Risk stratification in Dutch primary care: a promising approach to manage population health

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CHAPTER 5

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IDENTIFYING COMPLEX PATIENTS USING ADJUSTED CLINICAL GROUPS RISK STRATIFICATION TOOL

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Abstract

Objectives

To produce an efficient and practically implementable method, based on primary care data exclusively, to identify patients with complex care needs who have problems in several health domains and are experiencing a mismatch of care. The Johns Hopkins ACG System was explored as a tool for identification, using its Aggregated Diagnosis Group (ADG) categories.

Study Design

Retrospective cross-sectional study, using general practitioners' electronic health records, combined with hospital data.

Methods

A prediction model for patients with complex care needs was developed using a primary care population of 105,345 individuals. Dependent variables in the model included age, sex, and the 32 ADGs. The prediction model was externally validated on 30,793 primary care patients. Discrimination and calibrations were assessed by computing C statistics and by visual inspection of the calibration plot, respectively.

Results

Our model was able to discriminate very well between complex and noncomplex patients (C statistic = 0.9; 95% CI, 0.88-0.92), whereas the calibration plot suggests that the model provides overestimates of complex patients.

Conclusions

With this study, the ACG System has proven to be a useful tool in the identification of patients with complex care needs in primary care, opening up possibilities for tailored interventions of care management for this complex group of patients. Utilizing ADGs, the prediction model that we developed had a very good discriminatory ability to identify those complex patients. However, the calibrating ability of the model still needs improvement.

Introduction

As populations age and the presence of multimorbid and complex patients becomes the norm, the pressure on health systems, regarding workload as well as costs, is immense (1). Single-disease management approaches are no longer sufficient to meet the needs of an increasing number of complex patient groups, who need care oriented toward their overall health (2). In addition, strategies distinguishing different levels of complexity within a population are desirable. Population health management (PHM) approaches aim to allocate available health resources to the appropriate patient groups within the population. Risk stratification tools, such as the widely used Johns Hopkins Adjusted Clinical Groups (ACG) system, play an important role in the identification of specific patient groups for PHM, aiming to identify subgroups in whom avoidable adverse health events could be prevented. With predictive modeling, high-risk patients can be successfully selected for extensive and proactive care management programs (3).

One group for whom it seems beneficial to set up a PHM approach, including risk stratification, is that of patients with complex care needs, who have problems involving multiple health domains and experience a mismatch of care offerings with their needs. Often the consequence of this mismatch is high care utilization—in particular, of expensive and undesirable care, such as emergency or unplanned care. This group of patients was first described by Atul Gawande, MD, MPH, in his 2011 article in *The New Yorker*, “The Hot Spotters”(4). For this group of patients, it would seem that a multidisciplinary and personalized approach would be advantageous, but evidence for the effectiveness of this kind of approach is still ambiguous(5). One of the reasons is the incorrect assignment of patients to this intense but effective individualistic approach, leading to a greater mismatch in care. Hence, the first step in providing those complex patients with the appropriate necessary care is a practical and efficient identification of the population who is most likely to benefit from the intervention.

Different methods to identify patients with complex care needs have been utilized by different organizations, using various criteria and types of data sources. The heterogeneity of high-cost patients, including patients with unpreventable costs, makes a general identification based on claims data inefficient (6,7). A focus on hospitalizations or emergency department (ED) use has proven to be more effective (8). However, a complete profile of complex patients requires complete health profile data. In most health care systems, patient data are registered in fragmented silos with significant data linkage challenges; a wide application of risk stratification tools, based on complete patient profiles, is therefore limited. Clinically based predictive models, using medication and diagnostic data, are especially efficient for prospectively identifying candidates for care management programs (9). Especially in primary care led health systems, in which primary care physicians function as gatekeepers, we have the opportunity to look at more complete health profiles of patients, including medication and diagnostic data, without linkage of data between silos. Unfortunately, despite this great opportunity, evidence for validated risk stratification models to identify patients with complex care needs in primary care is lacking.

Various validated models to map different levels of multimorbidity are available. As multimorbidity plays an important role in complex patients, the level of multimorbidity is a useful tool, in conjunction with hospitalization and ED visits, in identifying these patients. Strong evidence exists for the ACG System as a tool to determine care burden or multimorbidity, as well as risks for hospitalization and ED utilization (10-12). With this research, we explored the possibilities of the ACG System as a potential tool to identify patients with complex care needs in primary care.

This study's aim is to produce an identification method for patients with complex care needs using primary care data in order to perform a PHM approach. Our goal was to answer this research question: "Is a prediction model using the ACG risk stratification tool to identify patients with complex care needs, defined as patients with problems in multiple health domains and high acute hospital care, statistically valid for use in primary care?"

Methods

Study Design and Study Population

This work was designed as a retrospective cross-sectional study. To identify patients with complex care needs, a prediction model was developed and externally validated, using 2 study populations from 2 different regions in the Netherlands. Population 1 (n = 105,345) and population 2 (n = 30,793) were used as training and validation sets, respectively. To ensure completeness of primary care data, patients were included only if they were registered with a participating general practice for the complete period from January 2016 until December 2016. As dates for registration and deregistration are unreliable within general practitioners' electronic health records (EHRs), the period of registration was established using reimbursed registration fees. For each registered patient, a registration fee is reimbursed by the general practice each quarter. As registration fees are recorded very well within the EHRs, patients were included only when 4 registration fees for 2016 were reimbursed, indicating that the person was registered with the general practice for the complete year. In supplementary table 1, all registration fee codes nationally used in the Netherlands are presented. In addition, patients were included only when linkage with the database of Statistics Netherlands, the Dutch central bureau for statistics, was possible.

For ethical reasons, deceased patients were excluded from this study.

Data and Linkage

For this study, data from different data sources were linked anonymously at the individual patient level. Data extracted from EHRs of participating general practices included individuals' general information and information on diagnoses and medications from January to December 2016. Encryption of the EHR data was performed by Statistics Netherlands under strict rules to secure individuals' privacy. A record identification number (RIN) was assigned to each individual based on birth date, gender, and complete postal code. With the RINs, linkage of EHR data with Statistics Netherlands' microdata was made possible within the secured environment of Statistics Netherlands. Microdata comprise different types of non–publicly available data on an individual level. Under strict conditions, these microdata are accessible for statistical and scientific research. For this study, we linked the encrypted EHR data to the number of acute care visits extracted from the Dutch medical specialty information system, available as microdata within the secured environment of Statistics Netherlands. Acute care visits were defined as acute hospital care visits to the ED or to another hospital department in which an emergency care practitioner was involved.

Definition of Patients With Complex Care Needs

Adapted from Gawande's "The Hot Spotters" definition, 2 prerequisites were set to define patients with complex care needs. The first prerequisite concerns having health problems in at least 2 of 3 different health domains registered within primary care. Problems relating to the chronic physical, the mental, and the social domains were identified by selecting corresponding International Classification of Primary Care version 1 (ICPC-1) diagnosis codes within the EHR data. Supplementary table 1 gives an overview of the ICPC-1 codes for all 3 domains. The second prerequisite concerns having at least 2 acute care visits in a 12-month period (January-December 2016), considered high acute care utilization. Acute care visits were identified from health care activity codes within the medical specialty data set available as microdata. Health care activity codes are used nationwide by health care insurers and providers. In supplementary table 1, the specific codes corresponding with acute health care use are presented.

Statistical Analysis

To assess the ACG System as an identification method for patients with complex care needs, we developed a prediction model by using logistic regression analysis in the first study population, then externally validated the model in the second study population. To investigate the similarity of both study populations, individuals' characteristics were compared by using χ^2 and independent *t* tests for categorical and continuous variables, respectively.

Dependent variables

The dependent variable, or the outcome, in the logistic regression analysis was whether or not a person was identified as a complex patient (as described above).

Independent variables

Aggregated Diagnosis Groups (ADGs), the ACG System's categorization of diagnosis types, were used as independent variables. ICPC-1 diagnosis codes are clustered into 32 ADGs by the ACG software. All 32 ADGs, as well as sex and age categories, were included as independent variables within the logistic regression model. Age categories were based on ACG age categorization and clustered into 6 categories: aged 0 to 11 years, aged 12 to 34 years, aged 35 to 54 years, aged 55 to 69 years, aged 70 to 79 years, and aged 80 years or older.

Assessment of the model

The prediction model was assessed on both discriminatory and calibrating ability. To assess the discriminatory ability of the model, C statistic values were calculated in both the training and validation data sets. Values below 0.6 were considered poor; between 0.6 and 0.7, sufficient; between 0.7 and 0.8, good; between 0.8 and

0.9, very good; and above 0.9, excellent (13). The calibrating ability of the model was assessed by dividing the validation data set population into deciles based on ascending predicted values for being a complex patient. For each group, the mean observed and expected values were plotted against each other in the calibration plot. Models with a 45-degree angle plot (mean observed value equals mean expected value) were considered perfectly calibrated. Models below this reference line are overestimating, whereas models above it are underestimating.

Results

Population Characteristics

Population characteristics were compared for both the training and validation data sets. Table 1 shows the differences in population characteristics between the 2 data sets. The 2 study populations had comparable mean ages of 40.8 and 40.6 years, respectively. The percentage of women was 51.4% and 50.1%, respectively, and the percentage of complex patients was comparable in both data sets at 0.9% and 0.8%.

Table 1: Patient Characteristics Compared Between the 2 Populations Used for the Prediction Models

	Population 1 (n = 105,345)	**Population 2 (n = 30,793)**	***P***
Age in years, mean	40.8	40.6	<.001
Sex, % women	51.4	50.1	<.001
Complex patients, %	0.9	0.8	.072
Acute care visits, mean number	0.16	0.10	<.001
≥2 acute care visits, %	2.7	1.6	<.001
Health domains, %			
Chronic physical	39.8	46.8	<.001
Social	10.9	20.2	<.001
Mental	26.6	40.6	<.001
Common conditions, %			
Depression	8.5	10.3	<.001
Diabetes	6.7	5.9	<.001
Hypertension	20.1	20.3	.422
Ischemic heart disease	2.5	3.6	<.001
Asthma	11.5	13.5	<.001
Chronic obstructive pulmonary disease	3.1	2.8	.003

Population 1 is the training data set; population 2 is the validation data set; for comparison, χ^2 tests for categorical and independent *t* tests for continuous variables were performed.

The percentage of individuals with at least 2 acute care visits in 1 year was lower in the validation data set than in the training data set: 1.6% vs 2.7%. There were more health problems observed in the validation data set. Somatic chronic diseases were more prevalent in the validation data set, at 46.8% compared with 39.8%. In addition, a higher prevalence was found of psychiatric health problems (40.6% vs 26.6%) and of social health problems (20.2% vs 10.9%). Common conditions such as depression, diabetes, hypertension, ischemic heart disease, asthma, and chronic obstructive pulmonary disease were comparably prevalent in both populations.

Model Performance

Odds ratios

Figure 1 provides an overview of the odds ratios (ORs) for each variable in the model. Supplementary table 2 gives additional information about the ORs along with their 95% CIs.

Age and sex were not statistically significantly associated with the outcome. The following main predictors were identified: ADG categories *chronic medical, stable* (OR, 2.78; 95% CI, 2.35-3.29) and *chronic medical, unstable* (OR, 2.89; 95% CI, 2.49-3.35); *stable psychosocial* ADGs (OR, 3.36; 95% CI, 2.92-3.86); and *unstable psychosocial* ADGs (OR, 2.95; 95% CI, 2.33-3.73). In addition to the chronic medical and the psychosocial ADGs, the 3 ADGs *time limited: major* (OR, 2.37; 95% CI, 1.73-3.25), *injuries/adverse effects: major* (OR, 2.30; 95% CI, 1.89-2.79), and *signs/ symptoms: uncertain* (OR, 2.95; 95% CI, 2.50-3.49) were also highly associated with the outcome.

Discriminatory ability

The discriminatory ability of the prediction model for identifying complex patients was assessed by calculation of C statistics. The C statistics, estimated for the training and validation data sets, are presented in table 2.

Calibrating ability

Figure 2 shows the calibrating ability of the prediction model. The model is overestimating, meaning that it is identifying more complex patients than were observed in the study population. In supplementary table 3, the observed number of complex patients, mean expected values, and standard errors are presented for each decile of population 2.

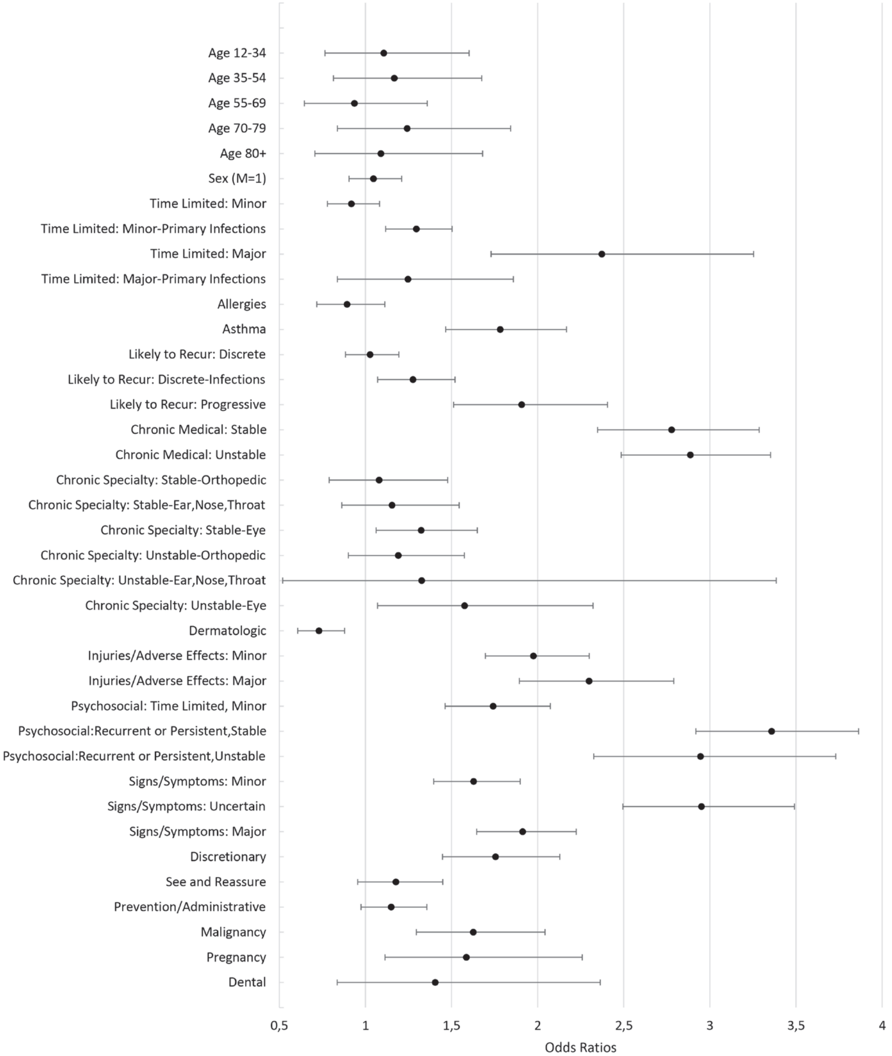

Figure 1: Estimated Odds Ratios and Their 95% Confidence Intervals. Variables include Aggregated Diagnosis Groups, a categorization of diagnosis types by the Johns Hopkins ACG System.

Table 2: Performance of Prediction Model for Being a Complex Patient

	C statistic	**95% CI**
Training data set	0.913	0.905 - 0.920
Validation data set	0.899	0.882 - 0.915

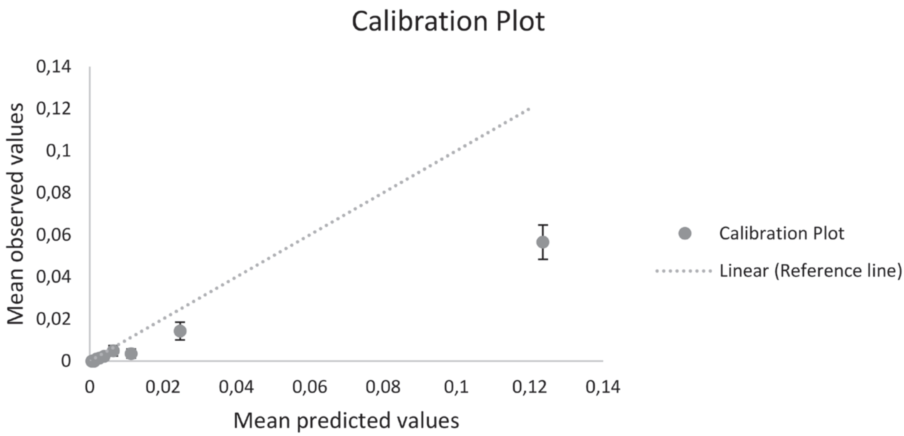

Figure 2: Calibration Plot: Observed vs Predicted Values (estimated by the prediction model for being a complex patient)

Discussion

With this study, we have developed a predictive model for patients with complex care needs. Although a good discriminatory performance is shown, the calibrating ability is modest because more complex patients were identified based on the predicted values than were observed. This study confirms results of previous studies, showing that the ACG System ADGs form a good tool to describe and determine the level of multimorbidity (14,15), which plays an important role in describing complex patient groups. With the highest weightings in the model for stable psychosocial problems, the proven prevalence of psychosocial conditions among our group of complex patients (16) is taken into account. Stable and unstable chronic medical problems and unstable psychosocial problems are strongly associated with the outcome. Following chronic medical and psychosocial problems, uncertain signs or symptoms also had a high predictive effect on being a complex patient.

In our study, a statistics-based quantitative tool was found to identify patients with complex care needs. As our model is overestimating complex patients, this tool based on routinely collected data should be used as a first screening method. Additional qualitative screening of identified complex patients is of great importance to select the right subpopulation for interventions. Additional qualitative screening also allows for distinction between patients with high care needs that can be avoided with proactive care, and patients in whom high care needs cannot be avoided. As our model was not built to distinguish between avoidable and unavoidable emergency care, this addition of qualitative screening is of great importance. It is therefore recommended, to investigate the practical use of our identification method, intervention studies with complex patients identified with our screening method should follow.

Further, high-quality registration is a necessary condition to be able to use complete health records for the identification of complex patients. Results of this study show that the prevalence of registered somatic chronic problems, as well as psychiatric and social health problems, differed between both study populations. These differences may have been due to dissimilar registration policies rather than differences in prevalence. For efficient and practical PHM approaches using data-driven identification methods to designate resources to the patient groups in which they will be most beneficial, good quality of registration is important. Once practitioners realize that registry data can be used for producing prediction models that are helpful in practice, improvement of registration habits is expected. In addition to the differences between the two study populations, the prevalence of social problems seemed lower than expected. As studies have shown that complex patients are more likely to have underlying social problems, such as low income, living alone, living in a deprived area, and being less likely to own a home (17-19), alongside chronic and psychosocial problems, the registration of social problems in primary care should be emphasized and stimulated. Alternatively, the identification of vulnerable and complex patient groups may be improved by creating access to social data sources. However, most risk stratification tools such as the ACG System do not currently include social data, as it is less routinely collected. In addition, linkage of social data to primary care data still entails significant information security and legal issues.

An accurate identification of complex patients in primary care can be of great value to health care systems. Not only can early identification and intervention prevent deterioration of patients' health, but health resources can also be put towards groups of patients who will benefit most from them. As general practitioners' workload is increasing, resulting in rising pressures on them in most European countries (20), allocation of available resources in primary care is of utmost importance. In situations in which different types of health care data can easily be combined, such as in integrated and managed care organizations, more complete profiles of patients can be used to allocate resources to the patient groups for whom they will be most beneficial. Risk stratification approaches to identify subpopulations have proven valuable in forms of both tailored care interventions and improved care management (21,22). Effective PHM interventions following identification of complex groups of patients may lead to improved health outcomes, not only for these complex groups, but for the whole population.

Limitations

This research is based on a definition of complex patients that is principally composed of biomedical characteristics. As social determinants are underrepresented in primary care registration, defining complex patients was mostly limited to the somatic physical and psychiatric diagnoses of patients. Although we believe that we have identified a group of complex patients with unmet health needs, the social health burden is most likely to be under recorded. This may have caused our selected population of complex patients (outcome) to ignore other important groups of patients. As our PHM approach using primary care data is a holistic approach, the biomedical focus of registry systems may still cause important gaps in patients' complete care profiles.

Further, the age categories used in this study are broad. We explored the use of smaller age categories (eg, 5-year age bands) and the use of age as a continuous variable, but age did not contribute statistically significantly to the identification of patients with complex care needs adjusting for other factors.

Lastly, by selecting people registered with one of the participating general practices for a period of 12 months, people born within this 12-month period were excluded from this study. However, there are very few infants who would meet our requirements to be classified as a patient with complex care needs according to our definition.

Conclusions

Using broad morbidity groups of diagnoses or comorbidities (such as ADGs) seems to be an effective approach to identify complex patients in primary care. Risk stratification tools are key methods in putting available registry data to good use to identify complex patient groups. In addition to biomedical health determinants, social determinants play an important role in the identification of complex patients. Effective identification of complex patients in primary care can result in appropriate and proactive care management for this group of patients, benefiting the total primary care population.

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Supplementary Material

Supplementary table 1: Overview of specific codes corresponding with different health domains and acute healthcare use:

Characteristic	Coding system	Specific codes
Diagnoses in the chronic physical domain	International Classification for Primary Care, version 1 (ICPC-1)	A28, A79, A90, B28, B72, B73, B74, B78, B79, B83, B90, D28, D74, D75, D76, D77, D81, D92, D94, D97, F28, F81, F83, F84, F91, F93, F94, H28, H80, H83, H84, H85, H86, K28, K73, K74, K76, K77, K82, K86, K87, K90, K91, K92, L28, L82, L84, L85, L88, L89, L90, L91, L95, L98, N28, N70, N74, N85, N86, N87, N88, R28, R84, R85, R89, R91, R95, R96, S28, S77, S81, S83, S87, S91, T28, T71, T78, T80, T81, T86, T90, T92, T93, U28, U75, U76, U77, U85, U88, W28, W72, W76, X28, X75, X76, X77, X83, X88, Y28, Y77, Y78, Y82, Y84
Diagnoses in the mental domain	ICPC-1	P01, P02, P02.01, P03 to P06, P09, P10, P10.01, P10.02, P11, P15 to P19.02 (not P17), P20, P21, P22, P23, P24, P25, P27, P28,P29, P70 to P77.02, P78, P79 to P80.01, P80.02, P 85, P98, P99, P99.01, T06 to T06.02.
Diagnoses in the social domain	ICPC-1	Z01 to Z29
Acute healthcare utilization	Dutch healthcare activities coding system	190060/190013 *in combination with emergency physician*, 190015, 190016

For the three health domains, ICPC-1 codes corresponding to the three health domains including the chronic physical, the mental and the social health domain, are presented. For acute healthcare utilization, specific healthcare activity codes are presented

Supplementary table 2: Odds ratios, including the 95% confidence intervals, for all in the model included independent variables

	Odds Ratio	**95% Confidence interval**	
		Lower bound	**Upper bound**
Age 12-34 year	1.107	0.765	1.602
Age 35-54 year	1.168	0.814	1.676
Age 55-69 year	0.936	0.645	1.359
Age 70-79 year	1.242	0.837	1.844
Age 80+ year	1.090	0.707	1.680
Sex (M=1)	1.047	0.905	1.211
1 Time Limited: Minor	0.918	0.779	1.082
2 Time Limited: Minor-Primary Infections	1.296	1.117	1.503
3 Time Limited: Major	2.372	1.730	3.254
4 Time Limited: Major-Primary Infections	1.247	0.837	1.859
5 Allergies	0.894	0.718	1.113
6 Asthma	1.783	1.467	2.167
7 Likely to Recur: Discrete	1.028	0.884	1.194
8 Likely to Recur: Discrete-Infections	1.276	1.071	1.520
9 Likely to Recur: Progressive	1.907	1.512	2.406
10 Chronic Medical: Stable	2.778	2.348	3.286
11 Chronic Medical: Unstable	2.886	2.485	3.352
12 Chronic Specialty: Stable-Orthopedic	1.080	0.789	1.477
13 Chronic Specialty: Stable-Ear, Nose, Throat	1.154	0.863	1.544
14 Chronic Specialty: Stable-Eye	1.324	1.062	1.650
16 Chronic Specialty: Unstable-Orthopedic	1.191	0.900	1.574
17 Chronic Specialty: Unstable-Ear, Nose, Throat	1.327	0.520	3.385
18 Chronic Specialty: Unstable-Eye	1.576	1.070	2.321
20 Dermatologic	0.731	0.607	0.879
21 Injuries/Adverse Effects: Minor	1.975	1.696	2.300
22 Injuries/Adverse Effects: Major	2.299	1.894	2.790
23 Psychosocial: Time Limited, Minor	1.741	1.462	2.073
24 Psychosocial: Recurrent or Persistent, Stable	3.358	2.919	3.863
25 Psychosocial: Recurrent or Persistent, Unstable	2.946	2.326	3.730
26 Signs/Symptoms: Minor	1.628	1.396	1.899
27 Signs/Symptoms: Uncertain	2.951	2.495	3.490
28 Signs/Symptoms: Major	1.913	1.646	2.224
29 Discretionary	1.755	1.447	2.128
30 See and Reassure	1.177	0.955	1.449
31 Prevention/Administrative	1.150	0.974	1.357
32 Malignancy	1.627	1.295	2.043
33 Pregnancy	1.586	1.114	2.259
34 Dental	1.406	0.836	2.364

Dependent variables include age categories, sex and 32 Aggregated Diagnosis Groups from the Johns Hopkins Adjusted Clinical Groups system. (Aggregated Diagnosis Groups are an aggregation of the International Classification of Primary Care diagnosis codes.)

Supplementary table 3: Summary statistics of the ten deciles of the population on which the calibration plot is based

Total n per group	Number of complex patients	Mean observed values	Mean predicted values	Standard Error
3291	0	0,000	0,001	0,000
2879	0	0,000	0,001	0,000
3062	0	0,000	0,001	0,000
3086	3	0,001	0,002	0,001
3073	4	0,001	0,003	0,001
3086	7	0,002	0,004	0,001
3080	15	0,005	0,006	0,001
3079	11	0,004	0,011	0,001
3081	44	0,014	0,025	0,002
3077	174	0,057	0,124	0,004