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Development and validation of predictive MoSaiCo (Modello Statistico Combinato) on emergency admissions: can it also identify patients at high risk of frailty?

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Summary. The prospective historical cohort study develops and validates a method of identifying patients at high risk of emergency admission to hospital in the population of the Province of Ravenna (no. = 296 641). The main outcome measure is: emergency hospital admission analyzed using multivariate logistic regression (MoSaiCo − Modello Statistico Combinato). To validate the findings, the coefficients for 30 most powerful variables found on half of the population (derivation data set) were then applied to the rest of the population (validation data set). The key predicting factors included some demographic variables, social variables, clinical variables and use of health/social services. Discriminatory power and validation both reached good results. Risk score increases when variables indicating the individual vulnerability raise. The predictive frailty risk resulting from MoSaiCo allows to stratify the population, to organize care services, to provide a practical planning tool in the field of case management and management of frail patients.

Key words: frailty, chronic care model, predictive model, score index.

Riassunto *(Sviluppo e validazione di MoSaiCo, Modello Statistico Combinato, sul ricovero non programmato: può identificare pazienti ad alto rischio?)*. Lo studio, di coorte prospettico storico, sviluppa e valida un metodo per identificare i pazienti ad alto rischio di ricovero urgente della popolazione della Provincia di Ravenna (n. = 296 641). La principale variabile di esito: il ricovero in emergenza è analizzato con un modello multivariato di regressione logistica (MoSaiCo − Modello Statistico Combinato). Per validare i risultati, i coefficienti di 30 variabili individuate su metà della popolazione (gruppo di derivazione) sono state applicate al resto della popolazione (gruppo di validazione). I principali fattori predittivi includono variabili demografiche, sociali, cliniche e di uso dei servizi sanitari e sociali. Il potere discriminante e la validazione hanno ottenuto buoni risultati. L'aumento del *risk score* corrisponde all'aumento delle variabili che indicano una situazione di vulnerabilità dell'individuo. Il rischio di predizione ottenuto permettono di stratificare la popolazione, pianificare gli interventi clinico-assistenziali, guidare la riorganizzazione dei servizi per gli interventi di *case management* e per la gestione del paziente fragile.

Parole chiave: fragilità, modello malattie croniche, modello predittivo, indice di rischio.

INTRODUCTION

Background

European health policies recently stressed the importance of the strategic role of long term condition management to prevent health deterioration. Supporting healthy ageing means both promoting health throughout the lifespan, aiming to prevent health problems and disabilities from an early age, and tackling inequities in health linked to social, economic and environmental factors [1]. To fulfil this aim, it is important to identify chronic subjects and consequently adopt health care interventions such as self/disease/case management and implement innovation of assistive technology (Chronic Care Model) [2].

In the past years there has been significant progress in improving care of patients with chronic illness by providing guidance on evidence-based pathways of care [3], setting targets for reduced hospital re-admission [4], funding more efforts to encourage self-care [5], identifying more accurately those at highest risk of admission [6], and encouraging effective case and disease management [7, 8].

To achieve these goals different methods have been proposed to identify patients at high risk of admission. Such methods are mainly based on three techniques [9]. The first is "threshold modelling" or "criterion-based modelling" which identifies any patient who meets a specific risk criterion (eg. age threshold

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to identify patients who have to undergo screening). The second is "clinical knowledge", which is based on the ability of the clinician to identify patients at high risk of future admissions [10]. The third is "predictive modelling", which tries to establish a relation between a set of variables in order to predict future outcomes using a regression model [11]. Whatever technique may be used, evidence shows that the prediction ability of the model depends on the number and the quality of patient characteristics: social, demographic and clinical variables, use of health and social services, functionality and perceived health status [9].

Many predictive algorithms, based on administrative data, have been produced in the United States to identify high risk of admission among elderly subjects [12, 13]. The risk stratification model based on admissions data, has been developed by the King's Fund, New York University, and Health Dialog, but currently this is only based on predicting readmission in those who have already experienced an admission [14]. A further step has been the development of a case finding algorithm to identify high risk patients accurately so as to enable preventive and targeted interventions [15]. The Combined Predictive Model [16] is heading precisely in this direction. It is based on a comprehensive dataset of patient information obtained by healthcare databases, including inpatient, outpatient, Accident & Emergency (A&E) and data from secondary care sources (such as electronic clinical records of primary care). Recently, new algorithms have been introduced that increase variables not only on previous hospital admissions, but on the use of social services, its related costs [17] and the influence of the deprivation index [18].

Finally, apart from being applied to the elderly population (> 65 years), these algorithms have been also applied to young subjects with an experience of emergency admission (> 40 years [19]) or to subjects of every age [20].

Although the previously mentioned models enabled recognition of the risk degree in different age groups, little attention has been paid to the role played by a range of social variables. In our opinion and on the basis of recent empirical [21] evidence, to include and analyse the role of such variables could increase the accuracy of the model's prediction.

Furthermore, in Italy there are still few validated models devoted to the stratification of the population into classes of risk and consequently to promoting forms of case-management along with social and health policies according to the needs of the population.

Objective

The aim of this study is to develop and validate a statistical combined model named MoSaiCo (Combined Statistical Model) to predict future emergency hospital admission or mortality in all individuals aged 18 or above in the following year in the Province of Ravenna. This model could be used by clinicians and policy makers to guide and implement proactive interventions.

METHODS

Study design and data source

We conducted a prospective historical cohort study among all residents alive on 1 January 2006 and aged ≥18 years (310 920), residing in the Province of Ravenna (Emilia Romagna Region, Northern Italy) and who were entered into the RAA (Ravenna Population Registry). The baseline was defined (296 641, *Figure 1*) after the initial period of 2 years (from 1 January 2006 to 31 December 2007) and follow-up occurred over the following year (from 1 January 2008 to 31 December 2008). Those subjects with either less than 2 years' history or less than 1 year of follow-up data were excluded.

The Ravenna Population Registry is a high quality database created over almost twenty years of activity. It attributes to each patient a unique identification number enabling a record linkage with all other available databases mainly derived and validated by the dataflow of Emilia Romagna Region [22]: SDO, Hospital Discharge Record; ESE, participation in the prescription charges; PS, Accident & Emergency data; ASA, Outpatient data; AFT, Territorial Drug Prescription; ADI, home care services; SA, lone elderly aged ≥ 75 years and elderly couples aged ≥ 75 years; SS, social services data; SM, mental health services data.

Baseline risk factors and outcome

During the observation period 2006-2008, for each individual a set of risk factors was detected. This set includes some variables derived from the English Combined Model [16], such as demographic and clinical variables, use of health services and further social variables and use of social services.

Demographic variables reflect the age group, gender and citizenship.

Social variables include: exemption from prescription charges for invalidity and primary social care network for the elderly (people living alone aged ≥ 75 years and elderly couples aged ≥ 75 years).

For those who had at least one hospitalization, some clinical variables were identified such as chronic diseases based on ICD9-CM in any diagnostic field in hospital discharge record (asthma, coronary artery disease, congestive heart failure, cancer, depression, chronic obstructive pulmonary disease, hypertension, diabetes, dementia) as well as the Charlson co-morbidity index [23].

The "use of social services" variables refer to the use of home care services and the use of the Mental Health Department.

The "use of the health services" variables include: emergency admission (number of visits, tests performed, non-injury medical diagnoses, arrived by ambulance), hospital admissions (number of inpatient admissions including passive inter-regional mobility, protected discharge), polipharmacy (at least 4

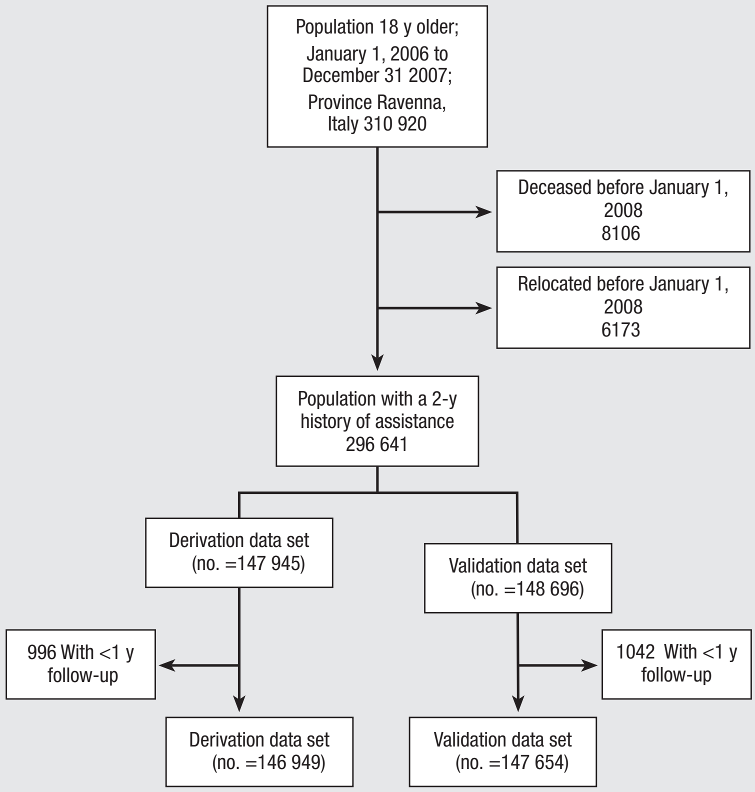

Fig. 1 | *Creation of derivation data set and validation data set.*

drug prescriptions in the last 3 months from different ATC-groups at Level 3).

Finally, the "use of social services" variables include the use of at least one social service (home meal delivery, tele-assistance, day care centres, etc.) and were collected with an *ad hoc* study in which all social services provided the names of their users.

For privacy reasons [24], in the final dataset a unique anonymous identification number was introduced.

The main outcome was a single binary variable, EAM (Emergency hospital Admission and Mortality), which includes both the first emergency hospital admission obtained from the hospital discharge record (field "Type of admission": 2 = emergency, 3 = forced mental health treatment, 5 = short-stay emergency observation) and mortality in the follow-up year derived from the Ravenna Population Registry, updated monthly.

Statistical methods

Risk factor variables are summarized as percentages.

The data set was split in half at random into a derivation data set and a validation data set (each corresponds to the 50% of the population). In the derivation data set, the main binary outcome of first emergency admission or mortality in the following year was modelled using logistic regression. From this model, odds ratio (ORs) and associated 95% confidence intervals (CIs) were obtained by exponentiating the regression coefficients. Absolute risk was estimated from the linear prediction starting from the log odds of the final model as a risk score, calculated for each individual from 1 to 100.

Model building

All initial bivariate and multivariable models were developed on the derivation set and the performance of the final models was tested using the validation set.

In order to potentially include confounding factors in MoSaiCo, a total of 57 variables were considered. Of these, a total of 37 had a frequency >5% and so these were included in subsequent multivariable modelling. Having a large number of covariates, we opted for a selection method based on the combination of stepwise logistic regression with a "right" critical p-value = 0.15 [25].

Model performance

The performance of the algorithm obtained from the derivation data set was tested on the randomly selected validation data set. Firstly, overall discrimination ability was assessed for the derived function on the derivation data itself, and secondly, this model was used on the validation data set. Discrimination was assessed using the c statistic, or area under curve, which is an estimate of the probability of assigning a higher risk to those who have an emergency admission in the following year compared with those who do not. This is an important criterion when ranking people by risk and is clearly essential for risk stratification.

The Brier score [26] has been used to determine the calibration of the model. The Brier score is a measure of suitable matching where lower values indicate better accuracy.

Finally, the c statistic, or area under curve, and calibration test were also calculated for the derived algorithm applied to the test validation data set. All analyses were implemented in SAS version 9 (SAS Institute Inc, Cary, North Carolina) statistical software.

RESULTS

The creation of derivation and validation cohorts is shown in *Figure 1*, while *Table 1* compares the characteristics of eligible patients in both cohorts. The baseline validation cohort characteristics were very similar to those in the derivation cohort, without statistically significant variations.

Table 2 describes the variables used in the model and gives the odds ratios for the factors in the final model (in the derivation cohort). Those who experienced an outcome of an emergency admission tended to be older and males (7.2% with slightly less difference for females).

The factors mainly related with the EAM variable (outcome of an emergency admission or mortality, rate 6.6%) proved to be age, both from 65 to 84 years (OR 2.42; CI 2.28-2.57) and from 85 years onwards (OR 5.69; CI 5.19-6.24), one or more emergency admissions over the last 30 days (OR 2.20; CI 1.85-2.63), three or more visits to the A&E (OR 1.77; CI 1.50-2.09).

ROC Analysis revealed reasonable predictive power of the risk score in the validation data set with a c statistic = 0.77; applying the model to the random split-half validation data set, discriminatory power was still good (c = 0.79). Calibration was good (Brier score was 0.053 for derivation data set and 0.054 for validation data set). *Figure 2* shows the curves of the expected and observed cases of risk of EAM divided into deciles of risk. The close correspondence between predicted and observed emer-

Table 1 | *Descriptive analysis of some population's features (> 18 years) in the derivation and validation cohort*

Descriptive variables	Derivation cohort No.	Derivation cohort %	Derivation cohort Emergency admissions No.	Derivation cohort Emergency admissions rate %	Validation cohort No.	Validation cohort %	Validation cohort Emergency admissions No.	Validation cohort Emergency admissions rate %
Population cohort	146 949	100.0	9691	6.59	147 654	100.0	9850	6.7
Age classes								
From 18 to 64 years	104 260	70.9	3516	3.37	104 447	70.7	3568	3.4
From 65 to 84 years	37 569	25.6	4494	11.96	37 885	25.7	4615	12.2
From 85 years onwards	5 120	3.5	1681	32.83	5322	3.6	1667	31.3
Female	70 352	47.9	4198	5.97	70 192	47.5	4226	6.0
Male	76 597	52.1	5493	7.17	77 462	52.5	5624	7.3
Foreign	5 204	3.5	241	4.63	5337	3.6	244	4.6
Without GP	576	0.4	16	2.78	586	0.4	31	5.3
With GP > 1000 assisted	121 629	82.8	7921	6.51	122 228	82.8	8003	6.5
With GP in group	46 711	31.8	3020	6.47	47 242	32.0	3112	6.6
One chronic pathology	7209	4.9	1365	18.93	7136	4.8	1335	18.7
Two or more chronic pathologies	3960	2.7	1377	34.77	4087	2.8	1473	36.0
Protected discharge in 2008	2248	1.5	2168	96.44	2341	1.6	2249	96.1
Became non self-sufficient in 2008	5653	3.8	3365	59.53	5702	3.9	3478	61.0
3 or more admissions over the 2 previous years	3978	2.7	192	4.83	4075	2.8	196	4.8
Total or partial invalidity	6250	4.3	1309	20.94	6353	4.3	1290	20.3
Lone elderly > 75 years (2007)	7071	4.8	1526	21.58	7274	4.9	1463	20.1
Elderly couples > 75 years (2007)	9888	6.7	1683	17.02	9842	6.7	1728	17.6
Assisted by social services (2007)	3110	2.1	1234	39.68	3258	2.2	1304	40.0
Access to Mental Health Services	2721	1.9	348	12.79	2.805	1.9	365	13.0
Domiciliary integrated assistance	1792	1.2	796	44.42	1.726	1.2	817	47.3
Pharmaceutical poliprescription	4.236	2.9	1.229	29.01	4.216	2.9	1250	29.6

Table 2 | *Resumed analysis of results of the unadjusted and adjusted analysis of the selected variables of the model. Sample derivation (no. = 146 949)*

Variables of the model	Unadjusted			Adjusted		
	OR	95% CI	p	OR	95% CI	p
Age classes						
From 18 to 64 years (Reference)	1.00	-	-	1.00	-	-
From 65 to 84 years	3.89	3.72-4.08	<0.0001	2.42	2.28-2.57	<0.0001
From 85 years onwards	14.01	13.10-14.98	<0.0001	5.69	5.19-6.24	<0.0001
Male gender *vs* female gender	1.21	1.17-1.27	<0.0001	1.07	1.02-1.12	0.0081
Foreign *vs* Italian	0.68	0.60-0.78	<0.0001	1.26	1.10-1.45	0.0011
Charlson Index ≥1	7.39	7.02-7.78	<0.0001	1.46	1.33-1.6	<0.0001
1 or more emergency admissions over the last 30 days	8.02	6.97-9.22	<0.0001	2.20	1.85-2.63	<0.0001
1 or more emergency admissions (30-90 days)	7.52	6.85-8.26	<0.0001	1.25	1.09-1.44	0.0011
1 or more emergency admissions (90-180 days)	6.87	6.31-7.48	<0.0001	1.46	1.29-1.65	<0.0001
1 or more emergency admissions (180-365 days)	3.58	3.27-3.925	<0.0001	1.21	1.07-1.36	0.0245
1 or more emergency admissions (365-730 days)	5.23	4.94-5.53	<0.0001	1.40	1.29-1.53	<0.0001
Partial or total invalidity	4.18	3.92-4.46	<0.0001	1.71	1.58-1.85	<0.0001
Lone elderly > 75 years (2007)	4.44	4.18-4.72	<0.0001	1.44	1.33-1.56	<0.0001
Elderly couples >75 years (2007)	3.31	3.12-3.50	<0.0001	1.36	1.27-1.46	<0.0001
Assisted by social services (2007)	10.53	9.77-11.35	<0.0001	1.58	1.42-1.76	<0.0001
Access to Mental Health Services	2.12	1.89-2.37	<0.0001	1.67	1.45-1.92	<0.0001
Domiciliary integrated assistance	12.24	11.12-13.47	<0.0001	1.47	1.29-1.67	<0.0001
Pharmaceutical poliprescription	6.49	6.05-6.96	<0.0001	1.59	1.45-1.74	<0.0001
Instrumental Test at the Emergency Unit (90-180 days)	3.12	2.91-3.35	<0.0001	1.41	1.28-1.55	<0.0001
Access to the Emergency Unit in Ambulance through 118 (30-90 days)	7.95	7.13-8.88	<0.0001	1.55	1.31-1.82	<0.0001
Non traumatic medical diagnosis (30-90 days)	4.08	3.79-4.39	<0.0001	1.53	1.36-1.71	<0.0001
Non traumatic medical diagnosis (365-730 days)	2.57	2.46-2.69	<0.0001	1.21	1.13-1.29	<0.0001
1 access to the Emergency Unit (180-365 days)	1.84	1.74-1.95	<0.0001	1.27	1.18-1.37	<0.0001
2 accesses to the Emergency Unit (180-365 days)	2.78	2.52-3.06	<0.0001	1.48	1.31-1.67	<0.0001
3 or more accesses to the Emergency Unit (180-365 days)	4.80	4.23-5.45	<0.0001	1.77	1.5-2.09	<0.0001
Admissions with mental illness diagnosis	5.82	5.10-6.63	<0.0001	1.51	1.27-1.79	<0.0001
3 or more admissions with different principal diagnosis (0-730 days)	6.38	5.86-6.96	<0.0001	1.13	1.01-1.28	0.0036
Previous admissions with coronary artery disease	7.56	6.94-8.24	<0.0001	1.16	1.03-1.30	<0.0001
Previous admissions with congestive heart failure	9.89	9.09-10.76	<0.0001	1.15	1.02-1.30	<0.0001
Previous admissions with cancer	3.94	3.65-4.26	<0.0001	1.63	1.47-1.81	0.0036
Previous admissions with chronic obstructive pulmonary disease	10.38	9.30-11.58	<0.0001	1.24	1.08-1.43	<0.0001

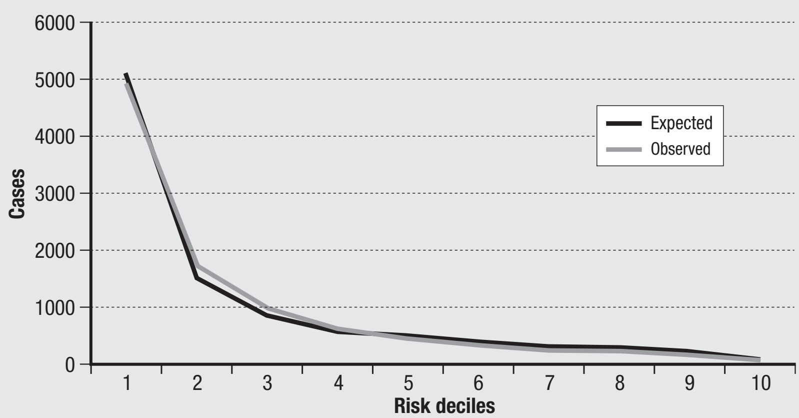

Fig. 2 | *Number of expected and observed cases of risk of EAM by 10th deciles of predicted risk.*
EAM: Emergency hospital Admission and Mortality.

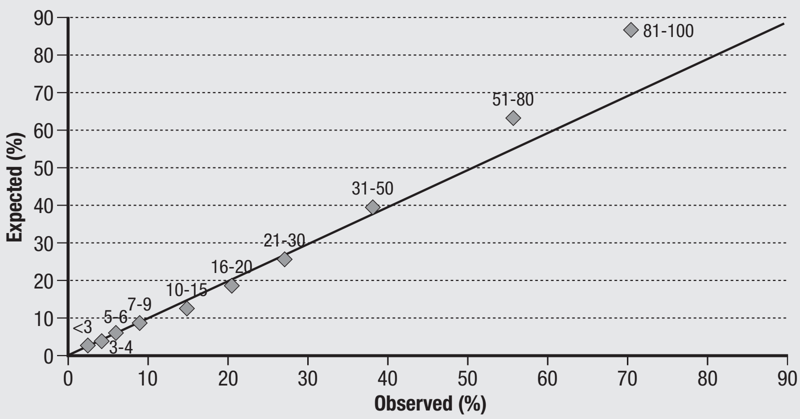

Fig. 3 | *Expected* versus *observed emergency admission in several risk categories (dots).*

gency admission risks within each decile (reaching 95% in the last decile) suggests that the model was well calibrated. The appropriateness of the calibration is further demonstrated in *Figure 3* illustrating observed versus expected EAM percentages in the several risk categories. Dots are aligned to the diagonal line that represents perfect calibration.

Table 3 indicates EAM risk categories with some descriptive variables which we believe to be indicative of frailty condition: the use of social services and being alone are, in fact, indicators of the paucity of the social network. The presence of chronic diseases and invalidity can indicate a decline in functional independence or a worsening of the health condition as well as becoming non self-sufficient. Such variables show a monotonic increase for each of the EAM risk categories. This trend reflects the possibility of also using such risk scores to predict long term frailty conditions.

DISCUSSION

The main result of this study is the calculation, for each subject, of the risk score of EAM. This was possible thanks to the MoSaiCo predictive algorithm, which, reasonably powerful and calibrated, is aimed at the stratification of the resident population to provide suggestions that could help planning health care interventions. From this point of view, this algorithm can be a precious tool to carry out a re-engineering of health and social services and improve different activities of case managers. Besides, this predictive model can help doctors to make decisions by providing more objective estimates of probability as a supplement to other relevant clinical information [27].

MoSaiCo is oriented on the assessment, coordination, monitoring and delivery of services to meet patients' needs [28], in the present case preventive and responsive care for patients aged over 65 years at high risk of emergency hospital admission [29]. Qualitative evidence suggests that access to case management added a frequency of contacts, regular monitoring, psychosocial support, and a range of proactive medicine initiatives on behalf of social care that had significant impact on rates of emergency admission [30, 31].

Table 3 | *Clinical properties of risk score in the validation data set*

Risk categories	No.	Means of age	Two or more chronic diseases	Became non self-sufficient in 2008	Lone elderly > 75 years	Total or partial invalidity	Assisted by Social Services in 2008	Pharmaceutical poliprescription
<3	69 164	42.9	0.0%	0.3%	0.0%	0.1%	0.1%	0.0%
3-4	27 873	41.4	0.3%	0.9%	26.4%	0.2%	0.5%	0.9%
5-6	17 867	64.0	0.8%	2.6%	10.1%	1.0%	1.6%	2.2%
7-9	13 539	70.7	1.6%	5.4%	27.8%	1.8%	4.2%	4.7%
10-15	7 837	72.5	7.4%	10.9%	32.7%	3.8%	11.2%	6.9%
16-20	3 778	78.9	11.5%	17.8%	24.3%	7.0%	21.6%	12.8%
21-30	3 242	79.2	22.1%	25.0%	24.6%	10.5%	28.7%	15.7%
31-50	2 579	80.7	35.9%	32.9%	22.4%	16.0%	30.9%	20.4%
51-80	1 522	83.5	51.4%	46.1%	15.8%	26.2%	33.3%	29.3%
81-100	253	85.0	70.4%	52.6%	13.3%	41.5%	36.1%	42.0%
All	147 654	52.2	2.8%	3.9%	25.3%	1.6%	4.1%	3.0%

In fact, decisions on admission to hospital are usually made with a holistic view of the patient's current state of health, existing co-morbidities, available social support, and the patient's concerns and expectations. Future guidance of health care services should incorporate perspectives from social services, primary care, patients, and carers [32] and also use the tool of MoSaiCo, that suggests the conditions on which institutions take decisions, the user of the service, the variety and quantity of services that should be supplied in order to provide an efficient service.

As reported in the recommendations by Hutt *et al.* [33], thanks to this tool Primary Care Groups (PCGs) will have a clear idea of the needs of the population at whom case management is targeted. Case management should be developed in close collaboration with social care providers to ensure that an appropriate range of health and social care services is available to prevent unplanned hospital admission. In addition to identifying people who will most benefit from case management, PCGs need to ensure that services are in place for people with less severe illnesses who nevertheless have significant health and social care needs. To conclude, all case-management initiatives should be evaluated in terms of their impact on the use of health services, including primary care and patient satisfaction. The whole of these initiatives can be realized through the use of MoSaiCo.

Comparing previous studies that calculate the emergency admission risk on the basis of administrative databases *(Table 4)* one can observe a certain tendency towards increased performance (AUC = area under curve) along with the introduction of different types of variables, namely social and use of social services ones (independent factors type).

The innovation of this study derives from the hypothesis that MoSaiCo can calculate a predictive risk not only of hospital re-admission, but also of frailty condition. In writings on the subject, in fact, frailty is defined as a decrease in the capacity to carry out the main social and practical activities of daily life [34]. It is a multidimensional concept that considers the complex interplay of physical, psychological, social, and environmental factors such as: medical and biological factors (chronic diseases), psychological factors (depression, coping skill) and social factors (relationships, interaction with the environment, social adaptability) [35]. As frailty can appear in different degrees of gravity, and even lead to adverse health-related outcomes such as an increased risk of morbidity, of emergency hospitalization and long term assistance, prevention and, where possible, treatment of frailty should be high on the medical [21] and social agenda.

The main tools used in the geriatric and medical field to carry out prognoses and to predict the degree of frailty is face-to-face interviews that contain several information possibly measurable from current data flows [36, 37]. Since MoSaiCo contains many information of this type, it could provide the possibility to predict the level of frailty in health areas,

Table 4 | *Comparisons of MoSaiCo and other emergency admissions or hospitalization prediction models*

Study	No.	Tool	Population	Data source	Data collection	Data pubblication	Age	AUC	Outcome	Indipendent factors type
Roland *et al.* [6]	227 206	No model	Cohort selected with two or more emergencies, discharged alive	HES	1998-9 to 2002-3	*BMJ*, February 2005	65+	-	-	-
Billings *et al.* [15]	10% sample of HES data	Patient at risk of re-admission (PARR)	Patients with previous emergency admission identified by discharge data from Inpatient and Archieve database	HES	1999-2004	*BM*, June 2006	65+	68.5	Emergency admission within 12 months of prior emergency admission	Demographic. clinical. use of health services
ISD (Information Service Division) Scotland [18]	214 047	Scottish patients at risk of re-admission anf admission (SPARRA)	Patients admitted as emergency admissions	Hospital admissions data in Scotland	2001-2003	*NHS*, August 2006	65+	67.9	Emergency admission during the calendar year 2004	Demographic. clinical. use of health services
	715 187				1 April 2003 - 31 March 2006	*NHS*, June 2008	all ages	75	Emergency admission during the calendar years 2006-2007	Demographic. clinical. use of health services
Donnan *et al.* [19]	410 000	Predicting emergency admissions over the next year (PEONY)	Population of Tayside, Scotland	Tayside general pratctice	1 January 1996 - 31 March 2004	*Arch Intern Med*, 2008	40+	80	The first emergency admission in the follow-up year after the initial 2-years	Demographic. social. clinical. use of health services
Falasca *et al.*	296.641	MoSaiCo (MOdello StAtIstico COmbinato)	Population of Ravenna, Italy	Administrative data	1 January 2006 - 31 December 2007	*Ann Ist Super Sanità*, 2011	18+	77.4	The first emergency hospital admission or mortality in the follow-up year (2008)	Demographic. social. clinical. use of health services. use of social services

using the existing electronic databases of the Italian National Health System. It would allow a systematic screening applied to the whole of the population and consequently expose the services less to the inverse care law [38, 39].

Strengths and weaknesses of the study

Among the strengths of this study, we can highlight the breadth of the population and the use of high quality administrative databases. The latter though, may contain errors due to misclassification (e.g. diagnosis of chronic diseases).

Another limit of the study is the absence of external validation in order to verify that the model performs as expected in new but similar patients.

Further improvements could be applied to the model by adding the variables linked to socio-economic variables (the deprivation index is under observation in the Emilia Romagna Region), the propensity score [40, 41] and other data provided by general practitioners.

The latter could provide the lists of their frail patients and include in the MoSaiCo model the information on deprivation index, social capital and, at the same time, give the patients a chance to be monitored and receive tailored preventive measures.

The hypothesis of using MoSaiCo to predict the frailty level offers a new perspective which requires further validation studies and a new assessment scenario on the impact of Health and Social care on long-term frail patients management. Bearing this in mind, as did Lyon *et al.* [42], we started a survey on a representative sample of the elderly population in order to detect the social and psychological characteristics that cannot be detected in the administrative flows. The goal of this survey is to create a tool (Frailty Risk Chart) which allows social and health operators the calculation of some (standardized and easy-to-use) indicators in order to timely examine the psychosocial conditions of individuals and calculate an individual score of frailty to implement preventive measures.

Conflict of interest statement

There are no potential conflicts of interest or any financial or personal relationships with other people or organizations that could inappropriately bias conduct and findings of this study.

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