Methodological paper

Hospital Readmission Ratio:

Methodological report of the 2021 model

Jan van der Laan
Corine Witvliet-Penning
Agnes de Bruin

2023

Index

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 produced Hospital Readmission ratio models in principle on a yearly basis. However, because of the disruptions caused by the COVID-19 pandemic in 2020 and 2021, it was decided to not calculate models for 2019 and 2020 as the use of these models would have been limited. The model for 2019 for example would have been applied to admissions in 2020. Because of the severe disruptions in hospital care that occurred in 2020, especially in the first COVID-19 wave, it was unlikely that the model would have resulted in useful predictions. Now, in 2023 it was decided to continue the calculation of readmission ratio models using data from 2020 (excluding the first COVID-19 wave) and 2021.

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.

1.4 Aim of the current project

In the current project we produced an updated version ('2021 model') of the intra-hospital model, excluding planned transfers, based on LBZ data of 2020 (excluding the first COVID-19 wave) and 2021. COVID-19 was added to the model as a separate diagnosis group. For readmissions after COVID-19 admissions, the model was based on 2021 data only.

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 2020-2021, 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 2022. 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

In the present '2021 model' we largely used the same methods as in the previous intra-hospital model ('2018 model'), which excludes transfers as readmissions (Van der Laan *et al.* 2020). There are three changes in the 2021 model compared to the 2018 model:

- admissions of healthy persons, such as admissions of healthy new-borns or healthy parents accompanying sick children, were excluded as index admissions and possible readmissions;
- an additional diagnosis group was added for COVID-19[1]; and
- a new variable was used to measure social economic status.

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[2]. In accordance with the HSMR, we further clustered these groups into 158 diagnosis groups (diagnosis group 158 was added for COVID-19[1], containing the ICD-10 codes U07.1, U07.2 and U10.9), 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.* 2022). 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.

[1] Main diagnoses of ICD-10 code U07.1 (COVID-19, virus identified (lab confirmed)), U07.2 (COVID-19, virus not identified (clinically diagnosed)) or U10.9 (Multisystem inflammatory syndrome associated with COVID-19, unspecified).
[2] See https://www.cbs.nl/-/media/_excel/2022/43/classification-of-variables-hsmr-2021.xlsx

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 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. 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.

Admissions that do not meet the billing criteria of the Dutch Healthcare Authority are removed from the data in all model years. This primarily, but not exclusively, concerns one-day inpatient admissions where the patient returned home after discharge. Based on an algorithm using LBZ data DHD has added a variable to the LBZ dataset (from 2019 onwards) that indicates whether the admission meets the billing criteria or not. This variable was used to exclude the admissions not meeting the billing criteria. 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.

For the 2021 model, admissions of healthy persons were also excluded. These are for example admissions of healthy newborns, a healthy parent accompanying a sick child, or other healthy boarders. These are identified based on the main diagnosis of the admission (ICD-10 code Z76.2-Z76.4) or based on procedure codes. Admissions were excluded based on procedure codes if for each bed-day of the admission a procedure code for a stay of a healthy person has been registered (Dutch procedure codes 190032, 190033 ('Zorgactiviteiten' codes), 339911 or 339912 ('CBV' codes)).

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.

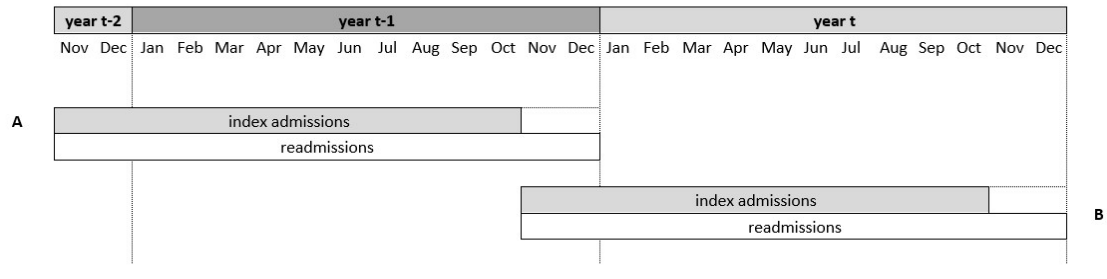
However, two of the three short-stay specialised hospitals participating in the LBZ were excluded from the hospital readmission model as these two hospitals treat patients with oncological diseases, which are excluded from the data (see paragraph 2.3.5).

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

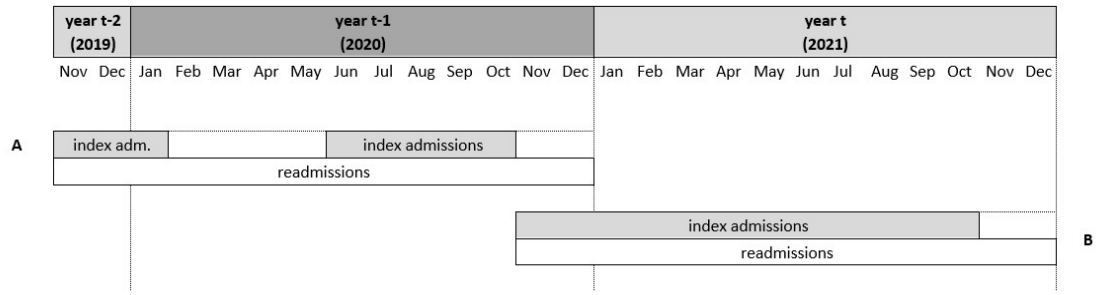
For the calculation of the current model, LBZ data of 2020 and 2021 was used. Previously we have shown that to identify the highest percentage of readmissions ending in year *t*, using index admissions with a discharge date from November 1st of year *t-1* up to October 31st of year *t* (study period) is optimal (Van der Laan *et al.* 2017). Thus, for study period 2020 ('year'=2020 in the model) we would normally select index admissions with a discharge date from November 1st 2019 up to October 31st 2020 and for study period 2021 we select index admissions with a discharge date from November 1st 2020 up to October 31st 2021 ('year'= 2021 in the model), see figure 2.3.4.1. However, for study period 2020 we excluded index admissions from February 1st up to May 31st as this covers most of the first COVID-19 wave of the pandemic in the Netherlands when hospital care was severely disrupted. For the current model the (adapted) study periods are displayed in figure 2.3.4.2. The occurrence of readmissions was analysed in the period between November 1st 2019 up to December 31st 2021. 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 Usual study periods 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

2.3.4.2 Study periods used for identifying index admissions and readmissions in the 2021 model.



A study period t-1 (2020) using hospital IDs from year t-1 (2020) for all admissions
B study period t (2021) using hospital IDs from year t (2021) for all admissions

Figure 2.3.4.2 shows which LBZ data is included in both study periods in the current 2021 model. 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 admission was not an admission of a healthy person. Admissions of healthy persons either have ICD-10 code Z76.2-Z76.4 as main diagnosis or each bed-day of the admission is registered with a procedure code for a stay of a healthy newborn or healthy mother (Dutch procedure codes 190032, 190033 ('Zorgactiviteiten' codes), 339911 or 339912 ('CBV' codes).
- The date of discharge was from November 1st 2019 up to January 31st 2020 or from June 1st up to October 31st 2020 ('year *t-1*'= 2020), or from November 1st 2020 up to October 31st 2021 ('year *t*'= 2021). For diagnosis group COVID-19 (diagnosis group 158, containing the ICD-10 codes U07.1, U07.2 and U10.9) only discharges of 2021 (year t) were included.

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 admission was not an admission of a healthy person. Admissions of healthy persons either have ICD-10 code Z76.2-Z76.4 as main diagnosis or each bed-day of the admission is registered with a procedure code for a stay of a healthy newborn or healthy mother (Dutch procedure codes 190032, 190033 ('Zorgactiviteiten' codes), 339911 or 339912 ('CBV' codes).
- 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 subsequent admission is unknown in this specific situation, the subsequent admission is not identified as a readmission. When the admission date of the subsequent admission in the same hospital precedes the discharge date of the index admission (overlapping admissions), the subsequent admission is not identified as a readmission either.

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 - Admissions that meet the billing criteria	- Inpatient admissions registered in the LBZ - Completely registered admissions with a registered main diagnosis - Admissions of Dutch residents - Admissions that meet the billing criteria
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 admission is not an admission of a healthy person (either main diagnoses Z67-2-Z67.4 or each bed-day registered with procedure code 190032, 190033 ('Zorgactiviteiten' codes), 339911, or 339912 ('CBV' codes)).	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). The admission is not an admission of a healthy person (either main diagnoses Z67-2-Z67.4 or each bed-day registered with procedure code 190032, 190033 ('Zorgactiviteiten' codes), 339911, or 339912 ('CBV' codes)).
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); date of discharge is not between February 1st and May 31st 2020.	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.

Note that the main diagnosis of the readmission does not have to be related to the main diagnosis of the index admission. This is also the case for the admissions with main diagnosis COVID-19, that can be identified as readmissions to admissions with other main diagnoses. As the location of the COVID-19 infection (hospital or elsewhere) is not known, it is in general not known whether these COVID-19 readmissions are actually related to 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, when index admissions are followed by a transfer, these index admissions (by definition) cannot have a readmission. Although index admissions that are followed by a transfer cannot have readmissions, these index admissions are not removed from the model.

Second, transfers cannot be readmissions. 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 0. 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.

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.

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.

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 158 diagnosis groups (as used for the HSMR) are fully excluded. Therefore, the model included 123 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).

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.* 2022). 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.* 2022). The socio-economic status (SES) variable has changed compared to the previous model. The previous SES variable was based on SES scores of the Netherlands Institute for Social Research (SCP). The current variable is calculated by Statistics

Netherlands and is based on the welfare (combination of income and wealth), level of education and recent labour participation of the households in a postal code area. For more details and a comparison between the scores see the HSMR report (Van der Laan *et al.* 2022). 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 index admissions with main diagnosis COVID-19 a slightly different set of covariates was used. First, this model is only estimated for year 2021. Therefore year is not included in the model. Second, as 'severity of main diagnosis' is based on historic data and no historic data on COVID-19 mortality is yet available, it was decided to use the three separate ICD10 subdiagnoses as separate categories in the model. Finally, for the COVID-19 model a more detailed variable 'month of admission 2021' was used instead of the 2 month variable. This new variable includes all months of the year as separate 1-month categories and includes an additional category 'before 2021' for admissions that started before November 2020. This new variable was introduced to be able to follow in more detail outcome of the different COVID-19 waves. By adding the category 'before 2021' admissions that had started in e.g. October 2020 are separated from admissions that had started in October 2021 (category 'October').

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*.
    - **ICD-10 subdiagnosis** (for COVID-19 instead of 'Severity of main diagnosis'): *U07.1, U07.2, U10.9*
- **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.*
    - **Month of admission 2021** (for COVID-19 instead of 'Month of admission'). 13 categories: *0-before 2021* (month of admission up to October 2020), *11-November, 12-December, 1-January, 2-February, …, 10-October.*
- **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 123 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 2021 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 (2020 and 2021). Specialised hospitals where patients are mostly treated for oncological disease (two in 2020 and 2021) were excluded.

3.1.1 Number of hospitals in the 2021 model.

Study period		General hospitals	University hospitals	Selected specialised hospitals[a)]	Total hospitals
2020	Total number	64	8	3	75
	Used in model	64	8	1	73
2021	Total number	64	8	3	75
	Used in model	64	8	1	73

a) Specialised hospitals participating in the LBZ (one eye hospital and two cancer hospitals)

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. Because for part of 2020 admissions were excluded, the number of admissions in 2020 is substantially lower than in 2021. In both years the number of admissions is lower than in the readmission model for 2018 (Van der Laan *et al.* 2020), because the COVID-pandemic caused a drop in total hospital admissions. The unadjusted readmission rates, however, are quite similar; in 2021 (8.6%) a bit lower than in previous years (9.0% in 2017, 8.9% in 2018, and 8.8% in 2020).

3.1.2 Admissions and readmissions in 2021 model.

	2020	2021
Total number of index admissions included in model	742 733	1 039 097
Number of identified readmissions	65 090	89 514
Unadjusted readmission rate	8.8%	8.6%

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 123 regression models (one for each diagnosis group, including the new diagnosis group COVID-19). Tables 3.2.1 and 3.2.2 show the total number of significant covariates and the total Wald statistics for the 123 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). As explained in section 2.6 the model for COVID-19 uses different variables for month of admission and severity. In the tables below (and also in the appendix)

these are included in the results for the regular month of admission and severity variables. The results for the COVID-19 model are discussed in more detail in section 3.4.

3.2.1 Statistical significance of the covariates for the 123 logistic regressions (summary), model 2021.

Covariate	No. of significant results	Covariate	No. of significant results
Age	92	Comorbidity 9	34
Comorbidity 13	69	Comorbidity 7	21
Urgency	67	Comorbidity 5	20
Severity[a]	66	Comorbidity 16	19
Comorbidity 3	63	Year	15
Comorbidity 6	57	Month of admission[a]	15
Comorbidity 10	54	Comorbidity 4	13
Sex	53	SES	13
Comorbidity 14	50	Comorbidity 12	8
Comorbidity 2	49	Comorbidity 17	6
Source of admission	48	Comorbidity 15	0
Comorbidity 1	45	Comorbidity 8	0
Comorbidity 11	41		

[a] For the model for COVID-19 the ICD-10 subdiagnosis was used instead of severity, and month of admission was also coded differently. See section 2.6.

3.2.2 Wald chi-square statistics for the 123 logistic regressions, model 2021.

Covariate	Sum of Wald statistics	Sum of df	Covariate	Sum of Wald statistics	Sum of df
Age	10 248	1 917	Comorbidity 10	718	118
Urgency	6 145	120	SES	689	537
Severity[a]	2 710	283	Comorbidity 11	551	79
Source of admission	1 982	205	Comorbidity 9	509	80
Comorbidity 13	1 658	112	Comorbidity 5	292	82
Sex	1 290	121	Comorbidity 7	211	93
Comorbidity 3	1 217	106	Comorbidity 16	209	95
Comorbidity 14	910	106	Year	191	122
Comorbidity 2	904	98	Comorbidity 12	88	55
Comorbidity 6	871	117	Comorbidity 17	68	19
Comorbidity 4	870	78	Comorbidity 8	5	6
Month of admission[a]	781	614	Comorbidity 15	2	2
Comorbidity 1	755	113			

[a] For the model for COVID-19 the ICD10 subdiagnosis was used instead of severity, and month of admission was also coded differently. See section 2.6.

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 2021 model (Van der Laan *et al.* 2022) this is also the case, indicating that these variables are relevant for both predicting readmissions and in-hospital mortality.
For the 2021 readmission model, sex and Charlson comorbidity 10 (Diabetes) are more important compared to the 2021 HSMR model, while for the 2021 HSMR model the Charlson comorbidities 16 (metastatic cancer) and 17 (severe liver disease) are more important than for the 2021 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 (metastatic cancer) 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.

Compared to the 2018 readmission model (Van der Laan *et al.* 2020), the current model was based on less data because of the drop in hospital admissions caused by the COVID-19 pandemic and the exclusion of several months of 2020 from the model. As a result, the number of significant covariates and the Wald statistics was slightly lower in the current model compared to the 2018 model. Nevertheless, the order of the variables remained largely comparable.

3.3 Model evaluation for the 123 regression analyses

Appendix II shows the Areas Under the Curve (AUCs; also known as C-statistics) for each of the 123 regression models. From these AUCs it can be concluded that most models have weak predictive power. This is comparable with earlier models. Of the 123 diagnosis groups, only 19 have an AUC of 0.70 or above. This is one less than for the 2018 model. The diagnosis groups with a AUC of 0.7 or above are largely (13/19) the same as in 2018. The average AUC is 0.651; for 2018 this was 0.645. Therefore, on average the AUCs have improved slightly compared to 2018. However, there are a number of models for which the AUC has changed substantially: both in positive and negative direction. There are 37 models for which the AUC has changed more than 0.02 and 9 models for which the AUC has changed more than 0.04. For an overview see table 3.3.1.

3.3.1 Diagnosis groups with a change in the AUC of larger than 0.04.

Diagnosis group		AUC 2018	AUC 2021	Difference
87	Lung disease due to external agents	0.64	0.76	0.11
5	HIV infection	0.73	0.64	-0.09
157	Residual codes; unclassified	0.73	0.65	-0.08
53	Multiple sclerosis and other degenerative nervous system conditions	0.71	0.63	-0.08
79	Influenza	0.62	0.70	0.08
134	Skull and face fractures, spinal cord injury	0.66	0.73	0.07
91	Disorders of mouth, teeth, and jaw	0.75	0.82	0.07
54	Paralysis and late effects of cerebrovascular disease	0.67	0.72	0.05
52	Parkinson`s disease	0.60	0.64	0.05
145	Poisoning by psychotropic agents, drugs, or other medications	0.70	0.66	-0.04

It is not always clear why the predictive power of the models has changed. Because of the COVID-19 pandemic there have been changes in the admissions in the hospitals. This is, for example, visible in the number of admissions and readmissions as will be discussed below. However, 3 years have passed since the last model and during that period there may also have been other changes in hospital care not related to COVID-19.

As mentioned before, the COVID-19 pandemic will have caused (temporary) changes in the admission and readmission policies of hospitals. To avoid large deviations in the models it was therefore decided to exclude the admissions in the first COVID-19 wave, where disruptions in hospital care were most severe. As was mentioned in section 3.1 the overall raw readmission rate of the admissions included in the model has not changed much since 2018. However, within specific diagnosis groups the changes can be larger. Table 3.3.2 shows the ten diagnosis groups with the largest change in the fraction of readmissions. A number of diagnosis groups from table 3.3.1 also show up in this table. For example for diagnosis group 157 (residual codes; unclassified) the number of admissions dropped by almost a factor three. The readmission rate increased by a factor 1.6 while the AUC decreased with 0.08. The relatively large change in this group can be explained by the exclusion of admissions of healthy persons from the model which mainly have diagnoses in this group (see section 0). For other diagnosis groups it is less clear what causes the changes.

3.3.2 The ten diagnosis groups with the largest absolute change in the readmission fraction.

		Number of admissions		Number of readmissions		Fraction readmissions	
Diagnosis group		**2018**	**2021**	**2018**	**2021**	**2018**	**2021**
87	Lung disease due to external agents	819	616	139	79	0.17	0.13
43	Cystic fibrosis	1 199	875	186	165	0.16	0.19
157	Residual codes; unclassified	34 244	11 678	1 725	969	0.05	0.08
44	Immunity and coagulation disorders, hemorrhagic disorders	5 517	3 950	917	772	0.17	0.20
111	Chronic kidney disease	7 578	5 281	1 464	916	0.19	0.17
1	Tuberculosis	788	542	89	51	0.11	0.09
150	Lymphadenitis and gangrene	2 634	1 372	289	125	0.11	0.09
105	Pancreatic disorders (not diabetes)	16 664	14 488	3 139	2 468	0.19	0.17
154	Poisoning by psychotropic agents, drugs, or other medications	5 359	2 995	613	396	0.11	0.13
81	Acute bronchitis	13 972	10 720	1 117	680	0.08	0.06

The changes in the model fit, number of admission and readmissions are larger than seen in previous years the model was estimated. It is likely that this is for a considerable part caused by the effects of the COVID-19 pandemic on hospital care. This also results in bigger changes in the estimated parameters. Therefore, although the overall model quality has remained largely the same, at individual level the current model can predict different readmission probabilities than the previous models. It is also not clear whether the changes seen in 2020 and 2021 still hold in later years. Therefore, one has to be extra cautious when applying these models to data of other years than that of 2020 and 2021.

3.4 COVID-19 model

The original set of 157 main diagnosis groups has been extended to 158 with a separate diagnosis group for admissions with main diagnosis COVID-19. This groups includes admissions with main diagnoses U07.1, U07.2 and U10.9. In principle the same model was used as for the other diagnosis groups. However, two changes were applied. First, as no historical data is present to determine the severity for the subdiagnoses within this group, the three ICD-10 codes of the subdiagnoses in this group were added as a covariate instead of the regular severity variable. The model can therefore estimate different average readmission probabilities for each of the three subdiagnoses. Second, as in 2021 the number of patients with COVID-19 varied substantially between the months and different variants of the virus were dominant in different months, it was decided to code month of admission in more detail. As explained in section 2.6, a variable with 13 categories was used.

3.4.1 Summary of model for COVID-19, 2021.

Covariate	Significant (95% confidence)	Wald score	Degrees of freedom
Sex	*	83	1
Age	*	624	20
Urgency	*	71	1
Severity (ICD-10 diagnosis)		2	2
Comorbidity 1	*	48	1
Comorbidity 2	*	30	1
Comorbidity 3	*	16	1
Comorbidity 4		0	1
Comorbidity 5		4	1
Comorbidity 6	*	37	1
Comorbidity 7	*	18	1
Comorbidity 8[a]	-	-	-
Comorbidity 9		0	1
Comorbidity 10		0	1
Comorbidity 11	*	24	1
Comorbidity 12		2	1
Comorbidity 13	*	57	1
Comorbidity 14	*	68	1
Comorbidity 15[a]	-	-	-
Comorbidity 16		0	1
Comorbidity 17		3	1
SES		3	5
Month of admission (separate months)	*	24	12
Source of admission	*	401	2
Year[a]	-	-	-

[a] *Not included in the model or the different categories of the variable did not have enough admissions or readmissions and were, therefore, removed from the model.*

The COVID-19 model was estimated only for the year 2021 (index admissions from November 2020 to November 2021). This resulted in 51 267 index admissions with a total number of 3 859 readmissions, resulting in a raw readmission rate of 7.5%. The estimated model has an AUC of 0.68 which is not high, but comparable to that of the other models (the average is 0.65).

Table 3.4.1 shows a summary of the model. Age and source of admission are the two most important predictors (highest Wald scores). The other covariates have only limited predictive power. Severity, as coded by the ICD-10 subdiagnosis, is not significant in the model. In the COVID-19 HSMR model (Van der Laan, 2022), severity had no high predictive power either. Apparently, the probability of readmission does not depend on the specific subdiagnosis of COVID-19. This may be partly caused by the fact that the number of admissions with subdiagnosis U07.2 (COVID-19, virus not lab confirmed) and U10.9 (Multisystem inflammatory syndrome associated with COVID-19) are small compared to the number of admissions with subdiagnosis U07.1 (COVID-19, virus lab confirmed). Month of admissions is significant in the model, but the effect is limited (low Wald score), despite the refinement of the variable in individual months. Comparable with the model for COVID-19 for the HSMR, the relatively low predictive power of urgency can be explained by the fact that 95% of the COVID-19 admissions are acute.

3.5 Regression coefficients

The file "coefficients intra-hospital readmission index 2021.xslx" contains the estimated regression coefficients (columns 'Estimate') for each of the 123 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.

3.6 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 2021, based on the model of 2021. DHD will use the estimated models to calculate the ratios using hospital data from 2022. 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. As was explained in section 3.3 the model of 2021 shows relatively large changes when compared to the model

for 2018. This is probably partly caused by the effects of the COVID-19 pandemic. As the effects of the pandemic on hospital care are probably different in 2022 compared to 2020-2021, it is likely that the 2021 model will fit not as good on new years of data than it did previously.

- 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

In general the quality of the 2021 models is similar to that of previous versions of the hospital readmission models. However, there have been some shifts in quality and estimated parameters for the models of some of the diagnosis groups. Partly this will be caused by three years of time between the current models and the previous set for 2018, but it is likely that the COVID-19 pandemic and the impact this had on hospital admissions in the current study periods also had its effect. Therefore, care has to be taken when applying these models to new years of data.

The models now also include an additional model for COVID-19. The performance of this model is comparable to the other models: the C-statistic is close to the average of the other models.

Like in the previous 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.

References

HSCIC (2016). Indicator Specification: Summary Hospital-level Mortality Indicator. Version 1.22, 24 February 2016. Health & Social Care Information Centre. https://digital.nhs.uk/data-and-information/publications/ci-hub/summary-hospital-level-mortality-indicator-shmi

Kansagara D., H. Englander, A. Salanitro, D. Kagen, C. Theobald, M. Freeman and S. Kripalani (2011). Risk prediction models for hospital readmission: a systematic review. The Journal of the American Medical Association 306(15), pp. 1688-98. DOI: 10.1001/jama.2011.1515.

R Core Team (2015). R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/

Van der Laan J., C. Penning and A. de Bruin (2017). Hospital Readmission Ratio. Methodological report of 2015 model. Statistics Netherlands, The Hague. https://www.cbs.nl/en-gb/our-services/methods/surveys/aanvullende%20onderzoeksbeschrijvingen/hospital-readmission-ratio-model-2015

Van der Laan J., C. Penning and A. de Bruin (2018). Hospital Readmission Ratio. Methodological report of 2016 models. Statistics Netherlands, The Hague. https://www.cbs.nl/en-gb/our-services/methods/surveys/aanvullende%20onderzoeksbeschrijvingen/hospital-readmission-ratio-models-2016

Van der Laan, J., C. Penning and A. de Bruin (2020). Hospital Readmission Ratio. Methodological report of the 2018 model. Statistics Netherlands, The Hague. https://www.cbs.nl/en-gb/our-services/methods/surveys/comprehensive-description/hospital-readmission-ratio-model-2018

Van der Laan, J., D. Kolk, C. Witvliet and A. de Bruin (2022). HSMR 2021: Methodological report, Statistics Netherlands, The Hague. https://www.cbs.nl/en-gb/our-services/methods/surveys/aanvullende%20onderzoeksbeschrijvingen/hsmr-2021-methodological-report

Appendix I: Results of the logistic regressions

Statistical significance (95% confidence) of the covariates for the 123 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[a]	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[a]	Source admission	Year
1	0	1	1	0	-	-	-	-	-	0	-	-	-	0	-	-	-	-	-	-	-	0	0	0	0
2	0	0	0	0	0	0	1	0	0	0	1	-	1	1	0	0	0	0	-	0	-	0	0	0	0
3	0	1	0	0	0	0	1	0	0	0	0	-	0	0	1	-	1	1	-	0	0	0	0	0	0
4	0	0	0	0	0	-	0	-	-	0	-	-	-	0	-	-	0	0	-	0	-	0	0	0	0
5	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	-	-	0	0	-	0
6	1	1	0	1	0	1	1	0	0	1	0	-	1	0	0	0	1	1	-	0	-	0	0	0	0
37	1	1	1	1	1	1	1	1	0	1	1	-	0	1	0	0	1	0	-	0	-	0	0	0	1
38	1	0	1	0	0	1	1	0	0	1	0	-	0	0	1	-	1	0	-	0	-	1	1	0	0
39	0	1	0	-	0	0	1	0	0	0	1	-	1	1	0	-	0	1	-	0	-	0	0	0	0
40	1	1	1	1	1	1	1	0	0	1	0	-	0	0	1	0	1	0	-	0	-	0	1	1	0
41	1	1	1	1	0	1	1	1	1	0	0	-	0	1	0	0	1	1	-	0	-	0	0	1	0
42	0	1	1	1	0	1	1	0	1	0	1	-	0	0	1	0	1	1	-	0	1	0	0	0	0
43	0	0	1	0	-	-	-	-	-	0	-	-	0	0	-	-	-	-	-	-	-	0	0	-	0
44	1	1	0	0	0	0	0	0	-	0	0	-	0	1	-	-	0	0	-	0	-	0	0	1	0
45	1	1	0	1	0	1	1	0	1	1	0	0	1	1	1	0	1	0	-	0	0	0	0	0	1
46	0	1	0	-	0	0	0	-	-	0	0	-	-	1	-	-	1	0	-	1	-	0	0	0	0
51	0	1	1	1	0	-	0	0	-	0	0	-	-	0	-	0	0	1	-	1	-	0	0	1	0
52	0	0	0	-	1	-	-	-	0	0	-	-	-	0	-	-	0	-	-	-	-	0	0	0	0
53	0	1	0	0	0	-	1	1	0	0	-	-	-	0	-	0	0	0	-	0	-	0	0	0	0
54	1	1	1	0	0	-	0	0	-	0	-	-	-	0	-	0	0	0	-	0	-	0	0	0	0
55	0	1	0	1	0	1	0	0	0	0	1	-	0	0	0	0	0	0	-	0	-	0	0	0	0
56	0	0	-	1	0	-	-	-	0	0	-	-	-	0	-	-	0	-	-	-	-	0	0	0	1
57	1	1	1	0	1	0	1	1	0	1	0	-	0	0	0	0	1	1	-	0	-	0	0	0	0
58	0	1	1	1	0	1	0	0	0	1	0	-	0	0	1	0	0	1	-	1	-	0	0	1	0
59	1	1	1	0	0	0	1	0	0	0	0	-	1	0	0	-	1	0	-	0	-	0	0	1	0
60	0	1	1	1	0	0	0	0	-	0	0	-	0	1	1	-	1	0	-	0	-	0	0	1	0
61	0	0	0	1	0	1	1	1	-	0	1	-	-	1	1	-	1	1	-	-	-	0	0	0	0
62	1	1	1	1	1	1	1	0	0	1	1	-	1	1	1	0	1	1	-	0	-	0	0	1	1
63	1	1	1	0	0	1	1	1	0	1	0	-	0	1	0	0	1	1	-	0	-	1	0	1	0
64	0	1	0	-	1	1	1	1	0	1	0	-	1	1	1	-	1	1	-	0	-	0	0	1	0
65	0	0	1	0	1	1	1	0	0	1	1	-	0	0	1	0	1	1	-	1	-	0	0	0	0
66	0	0	0	0	0	0	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	0	0	0	0
67	0	0	1	1	0	1	1	0	0	1	0	-	-	1	1	-	1	0	-	0	-	1	0	0	0
68	1	1	1	1	1	1	1	0	1	1	0	-	1	1	1	0	1	1	-	0	-	0	0	1	0
69	0	0	0	0	0	0	0	0	-	1	-	-	-	0	1	-	0	0	-	-	-	0	0	1	0
70	1	1	1	-	1	1	1	0	1	1	1	-	0	1	1	0	1	1	-	1	1	0	0	1	1
71	1	1	1	1	1	0	1	1	1	1	0	-	0	1	1	1	1	1	-	0	-	0	0	1	1

Diagnosis group	Sex	Age	Urgency	Severity[a]	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[a]	Source admission	Year
72	1	1	1	1	1	0	1	1	0	1	0	-	0	1	0	0	1	1	-	0	-	0	0	0	0
73	1	1	1	1	1	1	0	0	0	1	1	-	1	1	1	0	1	1	-	1	-	0	0	1	0
74	0	0	1	1	0	1	1	1	0	1	0	-	0	1	-	0	0	0	-	0	-	0	0	1	0
75	0	0	1	1	1	0	1	0	-	1	0	-	-	0	1	-	0	0	-	0	-	0	0	0	0
76	0	1	0	1	0	1	1	0	0	1	0	-	1	1	1	0	1	0	-	0	-	1	0	0	1
77	1	0	1	1	0	1	1	-	-	1	0	-	0	0	0	-	0	1	-	0	1	0	1	0	0
78	1	1	0	1	1	1	1	0	1	1	1	-	0	1	1	0	1	1	0	0	0	0	0	1	0
79	0	1	-	0	0	0	0	-	0	1	1	-	-	1	-	-	0	0	-	-	-	1	0	0	0
80	1	1	1	0	0	1	0	0	0	0	0	-	0	0	-	-	1	1	-	0	-	0	0	0	0
81	0	1	0	1	0	1	0	-	-	0	0	-	-	0	-	-	1	1	-	0	-	0	0	1	0
82	1	1	1	1	1	1	1	0	0	0	0	-	0	1	0	0	1	1	-	0	-	1	1	1	0
83	1	1	0	-	0	1	0	-	-	0	0	-	-	1	-	-	0	0	-	-	-	0	0	1	0
84	0	1	0	-	1	0	1	0	0	0	0	-	-	0	0	0	0	0	-	0	-	0	1	0	0
85	0	1	1	0	1	0	1	0	0	1	0	-	1	0	1	-	0	0	-	0	-	0	0	0	0
86	1	0	0	0	0	0	0	-	-	1	-	-	-	1	-	-	0	0	-	-	-	1	1	1	0
87	0	1	0	0	0	-	-	-	-	0	-	-	-	0	-	-	-	0	-	0	-	1	0	-	0
88	0	1	0	0	1	1	1	0	0	1	0	-	0	0	0	0	1	0	-	0	-	0	0	0	0
89	0	1	1	1	0	1	1	0	0	1	0	-	0	0	0	1	1	1	-	0	-	0	0	0	0
90	0	1	0	1	0	0	1	0	0	1	0	-	1	0	1	0	1	1	-	0	0	0	0	0	0
91	0	1	1	1	0	-	0	-	-	1	-	-	-	1	-	-	0	1	-	0	-	0	1	0	0
92	0	0	1	1	0	0	0	-	0	0	0	0	0	0	0	-	1	1	-	0	0	0	0	0	0
93	0	0	0	1	0	-	0	-	-	1	-	-	0	0	-	-	0	1	-	-	-	0	0	0	0
94	0	1	0	1	1	0	0	-	-	0	0	0	0	1	1	-	1	0	-	0	0	0	0	0	0
95	0	1	0	-	0	0	0	-	-	1	0	-	0	0	-	-	0	0	-	1	-	0	0	0	0
96	0	0	0	1	0	0	0	-	-	0	-	-	1	1	-	-	1	0	-	0	0	0	0	0	1
97	1	1	1	0	1	0	0	0	0	1	1	-	1	1	0	-	1	0	-	1	-	0	0	0	0
98	0	0	1	0	0	-	0	-	-	1	-	-	0	0	-	-	0	0	-	-	-	0	1	0	0
99	0	0	0	0	0	0	0	1	0	0	1	-	0	0	1	1	1	0	-	0	-	0	0	1	0
100	0	1	1	1	1	0	1	0	0	0	0	-	0	1	0	-	1	0	-	0	-	0	0	0	0
101	0	1	1	1	0	0	0	-	-	1	0	-	-	0	-	-	0	1	-	0	-	0	0	0	0
102	1	1	1	1	1	0	1	0	1	1	1	0	1	1	1	1	1	1	-	1	1	1	1	0	0
103	0	1	1	1	0	0	0	-	-	1	-	-	0	1	-	-	0	0	-	-	0	0	0	0	0
104	1	1	1	1	0	0	0	0	0	0	1	-	1	1	0	-	1	0	-	1	0	0	0	1	0
105	0	1	0	0	0	1	0	0	0	0	0	-	1	0	1	-	1	1	-	1	0	0	0	1	0
106	0	1	0	1	1	1	1	0	1	1	0	0	1	1	1	0	1	0	-	0	1	0	0	1	0
107	0	1	0	0	0	1	0	-	-	0	0	-	0	0	0	-	1	0	-	1	-	0	0	0	0
108	1	1	1	1	1	1	1	0	1	0	0	-	0	0	0	0	1	0	-	0	-	1	0	0	1
109	1	1	1	1	0	0	1	-	-	0	0	-	0	1	0	-	1	0	-	1	-	0	0	0	0
110	0	1	0	1	1	1	1	0	0	0	0	-	0	1	1	-	1	1	-	0	-	0	0	0	0
111	0	0	1	0	1	0	0	-	-	0	0	-	1	0	1	-	0	0	-	0	-	0	0	1	0
112	1	1	1	1	0	1	1	0	1	0	0	-	0	1	1	1	1	1	-	1	0	0	0	1	0
113	1	0	1	1	1	0	1	0	0	1	0	-	1	1	0	0	1	0	-	1	-	0	0	0	1
114	1	1	1	1	1	0	1	0	0	0	0	-	0	0	0	1	0	1	-	0	-	0	1	0	0
115	-	1	1	0	1	1	0	1	0	0	0	-	-	1	0	-	0	0	-	0	-	0	1	1	1

Diagnosis group	Sex	Age	Urgency	Severity[a]	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[a]	Source admission	Year
116	0	0	1	-	-	-	-	-	-	1	-	-	-	0	-	-	-	0	-	-	-	0	0	-	0
117	-	1	1	1	1	1	1	-	-	0	0	-	-	1	-	-	0	0	-	1	-	0	0	1	0
119	0	1	1	0	1	1	1	0	1	1	0	-	1	1	1	0	1	1	-	1	-	0	0	0	1
120	1	1	1	1	1	0	0	-	1	1	1	-	1	0	0	0	0	0	-	0	-	0	0	0	0
121	0	1	1	1	1	0	1	1	0	0	0	-	0	0	0	0	1	0	-	0	-	0	0	0	0
122	1	1	1	1	1	1	1	0	0	1	1	-	1	1	1	0	1	0	-	0	-	1	0	1	1
123	0	1	1	1	1	0	1	-	0	0	0	-	-	1	-	-	1	0	-	0	-	0	0	0	0
124	1	1	1	1	1	0	1	0	0	0	0	-	1	0	0	1	1	1	-	0	-	0	0	1	0
125	1	1	0	0	0	0	0	-	1	1	0	-	-	0	-	-	0	0	-	0	-	0	0	0	0
126	1	1	1	1	0	0	1	0	0	1	0	-	1	0	0	0	1	1	-	0	-	0	0	0	0
127	0	0	0	1	-	0	1	0	-	1	-	-	-	-	-	-	-	-	-	-	-	0	1	1	0
128	0	1	1	1	-	-	-	-	-	0	-	-	-	0	-	-	1	-	-	-	-	0	1	1	0
129	1	-	1	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	1	0
130	1	-	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	1	0
131	1	-	0	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	1	1	0
132	0	1	1	0	0	-	-	-	0	0	0	-	-	0	-	-	0	-	-	-	-	0	0	0	0
133	1	1	0	-	1	1	0	0	1	1	0	-	1	1	1	0	1	0	-	0	-	0	0	0	1
134	1	1	1	0	0	-	-	-	0	0	-	-	-	0	-	0	0	-	-	-	-	0	0	0	0
135	0	1	1	0	0	0	0	0	1	1	0	-	-	1	0	-	1	0	-	0	-	0	0	0	0
136	0	1	1	1	0	0	1	0	1	0	1	-	0	0	0	0	0	0	-	0	-	0	0	1	0
137	1	1	1	1	1	1	1	0	1	1	0	-	1	0	0	0	0	0	-	0	-	0	0	0	0
138	1	1	0	1	1	0	0	0	0	0	0	-	0	1	0	0	1	0	-	0	-	0	0	0	0
139	0	1	1	1	0	1	0	-	1	0	0	-	-	0	-	-	1	1	-	-	-	0	0	0	0
140	0	1	0	0	0	-	-	-	0	0	-	-	-	0	-	-	0	-	-	-	-	0	0	0	0
141	0	1	0	1	0	-	0	-	-	0	-	-	-	0	-	-	0	-	-	-	-	0	0	0	0
142	1	1	1	1	0	0	1	0	0	1	1	-	1	1	1	1	1	1	-	0	0	0	0	1	0
143	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	0	1	1	-	0	1	1	0	1	0
144	1	1	1	1	0	1	0	0	1	1	0	-	1	1	0	0	1	1	-	0	-	0	0	1	0
145	0	0	0	0	-	-	-	-	-	0	-	-	-	0	-	-	-	-	-	-	-	0	0	0	0
146	1	1	0	1	0	1	0	0	0	0	0	-	0	1	1	-	0	1	-	0	-	0	0	1	0
147	1	1	0	1	0	0	1	0	0	0	0	-	-	0	-	-	0	1	-	0	-	0	0	1	0
148	0	1	0	-	1	1	1	0	0	1	0	-	1	1	1	0	1	1	-	1	-	0	0	1	0
149	0	1	0	-	0	0	0	0	0	1	0	-	1	1	1	0	1	1	-	0	-	0	0	1	0
150	0	0	0	1	1	-	0	-	-	0	-	-	-	0	0	-	0	0	-	-	-	0	0	0	0
151	0	0	-	0	0	0	-	-	-	-	-	-	-	0	-	-	0	-	-	-	-	0	0	0	0
152	0	1	0	-	0	0	1	-	0	0	0	-	0	0	0	-	1	0	-	0	-	0	0	1	0
153	1	1	1	0	0	1	1	0	0	0	0	-	0	1	0	-	1	1	-	0	-	0	0	0	0
154	1	1	0	-	0	0	0	0	0	0	0	-	1	0	0	-	0	1	-	0	-	1	0	0	0
155	0	1	0	0	0	-	1	-	-	1	-	-	-	0	-	-	1	1	-	0	-	0	0	0	0
156	1	1	0	0	1	1	1	0	0	1	0	-	1	1	1	0	1	1	-	1	-	0	0	1	0
157	1	1	0	0	1	1	1	0	0	1	0	-	0	0	1	0	1	0	-	0	-	0	0	1	1
158	1	1	1	0	1	1	1	0	0	1	1	-	0	0	1	0	1	1	-	0	0	0	1	1	-
	53	92	67	66	45	49	63	13	20	57	21	0	34	54	41	8	69	50	0	19	6	13	15	48	15

[a] *For the COVID-19 model the ICD-10 subdiagnosis was used instead of severity and month of admission was also coded differently. See section 2.6.*

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 123 main diagnosis groups.

Diagnosis group[*)]		Number of index admissions	Number of readmissions	AUC
1	Tuberculosis	542	51	0.76
2	Septicemia (except in labor)	3 570	504	0.62
3	Bacterial infection; unspecified site	3 710	569	0.63
4	Mycoses	912	157	0.61
5	HIV infection	269	43	0.64
6	Hepatitis, viral and other infections	8 315	724	0.66
37	Other and unspecified benign neoplasm	26 450	1 363	0.66
38	Thyroid and other endocrine disorders	8 919	725	0.70
39	Diabetes mellitus without complication	5 210	392	0.69
40	Diabetes mellitus with complications	9 299	1 492	0.67
41	Nutritional deficiencies and other nutritional, endocrine, and metabolic disorders	22 035	1 610	0.67
42	Fluid and electrolyte disorders	12 143	1 506	0.65
43	Cystic fibrosis	875	165	0.63
44	Immunity and coagulation disorders, hemorrhagic disorders	3 950	772	0.62
45	Deficiency and other anemia	18 581	2 723	0.61
46	Diseases of white blood cells	3 201	546	0.60
51	Meningitis, encephalitis, and other central nervous system infections	3 130	299	0.69
52	Parkinson`s disease	2 026	186	0.64
53	Multiple sclerosis and other degenerative nervous system conditions	4 500	383	0.63
54	Paralysis and late effects of cerebrovascular disease	1 410	103	0.72
55	Epilepsy and convulsions	15 291	1 235	0.61
56	Coma, stupor, and brain damage	686	65	0.69
57	Headache and other disorders of the sense organs	22 230	878	0.66
58	Other nervous system disorders	19 886	1 178	0.67
59	Heart valve disorders	13 805	1 343	0.60
60	Peri-, endo-, myocarditis, and cardiomyopathy	7 704	808	0.64
61	Essential hypertension, hypertension with compl., and secondary hypertension	4 085	323	0.67
62	Acute myocardial infarction	55 646	3 695	0.65
63	Coronary atherosclerosis and other heart disease	38 353	2 640	0.64
64	Nonspecific chest pain	16 351	981	0.67
65	Pulmonary heart disease	11 962	821	0.65
66	Other and ill-defined heart disease	428	35	0.72
67	Conduction disorders (heart disease)	9 869	649	0.64
68	Cardiac dysrhythmias	45 159	3 471	0.67
69	Cardiac arrest and ventricular fibrillation	3 926	198	0.65
70	Congestive heart failure, nonhypertensive	45 094	6 180	0.60
71	Acute cerebrovascular disease	58 403	3 819	0.63
72	Transient cerebral ischemia, and other cerebrovascular disease	17 515	1 434	0.67

Diagnosis group*)		Number of index admissions	Number of readmissions	AUC
73	Peripheral and visceral atherosclerosis	17 744	3 008	0.64
74	Aortic and other artery aneurysms	10 041	1 108	0.58
75	Aortic and arterial embolism or thrombosis	4 376	691	0.61
76	Other circulatory disease	11 402	1 472	0.63
77	Phlebitis, varicose veins, and hemorrhoids	4 109	440	0.66
78	Pneumonia	34 002	3 699	0.62
79	Influenza	1 771	154	0.70
80	Tonsillitis and upper respiratory infections	17 030	998	0.65
81	Acute bronchitis	10 720	680	0.61
82	Chronic obstructive pulmonary disease and bronchiectasis	33 190	5 622	0.57
83	Asthma	8 511	701	0.65
84	Aspiration pneumonitis; food/vomitus	2 645	388	0.64
85	Pleurisy; pneumothorax; pulmonary collapse	8 504	1 212	0.61
86	Respiratory failure; insufficiency; arrest	1 450	183	0.69
87	Lung disease due to external agents	616	79	0.76
88	Other lower respiratory disease	8 013	934	0.60
89	Other upper respiratory disease	16 272	1 313	0.68
90	Intestinal infection	15 012	1 562	0.66
91	Disorders of mouth, teeth, and jaw	8 285	213	0.82
92	Esophageal disorders	4 537	494	0.64
93	Gastroduodenal ulcer	1 912	161	0.68
94	Gastritis, duodenitis, and other disorders of stomach and duodenum	2 863	456	0.66
95	Appendicitis and other appendiceal conditions	29 579	1 697	0.57
96	Peritonitis and intestinal abscess	1 986	396	0.63
97	Abdominal hernia	17 034	1 497	0.64
98	Regional enteritis and ulcerative colitis	7 143	1 007	0.60
99	Intestinal obstruction without hernia	12 879	1 955	0.57
100	Diverticulosis and diverticulitis	14 079	1 621	0.60
101	Anal and rectal conditions	7 386	650	0.62
102	Biliary tract disease	45 755	5 780	0.62
103	Liver disease; alcohol-related	2 685	665	0.63
104	Other liver diseases	6 674	1 574	0.66
105	Pancreatic disorders (not diabetes)	14 488	2 468	0.57
106	Gastrointestinal hemorrhage	14 192	2 064	0.61
107	Noninfectious gastroenteritis	4 179	526	0.62
108	Other gastrointestinal disorders	13 169	1 658	0.63
109	Nephritis; nephrosis; renal sclerosis	5 637	599	0.67
110	Acute and unspecified renal failure	5 734	919	0.61
111	Chronic kidney disease	5 281	916	0.60
112	Urinary tract infections	38 841	4 551	0.59
113	Calculus and other diseases of urinary tract	32 298	3 998	0.61
114	Genitourinary symptoms and ill-defined conditions	10 280	1 401	0.63
115	Hyperplasia of prostate and other male genital disorders	16 051	1 322	0.61
116	Nonmalignant breast conditions	5 235	124	0.67
117	Prolapse and other female genital disorders	23 456	923	0.67

Diagnosis group[*)]		Number of index admissions	Number of readmissions	AUC
119	Skin and subcutaneous tissue infections	19 379	1 644	0.66
120	Other skin disorders, chronic ulcer of skin	6 421	613	0.70
121	Infective arthritis and osteomyelitis	5 329	590	0.65
122	Osteoarthritis, rheumatoid arthritis, and other musculoskeletal deformities	91 506	3 257	0.65
123	Other non-traumatic joint disorders	3 971	202	0.75
124	Spondylosis, back problems, and osteoporosis	32 983	1 463	0.68
125	Pathological fracture	1 984	195	0.67
126	Other connective tissue disease	11 784	508	0.76
127	Cardiac and circulatory congenital anomalies	3 703	302	0.65
128	Noncardiac congenital anomalies	10 635	701	0.66
129	Short gestation; low birth weight; and fetal growth retardation	30 523	2 107	0.63
130	Intrauterine hypoxia, perinatal asphyxia, and jaundice	20 278	842	0.55
131	Other perinatal conditions	86 802	3 686	0.54
132	Joint disorders and dislocations; trauma-related; sprains and strains	8 083	239	0.77
133	Fracture of neck of femur (hip)	34 959	1 823	0.60
134	Skull and face fractures, spinal cord injury	3 901	149	0.73
135	Fracture of upper limb	15 634	861	0.75
136	Fracture of lower limb	19 714	1 931	0.70
137	Other fractures	17 105	803	0.62
138	Intracranial injury	13 600	643	0.69
139	Crushing injury or internal injury	7 511	432	0.64
140	Open wounds of head; neck; and trunk	1 819	78	0.72
141	Open wounds of extremities	1 785	122	0.73
142	Complication of device, implant or graft	37 305	5 044	0.64
143	Complications of surgical procedures or medical care	37 885	5 045	0.59
144	Superficial injury; contusion	19 029	639	0.77
145	Burns	1 439	87	0.66
146	Poisoning by psychotropic agents, drugs, or other medications	11 847	981	0.66
147	Other injuries and conditions due to external causes	4 510	353	0.68
148	Syncope	13 730	853	0.65
149	Fever of unknown origin	7 344	945	0.63
150	Lymphadenitis and gangrene	1 372	125	0.68
151	Shock	314	35	0.76
152	Nausea and vomiting	4 330	742	0.60
153	Abdominal pain	12 226	1 288	0.60
154	Malaise and fatigue	2 995	396	0.64
155	Allergic reactions	3 359	197	0.70
156	Rehabilitation and other aftercare, medical examination/evaluation/screening	29 305	1 910	0.62
157	Residual codes; unclassified	11 678	969	0.65
158	COVID-19	51 267	3 859	0.68

[*)] The diagnosis group numbers refer to the file 'Classification of variables' published together with the HSMR 2021 methodological report (see Van der Laan *et al*. 2022). In this file, the CCS-groups and corresponding ICD-10 codes of the 158 diagnosis groups used for the HSMR are given. For the readmission ratio only 123 of these groups are used, but the numbering was kept the same.

Explanation of figures

Empty cell	Figure not applicable
.	Figure is unknown, insufficiently reliable or confidential
*	Provisional figure
**	Revised provisional figure
–	(between two numbers) inclusive
0 (0.0)	Less than half of unit concerned
2022–2023	2022 to 2023 inclusive
2022/2023	Average for 2022 up to and including 2023
2022/'23	Crop year, financial year, school year, etc., beginning in 2022 and ending in 2023
2020/'21–2022/'23	Crop year, etc., 2020/'21 to 2022/'23 inclusive

Because of rounding, some totals may not correspond to the sum of the separate cells.
Revised figures are not marked as such.

Colophon

Publisher
Statistics Netherlands
Henri Faasdreef 312, 2492 JP The Hague
www.cbs.nl

Prepress: Statistics Netherlands
Design: Edenspiekermann

Information
Telephone +31 88 570 70 70
Via contact form: www.cbs.nl/information