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Development of a screening tool to flag older adults at a high risk of preventable medication-related readmissions

Nicole Schönenberger Ph.D.[1,2] | Thomas Beck M.D.[3] | Laura Werlen Ph.D.[4] | Balthasar L. Hug M.D., MBA, MPH[5,6] | Carla Meyer-Massetti Ph.D.[1,7]

[1]Clinical Pharmacology and Toxicology, Department of General Internal Medicine, Inselspital, Bern University Hospital, University of Bern, Bern, Switzerland

[2]Graduate School for Health Sciences, University of Bern, Bern, Switzerland

[3]Department of General Internal Medicine, Inselspital, Bern University Hospital, University of Bern, Bern, Switzerland

[4]Department of Clinical Research, University Hospital of Basel, University of Basel, Basel, Switzerland

[5]Department of Internal Medicine, Lucerne Cantonal Hospital, Lucerne, Switzerland

[6]Faculty of Health Sciences and Medicine, University of Lucerne, Lucerne, Switzerland

[7]Institute of Primary Healthcare (BIHAM), University of Bern, Bern, Switzerland

Correspondence
Nicole Schönenberger, Clinical Pharmacology, Department of General Internal Medicine, Inselspital, Bern University Hospital, Anna-von-Krauchthal-Weg 7, CH-3010 Bern, Switzerland.
Email: n.schoenenberger@gmx.com

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Abstract

Background: Preventable medication-related readmissions (pMRRs) are a significant contributor to older adult morbidity, mortality, and health care costs. There are currently no specific screening tools for identifying patients at a high risk of pMRRs. This study aimed to develop and internally validate a screening tool to identify general internal medicine patients aged 65 or older at risk of 30-day pMRRs.

Methods: Data on 500 patients discharged between January 1, 2022 and October 18, 2023, and readmitted within 30 days were reviewed, and 116 pMRRs were identified. An additional 500 control patients without pMRRs were selected. A multivariable logistic regression model was developed using the four pre-specified predictors of each patient's number of medications, hospitalizations in the past year, high-risk medications at discharge (anticoagulants, opioids, and sedatives), and the number of the following diagnoses: heart failure, diabetes, chronic kidney disease, and chronic obstructive pulmonary disease.

Results: The screening tool's performance was evaluated and internally validated using bootstrapping. The screening tool demonstrated moderate discriminatory power, with a C-statistic of 0.714 (95% confidence interval [CI]: 0.663–0.764). Overall performance was assessed as acceptable, with a Brier score of 0.177. Bootstrapping yielded an optimism-corrected C-statistic of 0.704 (95% CI: 0.654–0.755), indicating the tool's robustness.

Conclusions: The screening tool's discriminatory power suggested its potential utility for flagging patients at risk of pMRRs. External validation and a search for additional predictors will be necessary to enhance the tool's performance and generalizability. If validated, a cost-effectiveness analysis would be needed to ensure its feasibility for clinical implementation.

KEYWORDS
adults, aged, risk factors, safety

1 | INTRODUCTION

Hospital readmissions are highly correlated with increased patient morbidity and mortality,[1,2] yet a significant proportion of these readmissions are preventable. Many health care systems thus impose penalties on institutions with higher than expected readmission rates.[3,4] Various thresholds are used to define a readmission, with 30 days being the most common.

The complexity of medication regimens is increasing in parallel with the prevalence of polypharmacy and, consequently,[5,6] a considerable proportion of readmissions are medication-related. A systematic review by El Morabet et al. reported a 21% median prevalence (range 3%–64%) of medication-related readmissions (MRRs).[7] Notably, 69% (range 5%–87%) of these MRRs were considered preventable.[7] Some of the included studies focused solely on readmissions due to adverse drug events, whereas others applied broader criteria, classifying any readmission with an identified medication-related problem as an MRR. These problems included cases of underprescribed medications, where patients did not receive an indicated medication, resulting in readmission due to worsening symptoms or cases where communication failures resulted in medication-related problems significant enough to cause readmission.[7]

Identifying patients at a high risk of preventable medication-related readmissions (pMRRs) is important as it enables the implementation of targeted clinical pharmacy interventions that can effectively reduce the probability of such occurrences. This, in turn, enables the efficient allocation of scarce resources. Effective interventions to reduce pMRRs include medication reconciliation, medication reviews, medication counseling, and transition-of-care measures, such as improving communication at hospital discharge and conducting follow-up interventions.[8–11]

Several studies have sought to identify risk factors for MRRs,[12–15] and two specific prediction models have been developed, one focused on 1-year MRRs[16] and the other on 30-day MRRs.[17] Both demonstrated moderate predictive ability. Multiple prediction models have also been developed to predict all-cause readmissions,[18,19] with some emphasizing medication-related factors.[20–22]

Despite these efforts, no specifically designed tool currently exists to identify patients at a high risk of pMRRs. The present study thus aimed to develop and internally validate a screening tool able to flag patients aged 65 and older, discharged from a general internal medicine department, and at a high risk of a 30-day pMRR.

2 | METHODS

Reporting on this study was made in accordance with the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) statement.[23]

2.1 | Study design and population

A retrospective, case–control study was conducted to develop a screening tool for pMRRs. Case identification involved chart reviews in the electronic health record data collected during routine care. The sample size was determined based on the educated assumption that approximately 20% of all 30-day readmissions would be pMRRs. To ensure sufficient statistical power for a logistic regression model with four pre-specified predictors, we aimed for at least 100 pMRR cases, following the commonly recommended rule of at least 10 events per predictor variable.[24] Consequently, we screened 500 readmissions and selected an equal number of control patients, maintaining a 1:4 case-to-control ratio to optimize statistical efficiency.[24] To be eligible for inclusion, patients had to be at least 65 years old and have provided general consent for the use of their data in future research. The study sample ultimately consisted of 500 randomly selected patients hospitalized in the University Hospital of Bern's General Internal Medicine Department, discharged between January 1, 2022 and October 18, 2023, and readmitted within 30 days to any department in the same hospital, ensuring the inclusion of the most recent data and a sufficient number of readmissions.

Medication-relatedness was assessed using the Assessment Tool for identifying Hospital Admissions Related to Medications (AT-HARM10 tool), a validated instrument for classifying older adults' hospital admissions as potentially or unlikely to be medication-related.[25] Consequently, any readmission where a medication-related problem could not be ruled out was classified as an MRR. To identify readmissions as pMMRs, preventability was evaluated based on the Schumock statements, including factors such as inappropriate medication choice, dosage, monitoring, interactions, non-adherence, or contraindications.[26] The screening process was pilot-tested by one senior physician, one senior pharmacist, and one pharmacist who were trained with educational materials about the AT-HARM10 tool, and independently reviewed and analyzed 20 cases of readmission. Following this pilot, the two pharmacists independently reviewed all 500 readmissions. In cases of disagreement, the senior physician conducted an additional review. This process identified 116 pMRRs and then used them as cases for developing the screening tool.

Control patients were selected based on the same inclusion criteria but had not experienced a pMRR. Control patients had thus either not been readmitted within 30 days or had been readmitted within 30 days for non-medication-related reasons or for non-preventable medication-related reasons. The hospital's data science center randomly selected 500 control patients from this population, aiming for a 4 to 1 ratio of cases to controls to maximize statistical power.[24]

2.2 | Predictors of interest

The selection of predictors was informed by a combination of a previously published literature review and expert opinion.[27,28] The variables reflected established associations with pMRRs and their routine availability in clinical practice. The predictors selected were:

1. Number of prescribed medications at hospital discharge
2. Number of hospitalizations in the past year (limited to hospitalizations within the same hospital group)

3. Number of medications at hospital discharge commonly associated with pMRRs (defined as antithrombotics [anticoagulants and antiplatelets, excluding low-dose acetylsalicylic acid], opioids, and sedatives [benzodiazepines, Z-drugs, barbiturates])
4. Number of diagnoses at hospital discharge associated with pMRRs (including heart failure, diabetes, chronic obstructive pulmonary disease [COPD], and chronic kidney disease).

Anatomical Therapeutic Chemical (ATC) codes for the medications mentioned in point 3 and International Classification of Diseases (ICD-10-GM) codes for the diagnoses mentioned in point 4 were used to extract data on these factors from routine hospital records. All documented medications, regardless of whether they were prescribed or not, were included. Details of the ATC and ICD-10-GM codes used are provided in Appendix S1.

2.3 | Statistical analyses

All analyses were performed using R software (R Foundation for Statistical Computing, Vienna, Austria), version 4.3.3 (2024-02-29 ucrt).[29]

2.3.1 | Descriptive analyses

We summarized patients' baseline characteristics using descriptive statistics, reporting categorical variables using frequency and a percentage, and continuous variables using mean and standard deviation (SD) or median and interquartile range (IQR), depending on their data distribution. Summary statistics were also calculated for the case (patients with pMRR) and control (patients without pMRR) groups.

2.3.2 | Primary analysis

A multivariable logistic regression model was developed to identify the risk of a pMRR within 30 days, with 'pMRR (yes/no)' as the outcome variable. The screening tool included the four pre-specified predictor variables, and there were no missing data for any of them. The model was adjusted for its case–control design by using case–control weighting, as outlined by Rose et al.,[30] and by assuming a true pMRR incidence of 2% in the general population.

The screening tool's performance was assessed using receiver operating characteristic (ROC) curves, with the area under the curve (AUC or C-statistic) used to quantify the tool's discriminatory power. The Brier score was also analyzed.

We estimated the optimism in the tool's performance by conducting an internal validation using a bootstrapping method.[24] We resampled the data, with replacement, refitted the model to the resampled data, and calculated the pertinent performance metrics. This process was repeated 10 000 times. Optimism estimates for the AUC and Brier score were subtracted from the tool's apparent performance using these metrics to obtain corrected estimates. The final optimism-corrected AUC and Brier score are reported alongside the original metrics.

We made a decision curve analysis of the screening tool's net clinical benefit at relevant threshold probabilities that represented the minimum risk level at which further intervention would be justified.[31] At a given probability threshold, the net benefit is calculated as sensitivity $\times$ prevalence $-$ (1 $-$ specificity) $\times$ (1 $-$ prevalence) $\times$ w, where w is the odds of the event occurring at the threshold probability.

2.3.3 | Exploratory analysis

We conducted an exploratory analysis of the inclusion of additional potential predictors. Logistic regression models were fitted for every possible combination of the predictors included in the main screening tool, except for the composite variable of 'high-risk medication', which was analyzed using separate medication classes. This analysis was performed using R software's (R Foundation for Statistical Computing, Vienna, Austria) MuMIn package.[32] The exploratory analysis thus considered the following variables:

1. Number of medications
2. Diuretic use (no/yes)
3. Antithrombotic (anticoagulants and antiplatelets, excluding low-dose acetylsalicylic acid) use (no/yes)
4. Number of diagnoses associated with pMRR (defined as heart failure, diabetes, chronic kidney disease, and COPD)
5. Opioid use (no/yes)
6. Sedative (benzodiazepines, Z-drug, barbiturates) use (no/yes)
7. Number of hospitalizations in the past year
8. Type of health assurance (standard vs. private/semi-private assurance)
9. Language other than German, French, Italian, or English (no/yes)

Because data on eight patients' sedative use was missing, no imputation techniques were used, and they were excluded, resulting in a total of 608 observations in our exploratory analysis of complete cases. We reported the frequency with which each candidate variable appeared in the top 100 screening tools based on Akaike Information Criterion values. We also fitted a model incorporating every candidate variable and calculated the same performance metrics as those used in the main screening tool. We applied Firth's penalized-likelihood approach to stabilize the numerical results of the logistic regressions in this exploratory analysis.[33]

2.4 | Ethical considerations

The study protocol was reviewed by the Cantonal Ethics Committee of Bern, and formal ethics approval was waived due to its classification as a quality improvement study (submission number

TABLE 1 Baseline overall, case, and control characteristics.

Characteristic	Overall ($n = 616$)	Controls ($n = 500$)	Cases ($n = 116$)
Age in years, median [IQR]	79.0 [73.0, 85.0]	79.0 [73.0, 86.0]	78.0 [70.0, 84.0]
Sex = male, *n* (%)	366 (59.4)	300 (60.0)	66 (56.9)
Days hospitalized, median [IQR]	5.0 [3.0, 8.0]	5.0 [3.0, 8.0]	5.0 [3.0, 8.0]
Number of diagnoses at discharge[a] median [IQR]	16.0 [11.0, 22.0]	15.0 [10.0, 22.0]	17.0 [13.0, 21.2]
Number of hospitalizations (same hospital) in the past year, median [IQR]	1.0 [0.0, 2.0]	0.0 [0.0, 1.0]	2.0 [1.0, 3.0]
Number of medications at discharge, median [IQR]	10.0 [7.0, 14.0]	9.0 [6.0, 13.0]	12.0 [8.0, 15.0]
Diuretics = yes, *n* (%)	305 (49.5)	228 (45.6)	77 (66.4)
Antithrombotics = yes, *n* (%)	314 (51.0)	254 (50.8)	60 (51.7)
Opioids = yes, *n* (%)	135 (21.9)	104 (20.8)	31 (26.7)
Sedatives = yes, *n* (%)	79 (13.0)	57 (11.6)	22 (19.0)
Number of diagnoses potentially associated with a pMRR,[b] mean (SD)	1.3 (1.1)	1.2 (1.0)	1.8 (1.1)
Health assurance = private or semi-private assurance, *n* (%)	150 (24.4)	127 (25.4)	23 (19.8)
Language other than German, French, Italian or English, *n* (%)	22 (3.6)	15 (3.0)	7 (6.0)

Abbreviations: IQR, interquartile range; pMRR, preventable medication-related readmissions; SD, standard deviation.
[a]Measured using the number of ICD-10-GM diagnoses.
[b]Defined as heart failure, diabetes, chronic obstructive pulmonary disease, and chronic kidney disease.

2023-01025). All the patients included in the study had provided general consent for the use of their health data in future research.

3 | RESULTS

Among the 500 chart reviews of patients readmitted within 30 days, we identified 116 (23.2%) pMRRs. The most common medication-related problems were under-prescribing (29.3%), defined as the absence of a clinically indicated medication; other prescribing issues such as wrong dose or suboptimal medication selection (28.4%), referring to cases where the prescribed medication, dose, or formulation was inappropriate for the patient; and patient non-adherence (12.9%), meaning the patient did not take the medication as prescribed. Non-adherence was assessed based on clinical documentation in the electronic health records, including physician and nursing notes.

3.1 | Descriptive analysis

The baseline characteristics of the entire study population, classified by cases and controls, are summarized in Table 1. In the control group, 18 patients had a 30-day readmission, of which 6 were classified as non-preventable medication-related readmissions.

3.2 | Main screening tool

The multivariable logistic regression model, adjusted for case–control weighting, was developed using four pre-specified predictors: number of medications, hospitalizations in the past year and diagnoses associated with pMRRs. The estimates and odds ratios for these four predictors are provided in Table S1, and all of the regression coefficients and intercepts are presented in Table S2.

The main screening tool's Brier score was 0.177, indicating moderate accuracy. The C-statistic was 0.714 (95% CI: 0.663–0.764), reflecting moderate discriminatory power. The main screening tool's ROC curve is presented in Figure 1.

The screening tool's performance at different key thresholds is shown in Table 2.

3.3 | Internal validation

Internal validation using bootstrapping (10 000 resamples) provided optimism-corrected performance estimates. The optimism-corrected AUC was 0.704 (95% CI: 0.654–0.755), and the optimism-corrected-Brier score was 0.178, indicating minimal degradation in performance after correction.

3.4 | Decision curve analysis

Decision curve analysis demonstrated that the screening tool outperformed both the 'check all' and 'check none' strategies at low threshold probabilities (Figure 2). At Youden's *J* threshold probability of 0.021—where sensitivity and specificity are maximized—the tool achieved a net benefit of 0.007. This corresponds to identifying seven additional true cases of pMRR per 1000 patients checked (27 cases instead of 20, assuming a 2% prevalence).[31] This represents a 35% increase in true positives identified compared with the 'check all' strategy.

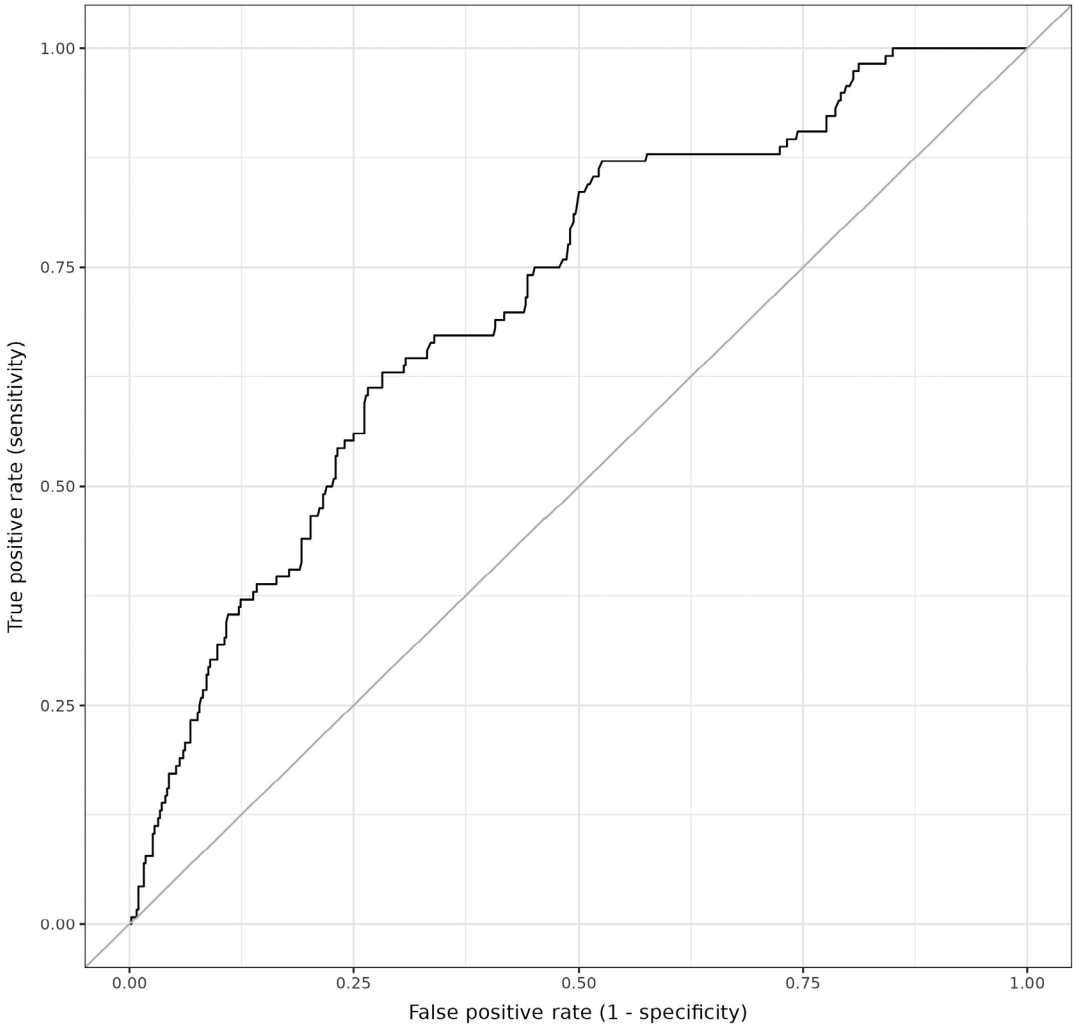

FIGURE 1 The main screening tool's ROC curve.

Scenario	Threshold probability	Sensitivity	Specificity	Accuracy
Euclidean distance	0.195	0.000	0.998	0.978
Youden's *J*	0.021	0.629	0.718	0.716
90% sensitivity	0.010	0.905	0.224	0.238
Maximum sensitivity	0.009	1.000	0.150	0.167

TABLE 2 The main screening tool's performance based on best cut-offs with their corresponding sensitivity, specificity, and accuracy.

3.5 | Exploratory analysis

We conducted an exploratory analysis of the inclusion of additional potential predictors in the screening tool for pMRR. Wishing to use complete case analysis, we excluded eight patients with missing data on sedative use. Table 3 presents the frequency with which each predictor was included in the top 100 tools ranked according to Akaike Information Criterion values. The number of medications at discharge appeared most frequently and were included in 72 of the top 100 tools. Two other important predictors that appeared around half the time were the number of hospitalizations in the past year (55 times) and the number of diagnoses associated with pMRR (45 times).

The performance of the exploratory tool incorporating all four potential predictors was evaluated. The estimates and odds ratios for all of the predictors examined in the exploratory analysis are presented in Table S3.

The Brier score for the exploratory tool including all nine predictors was 0.165, suggesting moderate accuracy, while the corresponding area under the ROC curve was 0.711 (95% CI: 0.660–0.761), indicating moderate discriminatory power. The exploratory tool's ROC curve is shown in Figure S1.

The exploratory tool's performance at different key thresholds is shown in Table 4. At the threshold sensitivity of 90%, the additional predictors were only able to improve overall specificity

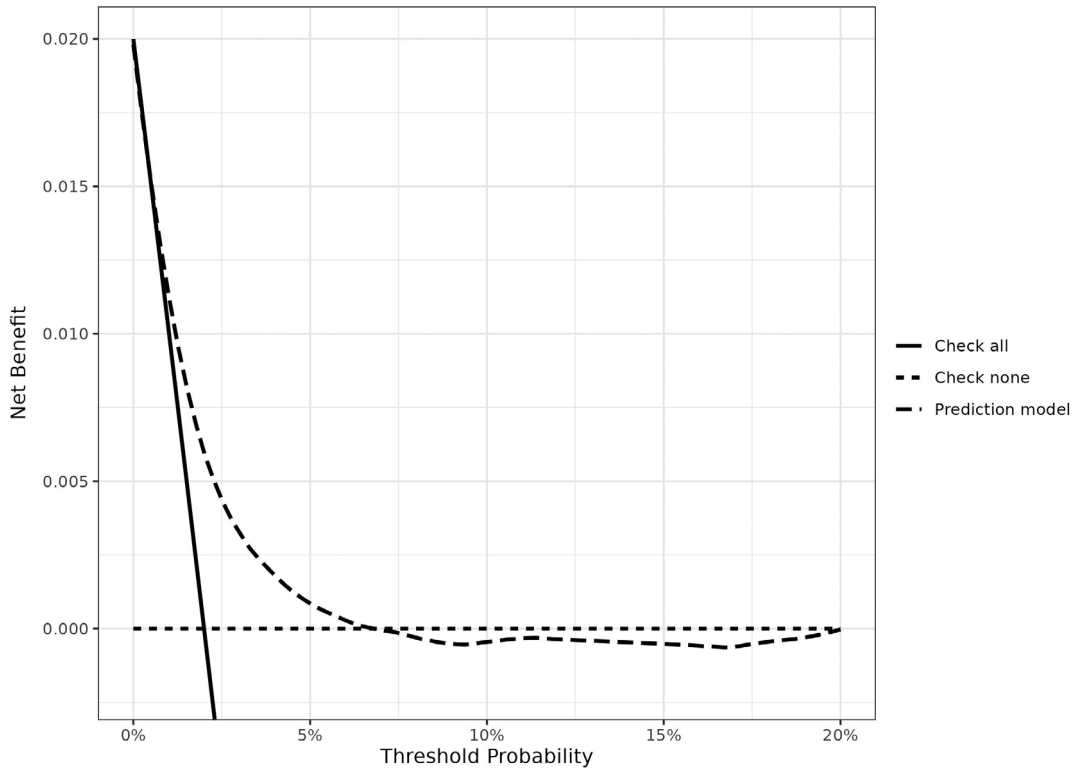

FIGURE 2 The decision curve displaying net benefit across a range of threshold probabilities.

TABLE 3 Frequency of predictor inclusion in the top 100 tools with the best Akaike Information Criterion values.

Predictor	Number of inclusions
Number of medications according to discharge letter	72
Number of hospitalizations (same hospital) in the past year	55
Number of diagnoses associated with a pMRR	45
Diuretics	28
Antithrombotics	28
Health assurance (standard vs. private/semi-private assurance)	28
Opioids	24
Sedatives	23
Language other than German, French, Italian, or English	9

Abbreviation: pMRR, preventable medication-related readmissions.

(0.341) by a small amount compared with the main screening tool (0.224).

4 | DISCUSSION

The present study developed a screening tool for identifying older adult general internal medicine patients at risk of 30-day pMRRs. The main screening tool demonstrated moderate discriminatory power and included the predictors of the number of medications, hospitalizations in the past year, specific medications at hospital discharge (defined as antithrombotics [excluding low-dose acetylsalicylic acid], opioids, and sedatives), and specific diagnoses at hospital discharge (including heart failure, diabetes, COPD, and chronic kidney disease). Including additional predictors in exploratory tools did not significantly improve the tool's performance.

To the best of our knowledge, this screening tool was the first to be specifically designed to flag patients at risk of pMRRs. The possibility of making direct comparisons with other tools, therefore, is limited. Two prediction models focusing on MRRs do exist; however, they are not concerned with preventability.[16,17] Aubert et al. created a model to predict 1-year MRRs among multimorbid older adult patients and incorporated seven predictors: chronic kidney disease, diuretic use, non-elective admissions, cirrhosis with portal hypertension, prior hospitalizations, hypertension, and oral corticosteroid use.[16] This model demonstrated moderate discriminatory power, with a C-statistic of 0.64. Similarly, Glans et al. developed the HOME Score (Hospitalizations, Own home, Medications, Emergency admission) to predict MRRs among older adults within 30 days of discharge.[17] This score included the number of prior hospitalizations, living arrangements, number of medications, and whether the admission was an emergency. The HOME Score achieved a C-statistic of 0.69 in its development cohort and 0.65 in its validation cohort.[17] While some predictors from these models, such as the number of medications and hospitalizations or specific diagnoses, were included in our tool for pMRRs, others, such as emergency admissions and living

Scenario	Threshold probability	Sensitivity	Specificity	Accuracy
Euclidean distance	0.484	0.000	0.998	0.978
Youden's *J*	0.056	0.612	0.711	0.709
90% sensitivity	0.033	0.905	0.341	0.353
Maximum sensitivity	0.018	1.000	0.010	0.030

TABLE 4 The exploratory screening tool's performance based on best cut-offs with their corresponding sensitivity, specificity, and accuracy.

arrangements, were not. Some predictors were excluded because of insufficient data availability, and some because our previous studies indicated that they were less relevant. For example, although living arrangements were identified as relevant for predicting pMRRs in both the literature and our prior Delphi study,[27,28] retrospectively extracting this information was unfeasible. Conversely, emergency admission was deemed less important and was thus excluded to mitigate the risk of overfitting, particularly given our limited sample size.[24]

Our tool's discriminatory power was slightly better than that of the models mentioned above and was comparable to models predicting all-cause readmissions.[16–21] The moderate discriminatory power observed across these models may reflect the multifactorial nature of readmissions, which complicates the goal of achieving high predictive accuracy.[34] None of the individual predictors in our tool were statistically significantly associated with the outcome, either in our univariate analyses or our multivariate model. Our screening tool nevertheless achieved moderate discriminatory power, likely due to the combined effects of multiple factors managing to capture more of the underlying risk than any single predictor alone could. While the tool's moderate discriminatory power highlights its utility as a preliminary screening tool, its effectiveness is enhanced when combined with expert clinical judgment, similar to other automated systems.

The predictors of the number of medications, hospitalizations in the past year, high-risk medications (antithrombotics, opioids, and sedatives), and specific chronic conditions (heart failure, diabetes, chronic kidney disease, and COPD) were consistent with previous studies identifying risk factors for pMRRs.[15,35–38] Patients with a higher number of medications at discharge are at increased risk due to the complexity of managing multiple medications and the potential for adverse drug events, drug–drug interactions, and problems with adherence. Frequent hospitalizations reflect a greater disease burden and more complex care needs, which elevate the risk of a pMRR.[39] The presence of specific high-risk medications at discharge further underscores the importance of careful medication management, as they are associated with a higher likelihood of medication-related problems.[40,41] Finally, patients with chronic conditions such as heart failure and chronic kidney disease often struggle to manage their conditions post-discharge, thus increasing their risk of readmission.[42] Clinically, the screening tool's moderate discriminatory power offers a foundation for future risk stratification improvements, allowing for the identification of those patients most susceptible to pMRRs. As a result, our tool could prove useful in resource allocation decisions by helping to prioritize high-risk patients for targeted clinical pharmacy interventions.

Our tool's Brier score was 0.177, reflecting its overall good performance. However, as the Brier score does not always accurately reflect clinical utility and may favor specificity over sensitivity in low-prevalence settings such as ours,[43] we conducted a decision curve analysis of the screening tool's practical value in improving clinical decision-making. This approach complemented the performance metrics that focused on sensitivity, specificity, and accuracy at specific thresholds.

The findings from our decision curve analysis suggested that the screening tool provided an advantage when identifying pMRRs at low threshold probabilities. With a net benefit of seven extra true pMRRs identified per 1000 patients and maximized sensitivity and specificity at this point, we recommend using Youden's *J* as the threshold probability for guiding resource allocation. However, the reasons for implementing the tool may be more motivated by costs than clinical outcomes. Unlike some other clinical interventions, the additional checks flagged by our tool pose no physical risk to patients. On the contrary, even if flagged patients do not experience a pMRR, pharmacist-led interventions to improve medication therapy and management could still reduce the risks of other medication-related issues, as several studies have shown.[9,44,45] The primary consideration, therefore, is whether the tool can save money and resources. A cost-effectiveness analysis would be the most appropriate next step in determining the tool's usefulness. This could clarify whether the value of preventing pMRRs outweighs the financial and operational costs, thereby providing a stronger foundation for clinical decision-making.

Beyond its potential cost-effectiveness, the tool may also improve patient care by enabling targeted clinical interventions. Identifying patients at high risk of pMRRs allows health care providers to allocate resources more efficiently, such as prioritizing medication reviews, structured counseling at discharge, and enhanced follow-up for flagged patients. Previous studies have shown that pharmacist-led interventions for high-risk patients can reduce medication-related problems,[9,44,45] suggesting that integrating this tool into clinical practice could help optimize patient outcomes and medication safety.

While our study focused on developing and validating the screening tool, its real-world implementation would require further assessment. Key considerations include the time required for its application in clinical workflows, the financial cost of integrating it into existing hospital systems, and the balance between its predictive value and the resources needed for follow-up interventions. Future studies should explore its feasibility in different health care settings and evaluate its cost-effectiveness in reducing preventable medication-related readmissions.

The exploratory analysis of additional potential predictors, such as type of health assurance and language, was not included in the

main tool's evaluation. However, the exploratory tool's predictive performance was not better than that of the main screening tool. Importantly, the main tool includes the most relevant factors, as these appeared most frequently in the top 100 models based on Akaike Information Criterion values. We thus recommend the main tool for clinical use due to its simplicity and relevance. Nonetheless, further research is needed on associations between pMMRs and social determinants of health, such as language and type of health assurance. Interestingly, while some models' predictive powers have improved with the inclusion of social determinants,[46,47] others have shown no significant enhancement.[48]

4.1 | Strengths and limitations

This study had several strengths. First, our specific focus on pMRRs addressed an important gap in the literature. By targeting pMRRs, the screening tool provides a practical method with a measurable net benefit in identifying high-risk patients, facilitating the prioritization of interventions such as medication reconciliation, counseling, and post-discharge follow-up. Furthermore, the concurrent use of the validated AT-HARM10 tool enhanced the reliability of our findings.

The study had some notable limitations, nonetheless. Despite its moderate predictive performance, the relatively small number of pMRR cases included ($n = 116$) may have limited our ability to include a broader set of predictors. Moreover, as the study was conducted in a single hospital, external validation in other health care settings would be necessary to confirm the screening tool's generalizability.[24,49] Finally, variables such as socioeconomic factors, patient adherence, and social support may influence pMRR risk[13,27,28] and were not included in the screening tool due to the unavailability of data, potentially limiting its predictive accuracy as they were perceived as important by experts.[27] Including these variables might limit the tool's practical implementation, however, as these data are not systematically available in many other health care settings. While medical records are relatively detailed, we cannot rule out that some cases classified as non-pMRRs may have involved preventable medication-related problems, as certain medication changes or non-adherence issues may not have been documented. However, because we had full access to complete inpatient medical records, we aimed to minimize this risk as much as possible.

5 | CONCLUSIONS

The present study developed a screening tool to identify older adult general internal medicine patients at risk of 30-day pMRRs. The tool demonstrated moderate discriminatory power and included clinically relevant predictors such as the number of medications, hospitalizations in the past year, high-risk medications, and specific chronic conditions. Given the relatively low prevalence of pMRRs, a cost-effectiveness analysis is essential to determine whether the tool's net benefit justifies the resources required for its implementation in clinical practice. External validation is crucial to assess its generalizability. Additionally, future research should explore the structured collection of information on the social determinants of health, like language levels or health assurance type, and examine their role in readmissions, as these factors may further enhance predictive accuracy.

AUTHOR CONTRIBUTIONS

All the authors were involved in developing the research plan. NS, CMM and TB conducted the readmission reviews, and LW performed the statistical analyses. NS drafted the manuscript, and all the authors reviewed and approved the final version. NS and CMM submitted the grant proposal to *Smarter Medicine – Choosing Wisely Switzerland*.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that supports the findings of this study are available in the supplementary material of this article.

ORCID

Nicole Schönenberger https://orcid.org/0000-0001-5530-8502
Laura Werlen https://orcid.org/0000-0001-5042-8353
Balthasar L. Hug https://orcid.org/0000-0003-4235-1995
Carla Meyer-Massetti https://orcid.org/0000-0002-3523-5729

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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