Risk Assessment of Acute, All-Cause 30-Day Readmission in Patients Aged 65+: a Nationwide, Register-Based Cohort Study

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BACKGROUND: Hospital readmission is considered an adverse health outcome in older people, adding additional pressure on clinical resources within health care services. Despite numerous studies on risk factors for readmissions, studies find different strengths of respective determinants and there is a need to explore and identify patterns of risk factors in larger cohorts.

OBJECTIVE: Exploring and identifying patterns of risk factors for acute, all-cause 30-day readmission in a Danish cohort of patients aged 65+.

DESIGN: Register-based cohort study using individual-level linkable information on demographics, social determinants, clinical conditions, health care utilization, and provider determinants obtained from primary and secondary health care.

PARTICIPANTS: Historic cohort of 1,267,752 admissions in 479,854 patients, aged 65+, discharged from Danish public hospitals from January 2007 to September 2010.

MAIN MEASURES: We included patient-level variables and admission-level variables. Outcome was acute, all-cause 30-day readmission. Data was analyzed by univariable and multivariable logistic regression. Strength of associations was analyzed using Wald test statistics. Receiver operating characteristic (ROC) analysis was used for quantification of predictive ability. For validation, we used split-sample design.

KEY RESULTS: Acute admission and number of days since previous hospital discharge were factors strongly associated with readmission. Patients at risk of future readmission suffered from comorbidity, consumed more drugs, and were frequent users of in- and outpatient health care services in the year prior to the index admission. Factors related to index admission were only weakly associated with readmission. The predictive ability was 0.709 (0.707–0.711) for acute readmission.

CONCLUSIONS: In a general population of older people, we found that pre-hospital factors rather than hospital factors account for increased risk of readmission and are dominant contributors to predict acute all-cause 30-day readmission. Therefore, risk for excess readmission should be shared across sectors and focus the care trajectory over time rather than distinct care episodes.

KEY WORDS: database; health services research; readmission; risk assessment.

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INTRODUCTION

Hospital readmissions, defined as a subsequent admission of recently discharged patients are recognized as a significant contributor to health care costs and having a negative social impact [1–3]. Readmissions are more complex and almost twice as likely to result in a further readmission [4]. In Denmark, in 2017, 18% of discharges of people aged 67+ were followed by acute readmission within 30 days [5]. Although rates of readmission vary across countries and populations, the incidence of hospital readmissions in Denmark is comparable to readmission rates in large international cohort studies [1, 6, 7].

In Western countries, hospital readmission reduction programs have become a political priority. [8–11] As an outcome indicator, readmission intersects organizational boundaries within the health care system and identification of risk factors for readmission may be useful to distinguish between low- and high-risk groups and thereby facilitating allocation of clinical resources and tailored interventions across sectors [12, 13].

Comprehensive reviews of risk factors for readmission indicated that the underlying causes of readmission were multifaceted and found inconsistency and lack of clarity in the patterns of determinants pertaining to readmission in heterogeneous populations [14–18]. Similarly, prediction of risk of readmission seems to be a complex endeavor [19]. In a systematic review of 26 unique risk prediction models for hospital readmission, Kansagara et al. found that most models incorporated variables for medical comorbidity and use of prior medical services, while some studies have found different strengths of these determinants. Including determinants associated with overall health, illness severity, or social conditions improved the predictive ability [20].

The population of older people is largely heterogeneous in terms of health, illness, and care trajectories [12, 21–23]. Despite numerous studies on risk factors and generalized or disease-specific models for predicting hospital readmissions, there is a need to abstract risk factors and corroborate their applicability to a Danish population of older people. Hence, based on comprehensive information obtained from Danish population-based registers, the overall aim of this study was to identify high-risk patients, high-risk admissions, and high-risk circumstances within a heterogeneous, though selected, group of older people with general hospital admissions. The aim was to explore and identify patterns of generalized patient-level and admission-level risk factors of acute 30-day hospital readmission in a Danish nationwide cohort of patients aged 65+.

METHODS

Setting

Health care utilization strongly depends on the structures of the health care system and health policy [24, 25]. The Danish health care system is a universal, tax-financed health care service for the entire population. Every Danish citizen has a general practitioner (GP), and outside regular office hours, GPs on call serve the patients from central regional clinics providing telephone and face-to-face consultations. The GPs serve as gatekeepers for access to specialized care, and except in emergencies, the GPs make referrals to hospitals and specialists. Acute hospital admission is also available through a 24-h emergency call service [26].

Study Design

This study was conducted as a register-based cohort study analyzing individual-level linkable data obtained from ten population-based Danish nationwide registers.

Since 1968, all Danish citizens are assigned a unique identification number, which makes it possible to link information between nationwide registers and to follow care trajectories over time through different parts of the public sector [27]. Statistics Denmark (SD) offers remote access to the individual-level data necessary to perform research. Based on the availability of these data sources, we developed a database that comprised information for each individual on demographics, education, income, employment, housing, health, clinical, and administrative information on pre-hospital as well as in-hospital health care utilization and death. Linking these data sources enables researchers to track care trajectories and readmissions across settings in the Danish health care system. A recent publication has described the development of this database and cohort design in further details [28].

The study was registered under the North Denmark Region's joint notification of health research (ID 2008-58-0028).

Study Population

In the Danish National Registry of Patients (DNRP), we identified all consecutive admissions of patients 65+, discharged from an inpatient hospital stay in a Danish hospital from 1 January 2007 to 30 September 2010 [29]. Inpatient stays in psychiatric, private hospitals and hospices were not included. Due to current policy incentives internationally to reduce the rates of hospital readmission among older people and for comparison with international research, we chose the chronological age 65 as cutoff.

The term *index admission* defined the initial inpatient stay in a series of admissions and determined the subsequent tracing of readmission in the follow-up period [28]. As patients could experience multiple admissions during the study period, each individual could contribute with several index admissions in the cohort.

Outcome

The outcome was a binary variable indicating whether the index admission was followed by a readmission and defined as the first acute, all-cause readmission within 30 days from index admission. The follow-up period was defined from date of discharge and extended for 30 days or until death, whichever came first.

Data Sources

The selection of candidate patient- and admission-level factors was inspired by previous research [6, 7, 16] and systematic reviews on risk factors and predictors of readmission [17, 18, 20] and afterwards discussed with experts according to clinical relevance. Potential risk factor variables comprised patient- and admission-level data, grouped into categories of socio-demographic, health status, and health care use as well as clinical and administrative determinants related to the pre-hospital and hospital setting. Using the personal identification number, clinical and administrative data on all inpatient admissions from the DNRP was linked with information from population-based registers and databases [25]. For each admission, we included variables to describe premorbid conditions and health care utilization 1 year prior to the index admission. In patients with multiple admissions, these variables were dynamic and varied for each admission.

Although the quality of information obtained from Danish nationwide registers has not been systematically validated, it is generally accepted that data quality as well as the completeness of the data in these registers is high [27].

For further details regarding the validation studies and quality of data sources used in this cohort study, see previous studies [27, 28, 30].

Baseline characteristics were described by mean and standard deviation (SD) for continuous variables and for categorical variables by numbers and percentages. As the majority of the non-negative variables were highly skewed, mean was preferred over median for reporting of continuous variables. We found high data completeness and few variables with missing observations. Following an examination of reasons for missing observations, missing data were included in the analyses as a category of "Unknown."

Statistical modeling distinguishes between explanatory and predictive modeling [31, 32]. In this study, we combined the explanatory approach quantifying strength of associations and the predictive approach quantifying predictive ability.

Data was analyzed by univariable and multivariable logistic regression. Readmission was the dependent variable, explained by various groups of potential risk factor variables associated with hospital readmission. The unit of analysis was any patient's index admission. For admission-level analysis, clustering was performed at individual level. Due to the need to examine non-linear associations, continuous variables entered the logistic regression model by restricted cubic splines with three knots [13]. Continuous variables with a high concentration in zero entered as categorical. For further details on how covariates entered the model, see Appendix (online).

The strength of the association would ideally be represented by the Wald test p value. However, due to the large sample size, many p values were calculated as zero. For each variable, we calculated a surrogate weight defined as the Wald test sum of squares divided by the degrees of freedom to quantify the associations [33]. As many of the variables were related and presumably correlated, we supplied the univariable weights with a multivariable weight, reflecting the importance of one variable when all others are considered known.

The quantification of the predictive ability measured by AUC using receiver operating characteristics (ROC) analysis was based on a multivariable and multilevel logistic regression including three models [34]. The overall model included all variables, the patient- and admission-level model included categories of patient-level variables or admission-level variables, and the final model included five subcategories of variables. Patient-level variables comprised various subcategories of demographic and socioeconomic variables, health characteristics, and previous health care utilization. Admission-level variables comprised subcategories of clinical and administrative variables related to the index admission. To adjust for bias due to overfitting and for internal validation, we chose a split-sample design for each category of variables when calculating AUCs [13, 35, 36]. For internal validation, the cohort was randomly divided into a two-third derivation cohort (n = 835,792) and a one-third validation cohort (n = 431,960) [13]. For external validation and trend analysis, the cohort was subsequently divided by making a non-random split according to the period of the index admission and divided into a two-third derivation (n = 845,165) and one-third validation cohort (n = 422,584). Bootstrap was used for producing confidence intervals (CIs).

All analyses were rerun for a population of acute-only index admissions. Statistical analyses were performed with STATA statistical software, version 14.0 (Stata Corporation, College Station, TX, USA).

Data Sharing Statement. Due to legal restrictions, no additional data is available.

RESULTS

We identified 1,267,752 index admissions in 479,854 patients aged 65+ in the entire cohort to be included in the analyses and in the acute-only cohort 908,696 index admissions in 395,398 patients. For socio-demographic characteristics, see Table 1. For health characteristics and health care utilization prior to the index admission and for clinical and administrative characteristics related to the index admission, see Table 2.

In the following 30 days, 239,077 (18.9%) admissions were followed by acute hospital readmission, while 272,490 (21.5%) resulted in either acute readmission or death. For the acute-only cohort, the percentage of 30-day readmission as well as readmission or death were higher, with 199,466 (21.9%) and 230,303 (25.3%), respectively. For the entire cohort, the majority of index admissions were acute (n = 908,696, 71.7%), primarily for medical reasons (n = 755,489, 59.6%), with a mean length of stay of 6.1 days (SD 10.4). For the acute-only cohort, the percentage of admission due to medical reasons increased remarkably to 638,729 (70.3%) and so did the mean length of stay of 7.0 days (SD 11.1). Almost half of the index admissions comprised patients with at least one comorbid condition. The mean number of reimbursed prescriptions 6 months prior to admission was 8.3 (SD 5.1) and 8.7 (SD 5.2) for the acute-only cohort.

The results of the explanatory analyses of patient- and admission-level factors associated with readmission for the entire cohort as well as the acute-only cohort are summarized in Table 3. Based on the size of weights obtained from multivariable analyses, the ten factors most strongly associated with readmission for both cohorts were listed (see Table 4). For the entire cohort, acute index admission and a recent discharge were the two factors most strongly associated with increased risk of future acute readmission. Other factors comprised gender, employment status, number of reimbursed prescriptions, and the Charlson comorbidity index score, as well as the number of consultations with GPs or GPs on call. Aside from acute index admission, clinical and administrative factors related to the index admission were only weakly associated with risk of subsequent readmission. A similar pattern remained for the acute-only cohort. However, while variable "Number of previous 30-day readmissions" disappeared from the list, variables "Receiving home health care services" and "Number of ED visits" entered the list for the acute-only cohort.

Table 1 Selected socio-demographic characteristics for the entire cohort (planned and acute index admissions) and the acute-only cohort (acute index admissions)

Characteristics	Entire cohort $n = 1,267,752$	Acute cohort $n = 908,696$
Gender, *n* (%)		
Male	605,503 (47.8)	425,100 (46.8)
Age in years, mean, (SD)	76 (7.8)	78 (8.0)
Age groups, *n* (%)		
65–69	293,380 (23.1)	179,059 (19.1)
70–74	276,333 (21.8)	180,085 (19.8)
75–79	255,669 (20.2)	181,465 (20.0)
80–84	218,549 (17.2)	172,386 (19.0)
85–89	148,394 (11.7)	126,714 (13.9)
90–94	60,015 (4.7)	54,514 (6.0)
95–99	14,086 (1.1)	13,211 (1.5)
100 and over	1326 (0.1)	1262 (0.1)
Educational level, *n* (%)		
Basic school (1–10 years)	596,061 (47.0)	428,704 (47.2)
Upper secondary school (11–12 years)	370,688 (29.2)	251,134 (27.6)
Further education (13 years–)	154,949 (12.2)	101,708 (11.2)
Unknown	146,054 (11.5)	127,156 (14.0)
Employment status, *n* (%)		
Self-employed	13,975 (1.1)	8488 (0.9)
Employed	23,729 (1.9)	13,769 (1.5)
Retired	1,137,617 (89.7)	807,574 (88.8)
Other	1823 (0.1)	1418 (0.2)
Unknown	90,608 (7.2)	77,447 (8.5)
Marital status, *n* (%)		
Married	608,524 (48.0)	405,963 (44.7)
Never married	64,520 (5.1)	48,608 (5.4)
Divorced	155,442 (12.3)	112,985 (12.4)
Widowed	435,707 (34.4)	338,728 (37.3)
Unknown	3559 (0.3)	2412 (0.3)
Persons in household, *n* (%)		
Lives alone	597,239 (47.1)	458,931 (50.5)
Lives with a cohabitant ($n = 1$)	622,232 (49.1)	414,642 (45.6)
Lives with more than one cohabitant ($n > 1$)	48,281 (3.8)	35,123 (3.9)

The predictive ability of the three models was tested in the randomly derived validation cohort and results for the entire cohort are shown in Table 5 and for the acute-only cohort in Table 6.

In the randomly derived validation cohort, AUC was 0.709 (Table 5) and 0.691 for the acute-only cohort (Table 6). For the patient- and admission-level model as well as the models based on subcategories of variables, the predictive ability for both cohorts were slightly lower. Interestingly, the predictive ability for the subcategory "Health care use" was higher for the acute-only cohort than for the entire cohort, with AUCs of 0.650 and 0.647, respectively. With an AUC of 0.71 in the periodically derived validation cohort, we did not find any time trend.

DISCUSSION

In this study on patterns of risk factors and predictors for readmission in a cohort of Danish patients aged 65+, patient-level factors were the dominant contributors to the increased risk of acute readmission, indicating that patients at risk of readmission can be identified based on pre-hospital information obtainable and assessable at the time of the index admission.

We found that acute index admission and a recent discharge prior to the index admission were the factors most strongly associated with a subsequent 30-day readmission. Patients at increased risk of future readmissions suffered from chronic illnesses and consumed more drugs. In addition, they were frequent users of in- and outpatient health care services in the year prior to the index admission. These results correspond with previously performed studies demonstrating that complex patterns of care trajectories prior to admission and post-discharge indicate a higher risk of readmission [7, 12, 37].

Similar to previous studies, we found that male gender [17, 18] and socioeconomic factors [3, 4] are associated with a higher risk of readmission. Surprisingly, we did not identify any associations between readmission and previously identified risk factors such as age [4, 38], prolonged length of stay, and specific medical conditions related to the index admission [6, 37–40].

A number of studies found that risk of readmission increased with functional decline and poor overall health condition [37, 41]. Given the nature of data sources, our study lacked valid measures of functional and cognitive status [28]. Instead, we used information on home health care services for personal and practical care 1 month prior to the index episode as proxy for functional decline and dependency in daily living. Receiving home health care was only associated with readmission for the acute-only cohort. However, in both cohorts, the number of drugs used and frequent use of health care services prior to the index episode indicate that the

Table 2 Selected health characteristics and health care use for the entire cohort (planned and acute index admissions) and the acute-only cohort (acute index admissions)

Characteristic	Entire cohort *n* = 1,267,752	Acute cohort *n* = 908,696
Patient level		
Health characteristics		
Home health care services*, *n* (%)		
No help required	673,573 (53,1)	461,333 (50.8)
Practical care	84,444 (6.7)	63,415 (7.0)
Personal care	31,669 (2.5)	26,304 (2.9)
Personal care and practical care	116,360 (9.2)	99,416 (10.9)
Unknown	361,706 (28.5)	258,228 (28.4)
Medication†		
Number of prescribed drugs, mean (SD)	8.3 (5.1)	8.7 (5.2)
Prescribed with morphine, *n* (%)	378,702 (29.8)	281,670 (31.0)
Prescribed with insulin, *n* (%)	67,038 (5.3)	51,012 (5.6)
Prescribed with anticoagulants, *n* (%)	146,052 (11.5)	107,678 (11.9)
Charlson comorbidity index score‡, *n* (%)		
None (0)	615,376 (48.5)	437,728 (48.2)
Low (1-2)	499,064 (39.4)	362,633 (39.9)
Moderate (3-4)	104,872 (8.3)	77,697 (8.6)
High (≥ 5)	48,440 (3.8)	30,638 (3.4)
Medical history (previous year), *n* (%)		
Dementia (primary or secondary diagnosis)	21,857 (1.7)	19.926 (2.2)
Neoplasm (primary diagnosis)	154,856 (12.2)	89,113 (9.8)
Health care use previous year, mean (SD)		
Visits§, general practitioner (GP)	9.0 (7.4)	9.0 (7.6)
Visits§, GPs on call	0.8 (2.0)	1.0 (2.2)
Visits, emergency department	0.7 (1.3)	0.8 (1.5)
Visits, outpatient-clinic, days	5.4 (13.4)	5.0 (13.7)
Number of inpatient hospital stays	1.7 (3.2)	1.6 (2.0)
Number of days hospitalized	9.2 (18.5)	9. 9 (19.2)
Number of 30-day readmissions	0.7 (2.7)	0.6 (2.0)
Admission level		
Index admission		
Intensive care needs‖, n (%)	38,817 (3.1)	26,063 (2.9)
Medical services at discharge, n (%)		
Medical	755,489 (59.6)	638,729 (70.3)
Surgical	512,263 (40.4)	269,967 (29.7)
Way of referral, n (%)		
Planned	359,056 (28.3)	N/A
Acute	908,696 (71.7)	N/A
Medical specialties involved, mean (SD)	1.1 (0.4)	1.2 (0.4)
Departments involved, mean (SD)	1.2 (0.6)	1.3 (0.6)
Length of stay¶, mean (SD)	6.1 (10.4)	7.0 (11.1)
Days with final diagnosis, mean (SD)	5.2 (7.8)	5.9 (8.4)

N/A not applicable
**Home health care services received 1 month prior to index admission*
†Subsidized prescription drugs according to ATC classification 6 months prior to index admission
‡The Charlson Comorbidity Index (CCI) score calculated from primary diagnoses (ICD-10 classifications) based on inpatient and outpatient contacts 5 years prior to index admission. Based on the CCI score, the severity of comorbidity was categorized into four grades: None, with CCI scores of zero, Low, with CCI scores of 1–2; Moderate, with CCI scores of 3–4; and Severe, with CCI scores ≥5
§Visits at general practitioner (GP) and GP on call indicate in-person encounters between physician and patients (either at the clinic or home visits)
‖Need of intensive care during index admission was determined by procedure codes for mechanical ventilation, acute hemodialysis, or intensive observation
¶Length of stay calculated from the date of the admission to the date of final discharge. Transfers between departments or hospitals were linked as one admission if registered within a timeframe of 5 h.

population at increased risk of readmission suffered from multiple morbidities and experienced serious health challenges and complex care needs [41–43].

Corresponding to previous research, we found that underlying comorbidities rather than diagnosis at the index admission were associated with increased risk of readmission [44]. In contrast, a systematic review indicated that specific medical conditions or comorbidities influenced the risk of readmission; however, there was no consensus on which conditions and comorbidities [18]. These divergent findings might reflect differences in the study populations and clinical settings, or various definitions and lack of valid data to determine premorbid conditions and diagnoses [45–47]. Furthermore, we used a composite measure of the total weight of broad categories of relative heterogeneous diagnoses, which might have masked associations between readmission and specific comorbidities and medical conditions.

As risk of readmission was strongly associated with frequent pre-hospital use of in- and outpatient health care services this is most likely a strong indicator of more serious health conditions. As males have higher rates of hospitalization compared to women, some acute readmissions might be explained through gender differences in health and health behavior [48–50]. In this study, more than 70% of the index admissions were

Table 3 Associations between acute hospital readmission and patient- and admission-level factors calculated as univariable and multivariable weights, reported separately for the entire cohort and acute-only cohort

Levels	Subcategories	Variables	Weights Univariable Entire	Weights Univariable Acute	Weights Multivariable Entire	Weights Multivariable Acute
Patient-level	Demographics	Age	269	113	23	11
		Gender	653	660	768	617
		Citizenship	10	3	<1	<1
		Ethnicity	2	<1	1	1
		Country of origin	9	4	<1	<1
	Socio-economics	Educational level	17	19	4	4
		Income	1320	1220	580	548
		Employment status	4283	3029	430	306
		Marital status	17	36	2	2
		Family type	17	4	4	5
		Number of persons in household	18	4	<1	<1
	Life events (Changes)	Marital status	2	4	1	2
		Family type	2	1	6	6
		Residence (municipality)	31	22	<1	4
		Employment status	6915	6547	4	2
		Number of persons in household	3	2	<1	<1
	Health status	Home health care services	578	263	52	51
	Medication	Number of drugs (ATC-codes)	5055	3367	308	221
		High-risk medication:				
		Prescribed with morphine	4249	3133	43	6
		Prescribed with insulin	586	432	7	9
		Prescribed with anticoagulants	445	268	1	2
	Comorbidity	Charlson comorbidity index score	5936	6053	415	322
		Comorbid conditions	774	738	58	43
		Number of unique ICD-10 diagnoses	13,397	11,664	24	1
	Medical history	Dementia	365	136	30	21
		Neoplasm (primary diagnosis)	3691	6738	34	3
	Health care use	Number of visits GPs/GPs on call	2079	1608	91	51
		Number of visits ED	1014	541	70	50
		Number of inpatient hospital stays	11,430	13,809	10	45
		Number of days hospitalized	11,621	10,076	46	27
		Number of 30-day readmissions	4135	4544	93	34
		Number of days since discharge	10,731	10,247	1288	962
		Number of discharging med. spec.	10,495	9880	47	49
Admission-level	Clinical	Diagnosis at admission	552	357	3	3
		Diagnosis at discharge	563	371	5	6
		Number of unique ICD-10 diagnoses	356	36	3	2
		ACS condition at admission	410	262	4	2
		ACS condition at discharge	397	231	2	2
		Intensive care needs:				
		Mechanical ventilation	159	15	40	2
		Acute hemodialysis	396	250	14	8
		Intensive observation	303	45	47	7
	Administrative	Season	46	6	11	8
		Region (hospital)	376	244	57	40
		Hospital	65	51	15	11
		Medical service at discharge	2418	9	89	52
		Way of referral (planned or acute)	15,679	N/A	6954	N/A
		Type of department at discharge	322	287	87	47
		Number of specialties involved	374	33	7	4
		Number of departments involved	409	33	2	2
		Length of stay, in total	543	107	24	15
		Number of days with final diagnosis	1600	254	12	10

N/A, not applicable; ATC, anatomical therapeutic clinical classification; ICD-10, tenth version of the World Health Organization International Classification of Diseases; ACS condition, ambulatory care sensitive condition; GP, general practitioner; ED, emergency department

Variables:

Life events: To record information on potentially significant events (changes), we compared data on selected socioeconomic variables from the date of the index admission with the status 12 months previously

Comorbidity: The Charlson comorbid conditions included 19 conditions and the Charlson index score (CCI) was calculated from primary diagnoses (ICD-10) based on inpatient and outpatient contacts 5 years prior to admission. CCI score was calculated according to the scoring system on weights established by Charlson et al. 1987. As we did not include admissions to psychiatric hospitals, we had incomplete data on dementia. A diagnosis of dementia (weight 1) was therefore not included in the calculated CCI score

Medical history: Comprised ICD-10 diagnoses of dementia (primary or secondary) or neoplasm (primary) within the previous 12 months

Number of visits GPs/GP on Call: Number of in-person contacts with either GPs or GPs on call, divided into visits at the clinic or at home

Diagnosis at admission: The diagnoses at admission assembled into 23 major diagnostic categories determined by ICD-10 classifications

Diagnosis at discharge: The diagnoses at discharge assembled into 23 major diagnostic categories determined by ICD-10 classifications

ACS condition: A condition for which hospital admission might be prevented by interventions in primary care (Purdy et al. 2009). In this analysis, we covered 19 selected diagnostic groups used by Danish Health Care authorities for definition of ACS condition

Intensive care needs: Procedure codes for Mechanical ventilation, Acute hemodialysis or Intensive observation during the index admission

Discharging med. spec.: Discharging ward categorized as 32 different medical specialties

Medical service at discharge: Discharged from either medical or surgical hospital services

Table 4 List of the ten most important patient- and admission-level factors associated with risk of acute readmission and acute readmission within 30 days

Sequence based on size of weights*	Readmission within 30 days (Entire cohort)	Qualitative description of association†	Readmission within 30 days (acute-only cohort)	Qualitative description of association
1	Acute index admission	Higher	Days since previous discharge	Decreasing
2	Days since previous discharge	Decreasing	Male gender	Higher
3	Male gender	Higher	Personal income	Decreasing
4	Personal income	Decreasing	Charlson comorbidity score	Increasing
5	Employment	Lower	Employment	Lower
6	Charlson comorbidity score	Increasing	Number of prescribed drugs	Increasing
7	Number of prescribed drugs	Increasing	Hospitalized due to medical reasons (index admission)	Higher
8	Number of previous 30-day readmissions	Increasing	Number of visits at the GP or GP on call	Wearing off
9	Number of visits at the GP or GP on call	Wearing off	Home health care services	Inverse U-shaped
10	Hospitalized due to medical reasons (index admission)	Higher	Number of ED visits	Increasing

**The sequence of risk factors was based on the size of weights obtained from multivariable regression analyses.*
†The qualitative description of the association between the variable and readmission was based on plots of the predicted risk vs. predictors and interpreted as: Higher, Lower, Decreasing, Increasing, Wearing off, Inverse U-shaped.
GP, general practitioner; ED, emergency department
Variables:
Days since previous discharge was included as a continuous variable (cubic spline with 3 knots) and considered the number of days between date of previous hospital discharge and date of index admission
Personal income considered the yearly income of each individual and entered the analysis in quartiles
Employment status was divided into five categories: Self-employed, Employed, Retired, Other, Unknown
Charlson comorbidity score entered the risk analysis as a continuous variable (cubic spline with three knots) calculated according to the scoring system established by Charlson et al. 1987. The comorbid conditions included 19 conditions and we calculated the comorbidity score from primary diagnoses (ICD-10) based on inpatient and outpatient contacts 5 years prior to admission
Number of prescribed drugs entered the risk analysis as a continuous variable (cubic spline with three knots) calculated from subsidized prescription drugs according to the ATC classification
Number of previous 30-day readmissions entered the risk analysis as a continuous variable (cubic spline with three knots), calculated as the number of repeat admissions within a timeframe of 30 days
Home health care services received 1 month prior to index admission divided into five categories: No help required, Practical care, Personal care, Practical and personal care, Unknown

unplanned; this indicates that acute referral to hospital could be due to exacerbation and progression of illness and/or limited access to alternative acute, non-hospital services. The potential impact of patient preferences and gender differences and the impact of accessibility to alternatives to hospital readmission needs further investigation. Given the universal health insurance in Denmark, everyone has equal access to care. Thus, in countries and health care systems with non-universal insurances, the pre-hospital and access factors may be otherwise associated with risk of readmission than in the current study. Furthermore, risk for excess readmission and interventions to prevent 30-day

Table 5 Predictive ability of all-cause 30-day readmission for the entire cohort—comparison of the logistic regression model between the overall model, patient- and admission-level model and the model based on subcategories of variables

The overall model including all variables AUC (95% CI)	Patient- and admission-level model AUC (95% CI)	Model based on subcategories of variables AUC (95% CI)
Overall 0.709 (0.707–0.711)	Patient-level 0.683 (0.681–0.685)	Socio-demographics 0.592 (0.589–0.595)
		Health characteristics 0.651 (0.649–0.652)
		Health care use 0.647 (0.646–0.650)
	Admission-level 0.643 (0.641–0.646)	Clinical 0.594 (0.593–0.597)
		Administrative 0.633 (0.631–0.635)

The predictive ability measure was evaluated by AUC for three models: a model based on all variables, a model based on patient-level and admission-level variables, and finally for a model based on five subgroups of variables. Due to the large sample size, AUCs and CIs are reported with three significant digits

Table 6 Predictive ability of all-cause 30-day readmission for the acute-only cohort—comparison of the logistic regression model between the overall model, patient- and admission-level model and the model based on subcategories of variables

The overall model including all variables AUC (95% CI)	Patient- and admission-level model AUC (95% CI)	Model based on subcategories of variables AUC (95% CI)
Overall 0.691 (0.688–0.693)	Patient-level 0.679 (0.677–0.682)	Socio-demographics 0.587 (0.584–0.590)
		Health characteristics 0.652 (0.649–0.654)
		Health care use 0.650 (0.647–0.653)
	Admission-level 0.606 (0.603–0.608)	Clinical 0.579 (0.577–0.582)
		Administrative 0.592 (0.588–0.595)

The predictive ability measure was evaluated by AUC for three models: a model based on all variables, a model based on patient-level and admission-level variables and finally for a model based on five subgroups of variables. Due to the large sample size, AUCs and CIs are reported with three significant digits readmission should be shared across sectors and support patient capacity for self-care [51].

The AUC of the overall model was 0.71 for acute 30-day readmission, which is considered acceptable [20] and comparable to similar studies [6, 7, 13, 52]. We found neither trend for season nor time. In models including patient- and admission-level variables, the predictive ability for the category of patient-level factors was higher than for admission-level factors. Finally, subcategories for health characteristics and health care use during the pre-index period accounted for the highest predictive ability among patient-level subcategories.

In this general population of older people, we would expect a huge amount of different pathways leading to readmission; each pathway represented with main effects and two- or maybe more-way interactions [12]. Including relevant interactions in the analysis might improve the predictive ability and would be feasible when analyzing specific subgroups and selected pathways, but omitted in this paper due to the general population at hand [31].

We opted for a general approach and included all patients aged 65+ admitted to a Danish hospital during a four-year period. Thus, the study population was heterogeneous and representative for an aging population. The large study size and the comprehensive database with the possibility to link demographic and social characteristics into patient pathways, including a complete medical history, comorbidity data, hospital data and follow-up data, and high data completeness, were major strengths of this study [28].

However, this study also exposed some weaknesses in register-based research. Due to the observational design, no firm causal explanations for readmission can be inferred. Furthermore, the interpretation, implications, and predictive ability within defined patient groups and specific clinical settings and health care systems might be limited [28, 30]. However, we did not intend to develop a predictive model centered on a specific patient population, clinical pathway, or clinical setting. Combining the explanatory and predictive approach, this analysis illustrates patterns of risk factors and predictors for readmission in a general Danish population of patients aged 65+. To improve the predictive ability, this general and complex model could be validated considering variable selection in different health care systems, clinical settings, and patient populations and improved by various subgroup analyses. For future research and longitudinal analyses, an update of the database would be preferable.

CONCLUSIONS

In a general population of older people, we found that pre-hospital factors rather than hospital factors account for the greatest risk of readmission and are the dominant contributors to predict acute all-cause 30-day readmission. Therefore, risk for excess readmission and approaches to prevent readmission should be shared across sectors.

PERSPECTIVES

The underlying causal relationships for readmission are multifaceted and simple explanatory and general predictive models based on broad categorically categories provide modest predictive value.

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