SUPPLEMENTARY MATERIAL S1

PIMS descriptives

Three different types of rules were identified: 1) medications that are always potentially inappropriate (e.g. glyburide), 2) medications that are potentially inappropriate if prescribed in combination with other medications (e.g. combinations of several anticholinergic medications), and 3) medications that are potentially inappropriate if a patient has a particular condition or syndrome (ex. Non-steroidal anti-inflammatories and a diagnosis of congestive heart failure) or a patient *does not* have particular conditions (e.g. proton pump inhibitors in patients without diagnosis of gastroesophageal reflux disease, gastrointestinal hemorrhage).

In total, 257 PIMs were identified from all possible criteria. PIMs which included medications available over the counter and or not covered under the public provincial formulary were excluded as these medications are not present in pharmacy claims data for dispensed medications. Thus, 192 (75%) of all PIMs were eligible for measurement. The majority (88/192 [46%]) are central nervous system agents followed by cardiovascular drugs (27 [14%]), and autonomic drugs (19 [10%]). Most eligible PIMs were medications which are potentially inappropriate in combination with a patient's conditions (78%), followed by 15% which are inappropriate in combination with other medications while the remaining 7% of medications are inappropriate on their own.

Calculation of Propensity Score

Covariates included in propensity score estimation were: age, sex, drug coverage status (full co-pay, partial co-pay, no co-pay), number of pre-admission hospitalizations, ED visits, ambulatory care visits, prescribers and dispensing pharmacies (based on prescription claims data), as well as "continuity of medication management" (proportion of all dispensed pre-admission medications

that were written by most frequent prescriber; based on the continuity of care index [1–3]), number of different medications in the community drug list per patient, binary indicators of the presence or absence of each of the 27 conditions found in the Charlson and Elixhauser comorbidity indices[4] and reason for admission (first letter of the ICD-10 classification). Overall, there was good overlap in the propensity score distributions between those with and without PIMs, and the model had good discrimination (C-statistic=0.82).[5]

Covariate Selection

Model goodness of fit statistics (AIC)[6] and change in the hazard ratio & odds ratio for number of prescribed PIMs[7] were used to determine which confounders measured at discharge to adjust for in our models.[8] To test and account for potential violations in both the proportional hazards assumption and linearity of the effects for continuous variables on the hazard, we used flexible spline-based extensions of the Cox model.[9]

Adverse drug event adjudication

We used the Leape and Bates approach by two clinical experts to independently adjudicate the presence, severity, and preventability of adverse drug events (ADEs) using patient self-reported information, chart data, and administrative health data. Patient self-reported information was collected via a modified version of the Australian two-step adverse reaction and drug event report, which collects data on potential adverse drug events and their characteristics which was administered via telephone interview within 30 days post-discharge from hospital. Chart data, which was abstracted by trained research assistants, and administrative health data was used to provide adjudicators with information on patients' acute and chronic health problems, medical services received post-discharge, medications that were started, stopped or continued at discharge, and medications dispensed post-discharge.

For patients that had any new health problem, two physicians at another academic health centre independently rated the likelihood that the problem was medication-related for each patient who reported a new or worsening health problem on interview or had an emergency department visit or re-admission to hospital within 30 days post-discharge. A third physician adjudicated any disagreement between the two reviewers. The agreement between the two reviewers was 80.3%.

TABLES AND FIGURES

Table S1. Medications prescribed at discharge according to appropriateness and their impact on re-hospitalizations, emergency department visits and death in 30-days post discharge in patients 65 years of age and older from internal medicine (n=1,287)

Medications prescribed at discharge	Incidence rate (95% CI) per 100 person days	Unadjusted HR (95% CI)	Adjusted HR (95% CI)
Binary			
No community PIMs	1.59 (1.39-1.80)	*Reference*	*Reference*
At least one community PIM	1.73 (1.54-1.95)	1.08 (0.91-1.29)	1.03 (0.85-1.25)
No new PIMs	1.57 (1.41-1.74)	*Reference*	*Reference*
At least one new PIM	1.93 (1.64-2.27)	1.33 (1.01-1.48)	1.26 (0.96-1.64)
Continuous			
Community non-PIMs	-	1.00 (0.98-1.03)	0.97 (0.94-1.01)
Community PIMs	-	1.04 (1.00-1.09)	1.03 (0.97-1.09)
New non-PIMs	-	1.02 (1.00-1.07)	1.04 (0.99-1.10)
New PIMs	-	1.08 (0.99-1.18)	1.13 (0.99-1.28)

Table S2 . Medications prescribed at discharge according to appropriateness and their impact on re-hospitalizations, emergency department visits and death in 30-days post discharge in patients 65 years of age and older from surgical units (n=1,115)

Medications prescribed at discharge	Incidence rate (95% CI) per 100 person days	Unadjusted HR (95% CI)	Adjusted HR (95% CI)
Binary			
No community PIMs	1.15 (0.99-1.13)	*Reference*	*Reference*
At least one community PIM	1.16 (1.37-1.83)	1.35 (1.10-1.66)	1.23 (0.99-1.54)
No new PIMs	1.30 (1.13-1.48)	*Reference*	*Reference*
At least one new PIM	1.40 (1.29-1.66)	1.08 (0.87-1.33)	1.19 (0.86-1.64)
Continuous			
Community non-PIMs	-	1.04 (1.00-1.08)	1.01 (0.97-1.06)
Community PIMs	-	1.14 (1.05-1.23)	1.11 (1.01-1.20)
New non-PIMs	-	1.09 (1.04-1.15)	1.06 (0.99-1.14)
New PIMs	-	1.17 (1.04-1.32)	1.17 (0.99-1.39)

Table S3. Medications prescribed at discharge according to appropriateness and their impact on drug related adverse events in 30-days post discharge in patients 65 years of age and older discharged from internal medicine (n=1,287)

Medications prescribed at discharge	Risk N (%)	Unadjusted OR (95% CI)	Adjusted OR (95% CI)
Binary			
No community PIMs	42 (7.0)	*Reference*	*Reference*
At least one community PIM	73 (10.6)	1.58 (1.07-2.35)	1.49 (0.96-2.29)
No new PIMs	80 (8.5)	*Reference*	*Reference*
At least one new PIM	35 (10.1)	1.21 (0.79-1.83)	1.34 (0.86-2.06)
Continuous			
Community non-PIMs	-	1.02 (0.97-1.07)	0.95 (0.89-1.02)
Community PIMs	-	1.13 (1.02-1.24)	1.11 (1.00-1.23)
New, non-PIMs	-	1.02 (0.93-1.12)	1.07 (0.96-1.17)
New PIMs	-	1.01 (0.81-1.24)	1.13 (0.87-1.46)

Table S4. Medications prescribed at discharge according to appropriateness and their impact on drug related adverse events in 30-days post discharge in patients 65 years of age and older discharged from surgical units (n=1,115)

Medications prescribed at discharge	Risk N (%)	Unadjusted OR (95% CI)	Adjusted OR (95% CI)
Binary			
No community PIMs	56 (9.0)	*Reference*	*Reference*
At least one community PIM	47 (9.1)	1.08 (0.72-1.62)	1.21 (0.78-1.87)
No new PIMs	56 (7.9)	*Reference*	*Reference*
At least one new PIM	47 (11.5)	1.51 (1.01-2.28)	1.52 (1.00-2.30)
Continuous			
Community non-PIMs	-	0.97 (0.90-1.05)	0.99 (0.90-1.08)
Community PIMs	-	1.05 (0.90-1.24)	1.08 (0.91-1.08
New, non-PIMs	-	1.05 (0.95-1.17)	1.07 (0.95-1.20)
New PIMs	-	1.28 (1.00-1.62)	1.32 (1.03-1.71)

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