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Use of a medication-based risk adjustment index to predict mortality among veterans dually-enrolled in VA and medicare

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ABSTRACT

Background: There is systemic undercoding of medical comorbidities within administrative claims in the Department of Veterans Affairs (VA). This leads to bias when applying claims-based risk adjustment indices to compare outcomes between VA and non-VA settings. Our objective was to compare the accuracy of a medication-based risk adjustment index (RxRisk-VM) to diagnostic claims-based indices for predicting mortality.
Methods: We modified the RxRisk-V index (RxRisk-VM) by incorporating VA and Medicare pharmacy and durable medical equipment claims in Veterans dually-enrolled in VA and Medicare in 2012. Using the concordance (C) statistic, we compared its accuracy in predicting 1 and 3-year all-cause mortality to the following models: demographics only, demographics plus prescription count, or demographics plus a diagnostic claims-based risk index (e.g., Charlson, Elixhauser, or Gagne). We also compared models containing demographics, RxRisk-VM, and a claims-based index.
Results: In our cohort of 271,184 dually-enrolled Veterans (mean age = 70.5 years, 96.1% male, 81.7% non-Hispanic white), RxRisk-VM (C = 0.773) exhibited greater accuracy in predicting 1-year mortality than demographics only (C = 0.716) or prescription counts (C = 0.744), but was less accurate than the Charlson (C = 0.794), Elixhauser (C = 0.80), or Gagne (C = 0.810) indices (all $P < 0.001$). Combining RxRisk-VM with claims-based indices enhanced its accuracy over each index alone (all models $C \geq 0.81$). Relative model performance was similar for 3-year mortality.
Conclusions: The RxRisk-VM index exhibited a high level of, but slightly less, accuracy in predicting mortality in comparison to claims-based risk indices.
Implications: Its application may enhance the accuracy of studies examining VA and non-VA care and enable risk adjustment when diagnostic claims are not available or biased.
Level of evidence: Level 3.

1. Background

The application of risk adjustment indices that use diagnosis codes derived from the International Classification of Diseases (ICD) is standard in health services research.[1,2] However, risk adjustment using ICD codes may introduce bias due to variation in coding practices (i.e., “under” or “over” coding).[3] This makes the accurate comparison of health outcomes across healthcare systems challenging. For example, there is systemic undercoding of comorbidities within administrative data derived from the electronic health records (EHR) of the Department of Veterans Affairs (VA). This is due, in part, to the uncoupling of diagnostic codes from reimbursement and because some Veterans only

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receive VA care for a subset of their conditions.[4] More specifically, in Veterans who receive care in both VA and non-VA healthcare settings via Medicare (i.e., dual users), VA administrative data only capture 33% of their comorbidities, whereas Medicare data capture 80%.[5,6] This discrepancy results in an ascertainment bias, potentially skewing studies that compare outcomes between VA and non-VA health systems, as VA beneficiaries appear less sick per ICD claims.[7]

Risk adjustment using pharmacy records is a potential solution to overcome these measurement biases. Additionally, pharmacy records may be used for risk adjustment when ICD codes are incomplete or unavailable, such as in Medicare Advantage beneficiaries.[7] One such medication-based index, RxRisk-V, was originally developed to predict cost of care and was subsequently validated to predict mortality in a cohort of Veterans using VA administrative data.[8,9] While RxRisk-V has been validated for use within VA, its prognostic accuracy has not been assessed using Medicare data.

Nearly 80% of VA beneficiaries also have an alternative form of private or public health insurance, and Veterans' receipt of non-VA care is anticipated to grow as the VA Mission Act of 2018 seeks to enhance VA's community care programs. Therefore, it is increasingly necessary to develop a non-biased method of risk adjustment that accurately accounts for Veterans' comorbidities treated both within and outside VA when comparing the quality of care across VA and non-VA systems.[10–14] Thus, we sought to modify the medication-based risk adjustment index, RxRisk-V, for use with combined VA and Medicare data and compare its accuracy to commonly used ICD claims-based risk adjustment methods in predicting 1 and 3-year all-cause mortality.

2. Methods

2.1. Study population and data sources

We conducted this study in a previously reported national cohort of all Veterans who were dually-enrolled in VA and Medicare Part D, had an active opioid prescription from either VA or Medicare in calendar year 2012, and were alive as of December 31, 2012.[15] We excluded patients in Medicare Advantage plans because their medical claims were incomplete.

We linked national patient-level data from VA and the Centers for Medicare and Medicaid Services (CMS) from calendar years (CY) 2012–2013 (January 1, 2012 through December 31, 2013). From VA, we used data from the Corporate Data Warehouse (CDW) to capture sociodemographic characteristics and ICD-9 codes documented in face-to-face clinical encounters, using previously described methods.[16] We used VA Pharmacy Benefits Management (PBM) data to record dispensed outpatient prescriptions and durable medical equipment (DME). We used the vital status file to determine 1- year (January 1, 2013–December 31, 2013) and 3-year (January 1, 2013–December 31, 2015) mortality. From CMS, we used the denominator file to capture enrollment and sociodemographic data. We used the MedPAR, carrier and standard analytic claims files (e.g., outpatient, home health, and hospice) to capture ICD-9 codes documented in face-to-face clinical encounters, and the Part D and Part B DME files for dispensed outpatient prescriptions and DME, respectively.

2.2. Modifying the RxRisk-V index

We updated and modified the RxRisk-V index (RxRisk-VM) in 3 key ways. First, we classified all VA medications and DME dispensed to Veterans that were not previously classified in prior iterations of RxRisk-V.[8,9] Three study investigators (TR, JH, and JN) mapped each unclassified medication or DME to 1 of 45 original RxRisk-V categories (Appendix Table A). Medications and DME that did not map to any of the 45 previously established categories were not included in the index. We reconciled all disagreements through a group discussion and consensus process (See Appendix A for a full description).

Second, we mapped all medications dispensed through Medicare Part D, in the same manner that we categorized VA medications and DME. Because DME is contained within VA PBM datasets and incorporated in RxRisk-V, we also incorporated all comparable DME dispensed through Medicare.

Third, as this was the first instance in which Medicare data has been integrated with VA data in the RxRisk-V model, we assigned new weights to each category using previously reported methods.[9] As per these methods, we used logistic regression to assigned weights based upon the magnitude of association (odds ratio) with 1-year all-cause mortality, controlling for age, sex, and race/ethnicity (Appendix Table B). As using the full sample to estimate new weights may over estimate predictive performance due to overfitting, we subsequently applied 10-k fold cross-validation to generate a more robust estimate of predictive performance. We compared these results with the estimates from the main analyses done in the overall cohort.

2.3. Outcome measures and covariates

Our outcome measures were the 1-year (January 1, 2013–December 31, 2013) and 3-year (January 1, 2013–December 31, 2015) all-cause mortality rates for the study cohort.

We created sociodemographic variables for age, sex, and race/ethnicity preferentially using VA data from CY2012, supplemented with CMS data as necessary. We used Medicaid enrollment status as a proxy of socioeconomic status and determined the percentage of Veterans who originally enrolled in Medicare due to disability. We also characterized Veterans as dual users of VA and Medicare health services based upon whether they received inpatient care, outpatient care, or medications from both a VA and a Medicare provider in CY2012.

2.4. Risk adjustment

Using data from CY2012, we calculated the RxRisk-VM score applying both the newly derived and original weights. We also determined prescription counts based upon the number of unique prescriptions captured within VA and Medicare data in CY2012 and calculated scores for the following diagnostic claims-based comorbidity indices: Charlson (Deyo adaptation), Elixhauser (van Walraven adaption), and Gagne. The Deyo adaptation of the Charlson Index assigns empirically-derived weights to 17 conditions, resulting in an overall risk score.[17,18] The van Walraven modification of the Elixhauser index combines the 30 standard Elixhauser conditions into a single weighted score.[19,20] Due to the redaction of ICD-9 codes for alcohol and substance use disorders in Medicare data, these conditions were excluded from Elixhauser. Lastly, the Gagne index is based on 20 conditions derived from the Charlson or Elixhauser indices.[21] This index has demonstrated superior accuracy in predicting 1-year all-cause mortality in comparison to the Charlson and Elixhauser indices.[21] Therefore, we used the Gagne index for analyses in which we compared RxRisk-VM to a single index.

2.5. Statistical analyses

We calculated descriptive statistics for sociodemographic variables for the overall cohort and sub-group of dual users of VA and non-VA care. We determined prescription counts, the mean weighted scores for each risk adjustment index, and the 1 and 3-year all-cause mortality rates for the overall cohort and dual use sub-group. We used the kappa statistic to compare the performance of RxRisk-VM and Gagne indices in identifying patients with specific conditions included in both indices.

Using the concordance (C) statistic, we compared the area under the curve (AUC) of RxRisk-VM in predicting 1 and 3-year all-cause mortality to alternative risk adjustment indices. Using VA and Medicare administrative data, we first fit a base model that contained baseline sociodemographics (i.e. age, gender, race/ethnicity, Medicaid enrollment, and disability status). In a series of separate models, we incorporated each of the following to the base model: RxRisk-VM, RxRisk-V incorporating Medicare and VA data using original weights, an unweighted count of unique prescriptions, and the following ICD claims-based comorbidity indices: Charlson (Deyo modification), Elixhauser (van Walraven modification), and Gagne. We compared each model's AUC using the Chi-squared goodness-of-fit test. To determine if the RxRisk-VM index enhanced the AUC of ICD claims-based indices alone, we also compared the AUCs for models containing baseline demographics, RxRisk-VM and either the Charlson, Elixhauser, or Gagne Indices. We then replicated these models and determined their prognostic accuracy in determining 3-year all-cause mortality in a similar fashion.

To determine if the data source affected the AUC, we conducted a sensitivity analysis in dual VA and Medicare users, comparing the AUC of each model using data from VA alone, Medicare alone, or from both sources. Additionally, to assess the calibration of the RxRisk-VM index in predicting 1-year mortality, we generated calibration curves for both RxRisk-VM and Gagne models. For each calibration curve, we compared the observed versus expected 1-year mortality using the Hosmer-Lemeshow goodness-of-fit test.

3. Results

3.1. Baseline characteristics of the study cohort

Of the 271,184 Veterans in the study cohort, the mean age was 70.5 (SD 11.8) years, 96.1% were male, 81.7% were non-Hispanic white, and 35.7% were Medicaid eligible. Of the overall cohort, 172,041 (63.4%) were dual users of VA and Medicare health services (Table 1).

3.2. Risk adjustment scores

For the overall cohort, the mean weighted RxRisk-VM score was 10.3 (SD 4.8). The mean number of unique prescriptions was 12.9 (SD 6.2). The mean weighted scores for RxRisk-V applying the original weights was 9.4 (SD 5.0). Mean weighted scores for the Charlson, Elixhauser, and Gagne indices were, 3.0 (SD 2.6), 4.7 (SD 7.3), and 2.4 (SD 3.0), respectively. There was poor agreement between the RxRisk-VM index and Gagne index for all conditions contained within both measures (Kappa < 0.50), with the exception of dementia (Kappa = 0.54) (Appendix Table C).

Among dual users, the mean RxRisk-VM score using VA and Medicare data was 10.7 (SD 4.9). Using VA data alone, the mean RxRisk-VM score among dual users was 6.1 (5.6), accounting for 57.0% of the total score. Using Medicare data alone, the mean RxRisk-VM score was 6.9 (SD 5.1), accounting for 64.4% of the total score. Due to overlap in medications prescribed in both VA and Medicare, the total of these percentages is greater than 100. For ICD claims-based comorbidity measures, VA captured fewer medical comorbidities than were captured within Medicare administrative claims (Appendix Table D). For example, among dual users, Gagne comorbidities captured within VA only accounted for 34.6% of the total score (0.9, SD 1.8), whereas comorbidities captured within Medicare accounted for 80.1% of the total score (2.1, SD 2.9) (Table 1).

3.3. Prognostic accuracy of the RxRisk-VM index

The 1 and 3-year all-cause mortality rates were similar for the overall and dual use cohorts – approximately 9% and 24%, respectively (Table 1). In the overall cohort, the AUC of both the RxRisk-V index using the original weights (C = 0.759) and the RxRisk-VM Index (C = 0.773) was greater than models using demographics alone (C = 0.716) or a prescription count (C = 0.744), but lower than models using Charlson (C = 0.794), Elixhauser (C = 0.800) or Gagne (C = 0.810, all P < 0.001) (Table 2). AUCs for RxRisk-VM derived

Table 1
Characteristics and weighted comorbidity index scores for the overall cohort and dual users of VA and medicare health services.

Characteristics	Overall Cohort (N = 271,184)	Dual Users (VA + Medicare)[a] (N = 172,041)
Age, mean (SD)	70.5 (11.8)	70.0 (11.7)
< 65 (%)	29.0	30.0
65-74 (%)	31.7	32.3
75-84 (%)	26.5	26.1
85+ (%)	12.8	11.6
Male sex (%)	96.1	96.1
Race/Ethnicity (%)		
Non-Hispanic White	81.7	81.3
Black	13.1	13.5
Hispanic	2.4	2.5
Other/missing	2.8	2.7
Medicaid Eligibility (%)	35.7	36.0
Disability Status[b] (%)	40.2	42.2
Comorbidity Index Scores, mean(SD)		
RxRisk-VM (fully modified version)		
Combined VA and Medicare pharmacy records[c]	10.3 (4.8)	10.7 (4.9)
VA pharmacy records only	-	6.1 (5.6)
Medicare pharmacy records only	-	6.9 (5.1)
Number of Unique Prescriptions[d]		
Combined VA and Medicare pharmacy records	12.9 (6.2)	13.8 (6.3)
VA pharmacy records only	-	7.5 (6.4)
Medicare pharmacy records only	-	7.7 (6.1)
RxRisk-V (Original Weights)		
Combined VA and Medicare pharmacy records	9.4 (5.0)	9.9 (5.2)
VA pharmacy records only	-	5.9 (5.5)
Medicare pharmacy records only	-	5.9 (4.8)
Charlson (Deyo) Index		
Combined VA and Medicare Claims	3.0 (2.6)	3.2 (2.7)
VA claims only	-	1.6 (1.8)
Medicare claims only	-	2.7 (2.6)
Elixhauser (van Walraven) Index[e]		
Combined VA and Medicare Claims	4.7 (7.3)	5.0 (7.5)
VA claims only	-	1.4 (4.3)
Medicare claims only	-	4.3 6.9)
Gagne Index		
Combined VA and Medicare Claims	2.4 (3.0)	2.6 (3.1)
VA claims only	-	0.9 (1.8)
Medicare claims only	-	2.1 (2.9)
All-Cause Mortality		
1 Year (%)	9.4	9.2
3 Year (%)	24.3	23.8

[a] Dual use was defined as any combination of an inpatient visit, outpatient visit or medication from both VA and Medicare during the study year. Among dual users, 49% had both visits and medication from both VA and Medicare.
[b] Disability as the original reason for Medicare Enrollment. Among patients < 65 years, 90.9% enrolled due to disability. Among patients of ≥65, 19.5% enrolled due to disability.
[c] Only combined scores are depicted for the overall cohort as not all Veterans received care from both VA and Medicare sources.
[d] Represents unique prescription count in 2012 and not weighted score.
[e] Elixhauser Index excludes alcohol and drug use due to the redaction of related-claims.

Table 2
Area under the curve (C-statistic) of the modified RxRisk-V index (RxRisk-VM) in comparison to and in combination with commonly used diagnostic claims-based indices.

	1-year mortality (95% CI)[a]	3-year mortality (95% CI)[a]
Individual Models		
Baseline Demographics (Demo)[b]	0.716 (0.713, 0.719)	0.729 (0.723, 0.731)
Demo + Unique Prescription Count	0.744 (0.740, 0.747)	0.753 (0.751, 0.755)
Demo + RxRisk-V (original weights)	0.759 (0.756, 0.762)	0.767 (0.765, 0.769)
Demo + RxRisk-VM (fully modified version)	**0.773 (0.770, 0.776)**	**0.779 (0.778, 0.781)**
Demo + Charlson	0.794 (0.791, 0.797)	0.792 (0.790, 0.794)
Demo + Elixhauser[c]	0.800 (0.798, 0.803)	0.796 (0.793, 0.797)
Demo + Gagne	0.810 (0.807, 0.813)	0.805 (0.803, 0.807)
Combined Models		
Demo + Charlson + RxRisk-VM	0.805 (0.802, 0.808)	0.803 (0.801, 0.805)
Demo + Elixhauser + RxRisk-VM	0.812 (0.809, 0.815)	0.809 (0.807, 0.811)
Demo + Gagne + RxRisk-VM	0.817 (0.814, 0.819)	0.813 (0.811, 0.815)

[a] Models for 1-year and 3-year mortality were compared separately. All comparisons were statistically significant when applying the Chi Square Test of the AUC ($p < 0.001$).
[b] Baseline demographic models (demo) includes categorical age (10 categories: < 50, 5-year categories between 50 and 89, and 90+), gender, race/ethnicity, Medicaid enrollment and disability status (original reason for Medicare enrollment).
[c] Elixhauser Index excludes alcohol and drug use due to the redaction of related-claims.

using 10-k fold cross validation were nearly identical to those derived in our primary analysis (Appendix Table E).

The accuracy in predicting 1-year all-cause mortality for the model containing demographics, RxRisk-VM, and the Gagne Index together was greater ($C = 0.817$, $P < 0.001$) than models containing the RxRisk-VM and other ICD claims-based comorbidity indices (Table 2).

There was a similar pattern of relative model performance for 3-year all-cause mortality; however, the performance of models that contained the RxRisk-VM ($C = 0.779$) and Charlson ($C = 0.779$) scores now approximated each other (Table 2).

Among dual users of VA and Medicare services, models that contained both VA and Medicare data exhibited greater prognostic accuracy than models that contained VA or Medicare data alone, across all the risk adjustment methods. Specifically, the AUC for RxRisk-VM was 0.761 when including both VA and Medicare data, but was 0.716 when using VA data alone and 0.720 when using Medicare data alone (Table 3).

The observed versus predicted proportion of 1-year all-cause mortality did not significantly differ for most RxRisk-VM scores, with the predicted mortality falling outside the 95% confidence interval of observed mortality for RxRisk-VM scores exceeding 23. The calibration curve for the RxRisk-VM model was similar to the Gagne Index calibration curve, which also exhibited divergence of the observed and predicted mortality rates at higher scores (Fig. 1).

4. Discussion

In a national cohort of Veterans dually-enrolled in VA and Medicare Part D, the RxRisk-VM index exhibited a high degree of, but slightly less, accuracy in predicting 1 and 3-year all-cause mortality relative to other commonly used ICD claims-based risk adjustment indices. When incorporated into models that also contained ICD-based indices, RxRisk-VM enhanced the prognostic accuracy over the use of each index alone. Additionally, among dual users, incorporating data from both VA and Medicare sources enhanced prognostic accuracy over the use of data from only one source.

Our findings suggest that RxRisk-VM is a viable alternative to commonly used ICD-based risk adjustment indices for use in VA and Medicare data, especially when diagnostic claims are not available or the use of claims-based indices may lead to an unacceptable degree of bias. Such bias has been shown to be especially problematic in studies that evaluate outcomes between VA and non-VA health systems or the impact of dual VA and non-VA health system use.[5–7] While the current standard when conducting such studies is to risk adjust by incorporating ICD claims from more than one healthcare system (i.e., VA and Medicare), potential pitfalls exist in applying this approach.[22] First,

Table 3
Area Under the Curve (C-Statistic) of the Modified RxRisk-VM Index in Predicting 1-year Mortality among Dual Users when Incorporating VA and/or Medicare Data (N = 172,041).

	VA + CMS data[a]	VA data only[a]	CMS data only[a]
Individual Models			
Baseline Demographics (Demo)[b]	0.694 (0.689, 0.698)	0.694 (0.968, 0.698)	0.694 (0.689, 0.698)
Demo + Unique Prescription Count	0.725 (0.721, 0.729)	0.701 (0.697, 0.705)	0.710 (0.706, 0.715)
Demo + RxRisk-V (original weights)	0.745 (0.741, 0.749)	0.713 (0.709, 0.717)	0.716 (0.712, 0.721)
Demo + RxRisk-VM (modified version)	**0.761 (0.757, 0.765)**	**0.716 (0.712, 0.720)**	**0.720 (0.716, 0.724)**
Demo + Charlson	0.785 (0.781, 0.789)	0.731 (0.727, 0.735)	0.776 (0.773, 0.780)
Demo + Elixhauser[c]	0.794 (0.791, 0.798)	0.729 (0.725, 0.733)	0.782 (0.778, 0.786)
Demo + Gagne	0.805 (0.801, 0.808)	0.740 (0.736, 0.744)	0.792 (0.789, 0.796)
Combined Models			
Demo + Charlson + RxRisk-VM	0.797 (0.794, 0.801)	0.735 (0.731, 0.739)	0.777 (0.773, 0.781)
Demo + Elixhauser + RxRisk-VM	0.807 (0.803, 0.810)	0.734 (0.730, 0.738)	0.783 (0.779, 0.787)
Demo + Gagne + RxRisk-VM	0.811 (0.808, 0.815)	0.743 (0.739, 0.747)	0.792 (0.789, 0.796)

[a] Models using VA + CMS Data, VA data only, and CMS data only were compared separately. All comparisons were statistically significant when applying the Chi Square Test of the AUC ($p < 0.001$).
[b] Baseline demographic models (demo) includes categorical age (10 categories: < 50, 5-year categories between 50 and 89, and 90+), gender, race/ethnicity, Medicaid enrollment and disability status (original reason for Medicare enrollment).
[c] Elixhauser Index excludes alcohol and drug use due to the redaction of related-claims.

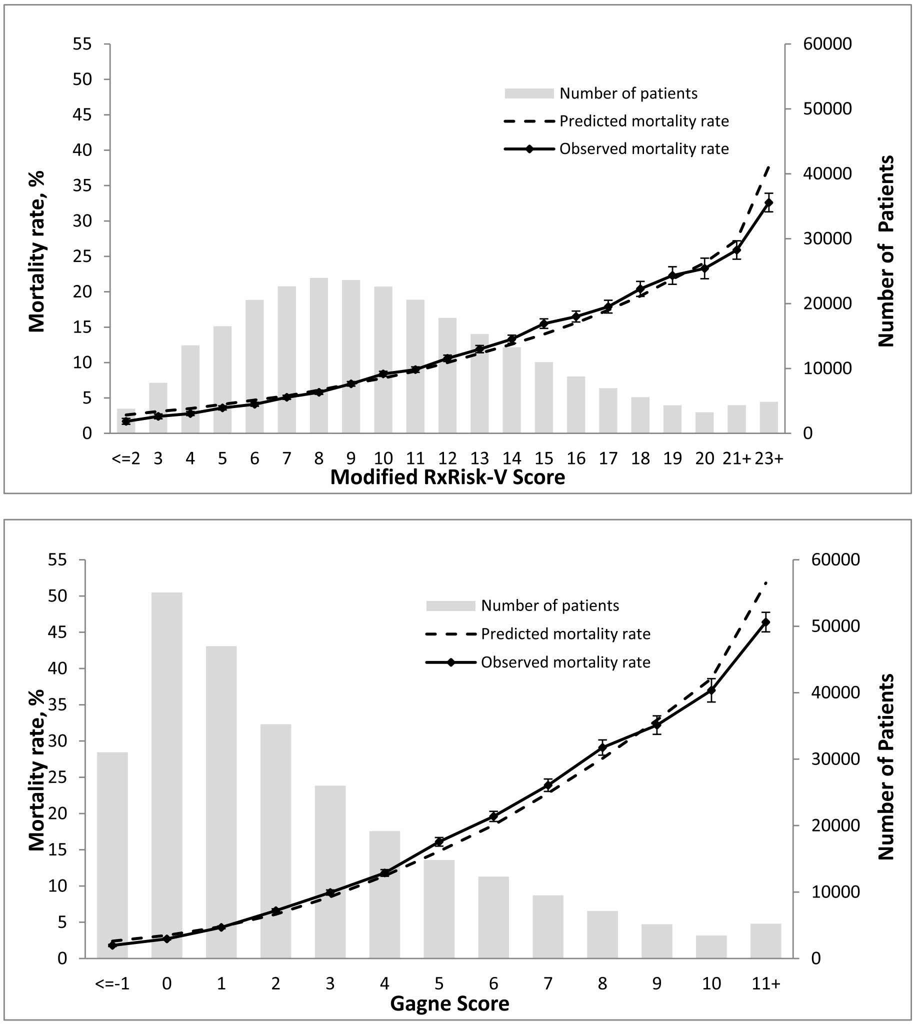

Fig. 1. Calibration curves of the modified RxRisk-V and gagne indices.

ICD claims are often incomplete for Veterans who also receive care through Medicare Advantage plans or private insurers, resulting in their exclusion from studies.[7] Second, even when claims are derived from both VA and non-VA sources, such analyses may under-account for important conditions commonly treated within VA, such as serious mental illness and substance use disorders.[4,7]

In addition to addressing several analytic challenges with ICD-based risk adjustment within VA, risk adjustment using RxRisk-VM or pharmacy records, in general, may become increasingly important given the complex nature of the recently implemented 10th Revision of the ICD (ICD-10). In comparison to ICD-9, ICD-10 contains nearly 5 times as many diagnostic codes (ICD-9 14,000 vs ICD-10 68,000).[1,2] This increased complexity may widen the current gap in coding between VA and non-VA healthcare settings, as non-VA settings become more exacting in their coding standards. Despite identifying disagreement in the identification of certain conditions contained both in RxRisk-VM and the Gagne Index, RxRisk-VM was marginally less accurate in comparison to Gagne and other ICD-based comorbidity measures. Our findings are similar to those of Lu et al., who compared RxRisk-V to the Charlson Index in a cohort of Australian Veterans.[23] Several other approaches to risk adjustment using pharmacy records have been validated and found to be comparable to ICD claims based indices; however, they have not been widely adopted in clinical or health services research.[24–28]

Our findings also have important implications for VA patients, researchers, and policy makers. Veterans' access to non-VA care is expanding through VA Community Care Programs, through which Veterans receive care from a non-VA provider that is paid for by VA.[13] Our findings may enable VA to more accurately assess the quality of non-VA care, empowering Veterans to make more informed healthcare choices when choosing to see a provider within or outside VA. Additionally, our findings align with prior work outside VA, which demonstrates that integrating diagnosis data, pharmacy records and other clinical values (e.g. laboratory values and vital signs) enhances the accuracy of models predicting outcomes such as cost of care and hospitalization.[29–33] Given the discrepancy in coding between VA and non-VA health systems, the integration of diagnoses derived from the VA EHR via methods such as natural language processing may further enhance the prognostic accuracy of models containing diagnosis codes and pharmacy data derived from administrative claims.

Despite its advantages, medication-based risk adjustment, in general, has potential limitations. Providers exhibit varying propensities to prescribe medications that are influenced by patient (e.g., socioeconomic status, severity of illness), provider (e.g., training, specialty), and health system (e.g. formulary restrictions, decision-support tools) factors. These varying propensities may introduce alternative forms of bias that should be explored in future research. Second, medications with multiple indications for use, such as gabapentin, may introduce measurement error and mischaracterize the prevalence of certain disease states if the medication is used other than designated in the index. Third, as RxRisk-VM and other medication-based indices rely upon pharmacy claims, poor patient adherence may also introduce bias or decrease the measure's prognostic accuracy.[33] These factors likely explain, in part, why RxRisk-VM exhibited slightly lower prognostic accuracy than the ICD claims-based indices included in our study.

Our study also contained some specific limitations. First, our cohort was a national sample of Veterans who had received an opioid prescription in CY2012 from either VA or Medicare. This has the potential to limit the generalizability of our findings. Second, the redaction of diagnosis codes for substance use disorders in the Medicare data may have affected the mean score for each ICD claims-based risk index. Both of these limitations may be investigated in future studies using data derived from the general population and from data without claims redaction. Third, prior studies have demonstrated that varying patterns and degree of dual use confer differential risk of mortality.[34] RxRisk-VM and other risk adjustment indices may therefore perform differently in Veterans with varying patterns of dual use.

5. Conclusion

Accurately accounting for the effect of comorbidity on health outcomes is essential but challenging within VA, where there is systematic undercoding of medical comorbidities within administrative claims.[4–7] RxRisk-VM exhibited a high degree of, but slightly less accuracy in predicting 1 and 3-year mortality relative to commonly used risk adjustment measures and may enhance the prognostic accuracy of current ICD-based measures when their use is appropriate. As momentum builds to enable Veterans to seek care outside VA, policy makers and healthcare consumers require unbiased information regarding the quality of care available from VA and non-VA sources. The RxRisk-VM index may enhance the accuracy of future risk-adjusted studies examining VA and non-VA care and serve as a viable method of risk adjustment when diagnostic claims are not available or the use of claims-based indices may lead to bias.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.hjdsi.2019.04.003.

For the RxRisk-VM model, the absolute difference between the observed and predicted probabilities are all < 1% except for two groups: 1) RxRisk-VM score = 15, 1.5% difference, 2) RxRisk-VM Score > 21, −3.4%. For the Gagne Model, the absolute difference between the observed and predicted probabilities are all smaller than 1.6% except −5.4% for Gagne Score ≥11.

Appendix B. Additional Methods in Modifying the RxRisk-VM Index

Grouping of Medications in RxRisk-VM Categories derived from VA and Medicare Data.

We matched prescription data from Medicare Part D and the VA National Formulary primarily using NDC Codes. Approximately 95% of Part D Prescriptions matched to VA Formulary Data using NDC codes alone and were subsequently assigned to the corresponding RxRisk-V category that contained that medication. For the remaining Medicare prescriptions that did not match to a VA medication/RxRisk-V category via an identical NDC code, they were assigned to the RxRisk-V category which contained the medication that most closely matched the following combination of data elements: generic name (GNN), dosage form code (GCDF), and strength (STR). For the remaining percentage of prescriptions (~0.03%) that were still unmatched, they were assigned to an RxRisk category after review by two members of the research team.

Appendix Table A
Example Medications Mapped to RxRisk-VM Categories

Pain	Pain/Inflammation
ACETAMINOPHEN/CAFFEINE/DIHYDROCODEINE	CELECOXIB
ACETAMINOPHEN/CODEINE	DICLOFENAC
ACETAMINOPHEN/HYDROCODONE	DICLOFENAC/MISOPROSTOL
ACETAMINOPHEN/OXYCODONE	DIFLUNISAL
ACETAMINOPHEN/PENTAZOCINE	DIPHENHYDRAMINE/IBUPROFEN
ACETAMINOPHEN/TRAMADOL	ETODOLAC
ASPIRIN/BUTALBITAL/CAFFEINE/CODEINE	FENOPROFEN
ASPIRIN/CARISOPRODOL/CODEINE	FLURBIPROFEN
ASPIRIN/OXYCODONE	HYDROCODONE/IBUPROFEN
BELLADONNA/OPIUM	IBUPROFEN
BUPRENORPHINE	INDOMETHACIN
BUPRENORPHINE/NALOXONE	KETOPROFEN
BUTORPHANOL	MECLOFENAMATE
CHLORZOXAZONE	MEFENAMIC ACID
CODEINE	MELOXICAM
CYCLOBENZAPRINE	NABUMETONE
FENTANYL	NALTREXONE
GABAPENTIN	NAPROXEN
GABAPENTIN ENACARBIL	NAPROXEN/SUMATRIPTAN
HYDROCODONE/IBUPROFEN	OXAPROZIN
HYDROMORPHONE	PIROXICAM
HYOSCYAMINE/METHENAMINE/METHYLENE BLUE/PHENYL SALICYLATE/SODIUM	SALSALATE
LEVORPHANOL	SULINDAC
LIDOCAINE	TOLMETIN

(continued on next page)

Appendix Table A (*continued*)

Pain	Pain/Inflammation
LIDOCAINE/TETRACAINE	
MEPERIDINE	
METAXALONE	
METHADONE	
MORPHINE	
NALBUPHINE	
NALOXONE/PENTAZOCINE	
ORPHENADRINE CITRATE	
OXYCODONE	
OXYCODONE/IBUPROFEN	
OXYMORPHONE	
PREGABALIN	
TAPENTADOL	
TRAMADOL	
TRAMADOL/ACETAMINOPHEN	
ZICONOTIDE	

Appendix Table B
Patients within each RxRisk-VM Category with Corresponding Odds Ratios and Updated Weights Derived from the Model for 1-year All-Cause Mortality

	Condition	Prevalence			aOR	P value*	New weight	Original weight
		VA + CMS Data (%)	VA data (%)	CMS data (%)				
1	Pancreatic Insufficiency	1.6	1.3	0.3	1.16	0.0048	1	2
2	ESRD	2.8	1.5	1.6	2.37	< .0001	6	6
3	HIV	3.4	2.4	1.2	1.35	< .0001	2	2
4	Anxiety and Tension	24.2	16.2	10.1	1.02	0.1645	0	2
5	Reactive Airway Disease	30.2	17.7	17.2	1.60	< .0001	3	4
6	Bipolar Disorder	0.7	0.5	0.3	0.68	0.0012	−1	0
7	IHD/Angina	15.5	7.4	9.8	1.19	< .0001	1	1
8	Anticoagulation	16.1	4.1	13.1	1.11	< .0001	1	1
9	Depression	39.2	22.1	21.9	1.35	< .0001	2	1
10	Diabetes	31.7	18.0	21.4	1.23	< .0001	2	2
11	Epilepsy	10.9	5.1	7.0	1.17	< .0001	1	1
12	Gastric Acid Disorder	51.4	30.5	27.5	1.14	< .0001	1	1
13	Glaucoma	8.3	4.2	4.9	0.92	0.0004	−1	0
14	Gout	10.1	4.6	6.6	1.10	< .0001	1	0
15	IHD/Hypertension	50.6	22.9	34.1	1.05	0.0018	1	0
16	Hyperlipidemia	65.0	36.9	36.9	0.633	< .0001	−1	−1
17	Hypertension	40.7	24.9	20.4	1.01	0.5407	0	0
18	Inflammatory Bowel Syndrome	1.2	0.7	0.6	0.90	0.1149	0	−1
19	Liver Failure	2.7	1.1	1.7	1.86	< .0001	5	1
20	Malignancies	2.9	1.3	1.8	2.12	< .0001	6	4
21	Pain	99.5	43.0	73.9	1.62	0.0002	4	2
22	Pain/Inflammation	31.5	15.8	18.5	0.68	< .0001	−1	2
23	Parkinson's Disease	5.2	2.2	3.8	1.20	< .0001	2	2
24	Psychotic Illness	10.7	6.1	5.7	1.76	< .0001	4	3
25	Hyperkalemia	0.7	0.2	0.5	1.67	< .0001	4	5
26	Steroid-Responsive Conditions	31.2	12.1	21.2	1.23	< .0001	2	3
27	Hypothyroidism	13.4	6.3	8.8	1.08	< .0001	1	0
28	Transplant	0.8	0.6	0.3	1.16	0.0568	1	3
29	Tuberculosis	0.4	0.2	0.3	1.33	0.0038	2	0
30	Alcohol Dependence	0.2	0.2	0.1	1.31	0.1294	0	3
31	Migraine	1.6	1.2	0.5	0.72	< .0001	−1	−1
32	Psoriasis	0.5	0.4	0.1	0.78	0.0193	−1	−1
33	Osteoporosis/Paget's	3.3	1.7	1.8	1.09	0.012	1	0
34	Malnutrition	1.5	1.1	0.5	2.45	< .0001	6	3
35	Urinary Incontinence	2.9	2.7	0.2	1.22	< .0001	2	4
36	Ostomy	2.3	1.1	1.3	1.53	< .0001	3	3
37	Hepatitis C	0.2	0.1	0.1	0.30	0.0002	−1	0
38	Dementia	6.4	2.2	5.0	1.60	< .0001	3	3
39	Benign Prostatic Hypertrophy	35.3	18.1	22.0	0.92	< .0001	−1	−1
40	Smoking Cessation	5.5	5.0	0.6	1.15	0.0003	1	2
41	Arrhythmias	8.4	2.7	6.6	1.58	< .0001	3	4
42	CHF/Hypertension	59.1	29.9	38.6	1.25	< .0001	2	2
43	Antiplatelet Agents	25.0	17.3	9.9	1.08	< .0001	1	2
44	Neurogenic Bladder	2.1	0.9	1.3	1.38	< .0001	2	0
45	Allergies	23.9	15.1	10.4	0.74	< .0001	−1	−1

*P-values were determined using logistic regression to estimate the magnitude of association (odds ratio) with 1-year all-cause mortality, controlling for age, sex, and race/ethnicity.

Appendix Table C
Agreement between the Modified RxRisk-V and Gagne Indices in Identifying Conditions contained Within Both Measures among the Study Cohort

RxRisk-VM Disease Category	Gagne Disease Category	Percent of Patients with each Selected Condition Identified by RxRisk-VM and/or Gagne					Overlap	Kappa
		RxRisk-VM or Gagne	RxRisk-VM	Gagne	RxRisk-VM only	Gagne only		
Congestive Heart Failure	CHF/ Hypertension	61.9	59.1	22.0	40.0	2.8	19.1	0.22
Dementia	Dementia	9.4	6.4	6.7	2.7	3.0	3.7	0.54
Renal Disease	End Stage Renal Disease	20.2	2.8	19.9	0.3	17.4	2.5	0.18
Tumor	Malignancies	21.6	2.9	20.5	1.1	18.8	1.8	0.10
Arrhythmias	Arrhythmias	28.9	8.4	27.8	1.1	20.5	7.3	0.32
Liver Disease	Liver Failure	7.3	2.7	5.1	2.2	4.6	0.6	0.11
Psychosis	Psychotic Illness	20.5	10.7	17.0	3.5	9.8	7.2	0.45
HIV/AIDS	HIV	3.5	3.4	0.8	2.7	0.06	0.7	0.34
Hypertension	Hypertension	83.0	40.7	80.8	2.2	42.3	38.5	0.20

Appendix Table D
Percentage of Veterans with a Diagnosis Code for an Elixhauser Conditions depicted by VA and/or Medicare Data

Elixhauser Conditions	VA + CMS data (%)	VA data (%)	CMS data (%)
1. Congestive heart failure	14.3	3.2	12.3
2. Valvular disease	7.1	1.1	6.3
3. Pulmonary circulation disorder	3.5	0.8	2.8
4. Peripheral vascular disorder	15.7	3.2	13.2
5. Hypertension, uncomplicated	56.1	24.4	41.5
6. Hypertension, complicated	13.8	2.5	12.1
7. Paralysis	3.1	0.9	2.6
8. Other neurological	11.1	3.0	9.3
9. Chronic pulmonary disease	25.6	8.9	20.0
10. Diabetes w/o chronic complications	22.1	13.2	16.9
11. Diabetes w/chronic complications	12.5	3.8	9.6
12. Hypothyroidism	9.6	2.9	7.3
13. Renal failure	15.0	4.5	12.4
14. Liver disease	3.6	2.0	2.0
15. Chronic Peptic ulcer disease	0.07	0.01	0.06
16. HIV and AIDS	0.73	0.5	0.4
17. Lymphoma	1.4	0.4	1.1
18. Metastatic cancer	1.8	0.4	1.5
19. Solid tumor without metastasis	11.4	4.1	8.2
20. Rheumatoid arthritis/collagen vascular disease	3.7	1.0	3.0
21. Coagulation deficiency	4.4	0.8	3.7
22. Obesity	10.7	5.1	6.1
23. Weight loss	4.4	0.9	3.5
24. Fluid and electrolyte disorders	14.2	2.5	12.2
25. Blood loss anemia	1.0	0.1	0.9
26. Deficiency anemias	18.4	4.4	14.9
27. Psychoses	12.6	7.6	6.3
28. Depression	17.6	8.2	10.4

Appendix Table E
Comparison of the AUCs of the Modified RxRisk-VM Index (RxRisk-VM) alone and in Combination with Commonly Used Diagnostic Claims-Based Indices in Primary Analysis and when applying 10K Fold Approach to Train the Models.

	1-Year Mortality, AUC (95% CI)	
	Primary Analysis	10K Fold Validation
Demo + RxRisk-VM	0.7730 (0.7700, 0.7759)	0.7730 (0.7698, 0.7757)
Demo + Charlson + RxRisk-VM	0.8051 (0.8024, 0.8079)	0.8049 (0.8022, 0.8077)
Demo + Elixhauser + RxRisk-VM	0.8122 (0.8095, 0.8149)	0.8120 (0.8093, 0.8147)
Demo + Gagne + RxRisk-VM	0.8167 (0.8141, 0.8193)	0.8165 (0.8138, 0.8191)
	3-Year Mortality AUC (95% CI)	
	Primary Analysis	10k Fold Validation
Demo + RxRisk-VM	0.7791 (0.7771, 0.7812)	0.7790 (0.7770, 0.7810)
Demo + Charlson + RxRisk-VM	0.8031 (0.8012, 0.8050)	0.8030 (0.8011, 0.8049)
Demo + Elixhauser + RxRisk-VM	0.8089 (0.8070, 0.8108)	0.8088 (0.8069, 0.8107)
Demo + Gagne + RxRisk-VM	0.8127 (0.8108, 0.8146)	0.8126 (0.8107, 0.8144)

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