	0	-	0	1	1	1	0	1	-	0	-	0	0	0	0
73	1	1	1	1	1	1	1	0	1	0	1	-	0	1	1	0	1	0	-	0	-	0	0	0	0
74	1	0	1	1	0	0	0	0	0	0	0	-	0	0	0	0	1	0	-	0	-	1	0	0	0
75	1	1	1	1	0	1	1	0	0	0	0	-	-	0	1	-	1	0	-	0	-	0	1	0	0
76	1	1	0	1	1	1	1	1	0	1	0	-	1	0	1	0	1	0	-	0	-	0	1	0	0
77	1	1	1	1	0	0	1	0	0	1	1	-	1	1	1	-	1	1	-	0	1	0	0	0	0
78	1	1	1	1	1	1	1	0	1	1	1	-	0	0	1	0	1	1	0	0	0	0	1	1	0
79	1	0	0	0	1	1	0	0	1	1	0	-	0	0	0	0	1	1	-	0	-	0	0	0	0
80	1	1	1	0	0	1	1	0	1	1	1	-	1	1	0	1	1	1	-	0	-	0	0	0	0
81	0	1	0	0	0	0	0	0	1	0	0	-	-	0	-	-	0	1	-	0	-	0	1	1	0
82	1	1	1	1	1	1	1	0	1	0	0	-	1	1	0	0	1	1	-	0	0	1	1	1	1
83	0	1	0	-	0	1	0	1	0	1	1	-	0	1	0	-	0	0	-	-	-	0	0	1	1
84	1	1	0	-	0	0	1	1	1	1	-	-	-	0	0	0	0	0	-	0	-	0	0	0	0
85	1	1	1	1	0	1	1	1	0	0	0	-	1	1	0	-	1	0	-	0	-	0	0	1	0
86	0	0	0	0	0	1	0	0	-	1	-	-	1	0	-	-	1	0	-	0	-	0	0	1	0
87	0	1	0	0	0	-	-	-	-	0	-	-	-	0	-	-	-	0	-	0	-	0	0	-	0
88	0	1	0	1	1	1	1	0	0	1	0	-	0	0	0	0	1	1	-	0	-	0	0	1	0
89	0	1	1	1	1	1	1	0	0	1	0	-	1	1	1	1	1	1	-	0	-	0	1	0	0
90	0	1	0	1	1	1	1	0	1	1	0	-	1	0	1	0	1	1	-	0	0	0	0	0	0
91	0	1	1	1	0	-	1	-	-	0	-	-	-	1	-	-	0	1	-	0	-	0	0	0	0
92	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	-	0	1	-	0	0	0	0	0	0
93	0	0	0	0	0	-	1	-	-	0	-	0	0	1	-	-	0	1	-	-	-	0	0	-	0
94	1	1	0	1	1	0	1	-	-	0	0	0	0	1	1	-	0	0	-	0	0	0	0	0	0
95	1	1	0	-	0	0	1	-	-	0	0	-	0	1	-	-	1	1	-	0	-	0	0	0	0
96	0	1	1	0	0	-	1	-	-	0	-	-	0	0	-	-	1	0	-	0	0	1	0	0	0
97	1	1	1	0	1	1	1	0	0	1	0	-	1	1	0	-	1	1	-	0	-	0	0	0	0
98	1	0	1	-	0	-	1	-	-	0	-	-	0	0	-	-	0	0	-	-	-	0	0	0	0
99	1	1	0	0	0	0	0	0	0	1	0	-	0	1	1	0	0	0	-	0	-	0	0	0	0
100	1	1	1	1	1	0	1	0	0	1	0	-	0	1	0	-	1	1	-	0	-	0	0	1	0
101	1	1	1	1	0	0	0	-	0	0	0	-	0	0	0	-	1	1	-	0	-	0	0	0	0
102	1	1	1	1	1	0	1	0	0	1	0	0	1	1	0	1	1	1	-	1	1	0	0	0	1
103	0	1	1	1	0	0	0	-	-	0	-	0	0	0	1	-	1	1	-	-	1	1	0	1	0
104	1	1	1	1	1	0	1	1	0	0	0	-	1	1	0	-	1	0	-	0	1	1	0	1	0
105	0	1	0	1	0	0	0	0	1	0	0	-	0	0	0	-	1	1	-	0	0	0	0	0	0
106	0	1	1	1	1	1	1	0	1	1	0	0	1	1	0	0	1	0	-	0	1	0	0	0	0
107	0	1	1	1	0	0	0	0	0	0	0	-	1	0	0	-	1	0	-	0	-	0	0	0	0
108	1	1	1	1	1	1	1	0	0	1	1	-	1	1	1	0	1	0	-	0	-	0	0	0	0
109	1	1	0	1	0	0	0	-	-	0	0	-	0	1	0	-	1	1	-	0	-	0	0	0	0
110	0	1	0	0	0	1	0	0	1	0	1	-	0	0	1	-	1	0	-	0	1	0	0	0	0
111	0	1	1	0	1	0	1	0	0	0	1	-	1	0	0	-	1	1	-	0	-	0	1	0	0
112	1	1	1	1	1	1	1	0	1	1	1	-	1	1	1	0	1	1	-	1	0	1	0	0	0
113	1	1	1	1	1	0	1	0	0	0	0	-	0	1	1	1	1	1	-	1	-	0	0	1	1
114	1	1	1	1	1	0	1	0	1	0	0	-	0	1	0	-	0	0	-	0	-	0	0	0	0
115	-	1	1	1	1	1	0	0	0	1	0	-	0	0	1	-	0	0	-	0	-	0	0	0	0

Diagnosis group	Sex	Age	Urgency	Severity	Comorbidity_1	Comorbidity_2	Comorbidity_3	Comorbidity_4	Comorbidity_5	Comorbidity_6	Comorbidity_7	Comorbidity_8	Comorbidity_9	Comorbidity_10	Comorbidity_11	Comorbidity_12	Comorbidity_13	Comorbidity_14	Comorbidity_15	Comorbidity_16	Comorbidity_17	SES	Month admission	Source admission	Year
116	0	1	1	-	-	-	-	-	-	0	-	-	-	0	-	-	-	0	-	-	-	0	0	-	0
117	-	1	1	1	0	1	1	-	1	0	0	-	0	1	-	-	1	1	-	0	-	0	0	0	0
119	0	1	1	1	1	1	1	0	1	1	1	-	1	1	1	0	1	1	-	0	1	1	0	0	0
120	1	1	1	1	1	0	1	0	1	0	0	-	1	1	1	0	1	0	-	0	-	0	1	0	1
121	0	1	1	1	0	0	1	0	0	0	0	-	1	1	0	0	1	0	-	0	-	0	0	0	0
122	1	1	1	1	1	1	1	0	0	1	1	-	1	1	1	1	1	1	-	0	-	0	1	1	0
123	0	1	1	0	1	0	0	0	1	0	0	-	-	0	1	0	0	0	-	0	-	0	0	0	0
124	0	1	1	1	0	1	1	0	0	1	0	-	1	1	1	1	1	1	-	0	-	0	0	0	0
125	0	1	0	0	0	0	0	-	0	1	0	-	-	0	-	-	0	1	-	1	-	0	0	0	1
126	1	1	1	1	1	1	1	0	0	1	1	-	1	1	1	1	1	1	-	0	-	0	0	0	0
127	0	1	0	1	-	0	1	1	-	0	-	-	-	0	-	-	-	-	-	-	-	0	0	1	0
128	0	1	1	1	-	-	-	-	-	0	-	-	0	0	-	-	1	-	-	-	-	0	0	0	1
129	1	-	1	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	1	1
130	1	-	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	0	0
131	1	0	0	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	0	0
132	0	1	1	0	0	-	0	-	0	1	0	-	-	1	-	-	0	-	-	-	-	0	0	0	0
133	1	1	0	-	1	1	1	1	1	1	0	-	1	1	1	0	1	1	-	0	-	0	0	0	0
134	0	1	1	0	0	-	1	0	0	0	-	-	-	0	-	0	1	-	-	-	-	0	0	0	0
135	1	1	1	-	1	0	0	0	0	1	0	-	0	1	0	1	0	0	-	0	-	0	0	0	0
136	0	1	1	1	0	0	0	1	0	1	0	-	0	1	0	0	0	1	-	0	-	0	1	1	0
137	1	1	1	1	1	1	1	0	0	1	0	-	1	0	0	0	1	0	-	0	-	0	0	0	0
138	0	1	0	1	0	1	0	0	0	1	0	-	0	0	0	0	0	0	-	0	-	0	0	0	0
139	0	1	1	1	1	0	1	0	0	1	0	-	1	0	-	-	1	0	-	-	-	0	0	0	0
140	0	1	0	0	0	-	1	-	0	0	-	-	-	1	-	-	0	-	-	-	-	1	0	0	0
141	1	1	0	1	0	-	1	-	-	1	-	-	-	0	-	-	0	-	-	-	-	0	0	0	0
142	1	1	1	1	0	1	1	0	0	0	1	-	1	1	1	1	1	0	-	1	0	0	0	1	0
143	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0	-	1	0	0	0	1	0
144	0	1	0	0	1	1	1	0	1	1	1	-	0	0	1	0	1	0	-	0	-	0	0	0	0
145	1	0	0	0	-	-	-	-	-	0	-	-	-	1	-	-	-	-	-	-	-	0	0	0	0
146	1	1	0	1	0	1	1	0	0	1	0	-	0	1	1	0	1	0	-	0	-	0	0	1	0
147	1	1	1	0	0	0	1	0	0	0	-	-	0	0	0	-	0	0	-	0	-	0	0	1	0
148	1	1	0	-	1	1	1	1	0	1	0	-	1	1	1	0	1	1	-	0	-	0	0	1	0
149	1	1	1	-	0	0	1	0	0	0	0	-	0	0	0	0	1	1	-	0	1	0	0	1	0
150	0	1	0	1	1	0	1	-	-	0	-	-	-	0	1	-	0	0	-	-	-	0	1	0	0
151	0	1	-	0	0	0	-	-	-	-	-	-	-	0	-	-	0	-	-	-	-	1	0	0	0
152	0	1	0	-	1	1	0	0	0	0	0	-	0	0	1	0	1	0	-	0	-	0	0	0	1
153	1	1	1	0	0	1	1	0	0	1	0	-	1	1	0	-	1	0	-	0	0	0	0	0	0
154	1	1	1	-	0	1	0	0	0	0	0	-	0	1	0	-	1	1	-	0	-	0	0	0	1
155	0	1	0	0	0	-	1	-	-	0	-	-	-	1	-	-	1	0	-	0	-	0	0	1	0
156	1	1	1	0	1	1	1	0	0	1	0	-	1	1	1	0	1	1	-	1	-	0	0	1	0
157	1	1	1	0	0	0	1	0	0	1	0	-	0	0	1	0	1	1	-	1	-	1	0	1	0
	63	**106**	**77**	**70**	**54**	**56**	**75**	**14**	**30**	**56**	**26**	**1**	**39**	**64**	**49**	**12**	**82**	**51**	**0**	**14**	**11**	**18**	**13**	**39**	**17**

The numbers of the comorbidity groups in the header of the table above are the following comorbidities:

Comorbidity_1 - Acute myocardial infarction
Comorbidity_2 - Congestive heart failure
Comorbidity_3 - Peripheral vascular disease
Comorbidity_4 - Cerebral vascular accident
Comorbidity_5 - Dementia
Comorbidity_6 - Pulmonary disease
Comorbidity_7 - Connective tissue disorder
Comorbidity_8 - Peptic ulcer
Comorbidity_9 - Liver disease / Severe liver disease
Comorbidity_10 - Diabetes / Diabetes complications
Comorbidity_11 - Diabetes complications
Comorbidity_12 - Paraplegia
Comorbidity_13 - Renal disease
Comorbidity_14 - Cancer
Comorbidity_15 - HIV
Comorbidity_16 - Metastatic cancer
Comorbidity_17 - Severe liver disease

Appendix II: AUC

The area under the curve (AUC) or C-Statistic for the logistic regressions of the 122 main diagnosis groups.

Diagnosis group*)		Number of index admissions	Number of readmissions	AUC
1	Tuberculosis	788	89	0.73
2	Septicemia (except in labor)	6 809	909	0.62
3	Bacterial infection; unspecified site	4 023	590	0.61
4	Mycoses	1 053	190	0.64
5	HIV infection	419	72	0.73
6	Hepatitis, viral and other infections	13 576	1 183	0.65
37	Other and unspecified benign neoplasm	37 503	2 128	0.64
38	Thyroid and other endocrine disorders	12 525	952	0.69
39	Diabetes mellitus without complication	7 867	665	0.66
40	Diabetes mellitus with complications	12 328	2 137	0.65
41	Nutritional deficiencies and other nutritional, endocrine, and metabolic disorders	28 666	2 299	0.67
42	Fluid and electrolyte disorders	17 855	2 300	0.66
43	Cystic fibrosis	1 199	186	0.62
44	Immunity and coagulation disorders, hemorrhagic disorders	5 517	917	0.64
45	Deficiency and other anemia	21 817	3 443	0.62
46	Diseases of white blood cells	4 154	699	0.59
51	Meningitis, encephalitis, and other central nervous system infections	5 540	438	0.67
52	Parkinson`s disease	3 334	285	0.60
53	Multiple sclerosis and other degenerative nervous system conditions	7 156	715	0.71
54	Paralysis and late effects of cerebrovascular disease	2 168	147	0.67
55	Epilepsy and convulsions	21 039	1 717	0.59
56	Coma, stupor, and brain damage	1 193	132	0.66
57	Headache and other disorders of the sense organs	36 231	1 541	0.66
58	Other nervous system disorders	47 727	2 314	0.67
59	Heart valve disorders	19 520	1 861	0.59
60	Peri-, endo-, myocarditis, and cardiomyopathy	10 068	1 004	0.62
61	Essential hypertension, hypertension with compl., and secondary hypertension	5 882	469	0.67
62	Acute myocardial infarction	64 258	4 862	0.63
63	Coronary atherosclerosis and other heart disease	66 220	5 068	0.63
64	Nonspecific chest pain	35 149	2 183	0.64
65	Pulmonary heart disease	15 859	1 193	0.64
66	Other and ill-defined heart disease	1 088	101	0.73
67	Conduction disorders (heart disease)	12 127	846	0.62
68	Cardiac dysrhythmias	64 601	5 381	0.66
69	Cardiac arrest and ventricular fibrillation	4 814	291	0.62
70	Congestive heart failure, nonhypertensive	53 391	7 939	0.59
71	Acute cerebrovascular disease	66 515	4 657	0.63

Diagnosis group*)		Number of index admissions	Number of readmissions	AUC
72	Transient cerebral ischemia, and other cerebrovascular disease	23 659	1 918	0.65
73	Peripheral and visceral atherosclerosis	21 232	3 648	0.64
74	Aortic and other artery aneurysms	12 992	1 487	0.58
75	Aortic and arterial embolism or thrombosis	7 271	1 219	0.61
76	Other circulatory disease	15 266	2 131	0.62
77	Phlebitis, varicose veins, and hemorrhoids	6 694	681	0.65
78	Pneumonia	67 120	7 176	0.61
79	Influenza	12 676	1 124	0.62
80	Tonsillitis and upper respiratory infections	40 195	2 393	0.67
81	Acute bronchitis	13 972	1 117	0.62
82	Chronic obstructive pulmonary disease and bronchiectasis	64 205	11 425	0.56
83	Asthma	15 465	1 434	0.63
84	Aspiration pneumonitis; food/vomitus	3 290	522	0.62
85	Pleurisy; pneumothorax; pulmonary collapse	12 069	1 765	0.62
86	Respiratory failure; insufficiency; arrest	2 630	366	0.65
87	Lung disease due to external agents	819	139	0.64
88	Other lower respiratory disease	13 253	1 672	0.60
89	Other upper respiratory disease	33 526	2 485	0.72
90	Intestinal infection	27 405	2 646	0.64
91	Disorders of mouth, teeth, and jaw	11 077	285	0.75
92	Esophageal disorders	7 145	784	0.63
93	Gastroduodenal ulcer	2 288	226	0.64
94	Gastritis, duodenitis, and other disorders of stomach and duodenum	3 872	586	0.66
95	Appendicitis and other appendiceal conditions	33 531	2 064	0.56
96	Peritonitis and intestinal abscess	2 187	434	0.63
97	Abdominal hernia	25 199	1 970	0.65
98	Regional enteritis and ulcerative colitis	9 350	1 380	0.59
99	Intestinal obstruction without hernia	15 467	2 280	0.57
100	Diverticulosis and diverticulitis	18 568	2 098	0.62
101	Anal and rectal conditions	11 157	1 083	0.60
102	Biliary tract disease	67 800	8 882	0.64
103	Liver disease; alcohol-related	3 247	851	0.64
104	Other liver diseases	8 375	2 037	0.66
105	Pancreatic disorders (not diabetes)	16 664	3 139	0.55
106	Gastrointestinal hemorrhage	18 097	2 572	0.61
107	Noninfectious gastroenteritis	6 706	818	0.62
108	Other gastrointestinal disorders	21 016	2 761	0.61
109	Nephritis; nephrosis; renal sclerosis	7 158	769	0.65
110	Acute and unspecified renal failure	8 171	1 350	0.60
111	Chronic kidney disease	7 578	1 464	0.60
112	Urinary tract infections	47 458	5 821	0.59
113	Calculus and other diseases of urinary tract	43 829	5 791	0.62
114	Genitourinary symptoms and ill-defined conditions	14 363	1 865	0.66
115	Hyperplasia of prostate and other male genital disorders	22 001	1 746	0.61
116	Nonmalignant breast conditions	8 941	238	0.68

Diagnosis group*)		Number of index admissions	Number of readmissions	AUC
117	Prolapse and other female genital disorders	34 705	1 484	0.67
119	Skin and subcutaneous tissue infections	28 285	2 354	0.66
120	Other skin disorders, chronic ulcer of skin	10 163	970	0.70
121	Infective arthritis and osteomyelitis	6 806	773	0.63
122	Osteoarthritis, rheumatoid arthritis, and other musculoskeletal deformities	128 700	5 234	0.65
123	Other non-traumatic joint disorders	7 628	400	0.73
124	Spondylosis, back problems, and osteoporosis	47 394	2 425	0.67
125	Pathological fracture	2 990	304	0.65
126	Other connective tissue disease	22 655	953	0.75
127	Cardiac and circulatory congenital anomalies	4 612	426	0.62
128	Noncardiac congenital anomalies	14 496	899	0.67
129	Short gestation; low birth weight; and fetal growth retardation	31 380	2 410	0.66
130	Intrauterine hypoxia, perinatal asphyxia, and jaundice	24 289	1 114	0.54
131	Other perinatal conditions	100 840	4 673	0.53
132	Joint disorders and dislocations; trauma-related; sprains and strains	16 542	394	0.77
133	Fracture of neck of femur (hip)	39 970	2 464	0.60
134	Skull and face fractures, spinal cord injury	5 931	237	0.66
135	Fracture of upper limb	22 735	1 275	0.73
136	Fracture of lower limb	26 394	2 252	0.70
137	Other fractures	22 555	1 185	0.62
138	Intracranial injury	18 269	761	0.70
139	Crushing injury or internal injury	10 646	558	0.67
140	Open wounds of head; neck; and trunk	2 943	129	0.72
141	Open wounds of extremities	2 676	195	0.74
142	Complication of device, implant or graft	48 513	6 834	0.65
143	Complications of surgical procedures or medical care	49 901	6 681	0.59
144	Superficial injury; contusion	26 390	1 098	0.74
145	Burns	1 948	104	0.70
146	Poisoning by psychotropic agents, drugs, or other medications	15 389	1 103	0.66
147	Other injuries and conditions due to external causes	5 365	417	0.68
148	Syncope	22 221	1 336	0.63
149	Fever of unknown origin	12 295	1 733	0.62
150	Lymphadenitis and gangrene	2 634	289	0.72
151	Shock	394	45	0.78
152	Nausea and vomiting	6 976	1 142	0.58
153	Abdominal pain	22 753	2 484	0.59
154	Malaise and fatigue	5 359	613	0.66
155	Allergic reactions	4 908	255	0.68
156	Rehabilitation and other aftercare, medical examination/evaluation/screening	51 961	3 384	0.62
157	Residual codes; unclassified	34 244	1 725	0.73

*) The diagnosis group numbers refer to the file 'Classification of variables' published together with the HSMR 2018 methodological report (see Van der Laan *et al*. 2019b). In this file, the CCS-groups and

corresponding ICD-10 codes of the 157 diagnosis groups used for the HSMR are given. For the readmission ratio only 122 of these groups are used, but the numbering was kept the same.

Explanation of symbols

Empty cell	Figure not applicable
.	Figure is unknown, insufficiently reliable or confidential
*	Provisional figure
**	Revised provisional figure
2019–2020	2019 to 2020 inclusive
2019/2020	Average for 2019 to 2020 inclusive
2019/2020	Crop year, financial year, school year, etc., beginning in 2019 and ending in 2020
2017/18–2019/20	Crop year, financial year, etc., 2017/18 to 2019/20 inclusive

Due to rounding, some totals may not correspond to the sum of the separate figures.

Colophon

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