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Evaluating cross-country applicability of morbidity scores: validation of the Multisource Comorbidity Score in Catalonia

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Abstract

Multimorbidity places increasing pressure on healthcare systems, requiring effective tools to assess clinical complexity. Existing comorbidity indices are often setting-specific and lack generalizability. The Multisource Comorbidity Score (MCS), developed in Italy, has shown strong predictive value. This study aimed to externally validate MCS and to test recalibrated and context-adapted versions to enhance its performance in a different healthcare system. A longitudinal observational study included 198 753 residents aged ≥50 in the Barcelona-Esquerra health district, followed between 2016 and 2019. The original MCS was validated, and two adapted versions were tested: a recalibrated MCS with locally derived weights and an enhanced MCS incorporating primary care data. Predictive validity for 1-year mortality (primary outcome) and secondary outcomes (4-year mortality, hospitalizations, and healthcare use) was assessed using the Area Under the Receiver Operating Characteristic (AUROC) curve, survival analysis, and net reclassification improvement (NRI). All MCS versions showed good discrimination. AUROCs for 1-year mortality were 0.742 (original), 0.756 (recalibrated), and 0.771 (enhanced). Adapted versions achieved better risk reclassification and higher discrimination for long-term mortality. Higher MCS scores were associated with progressively lower survival probabilities and increased healthcare resource utilization. The MCS demonstrated satisfactory external validity in the validation context, with adapted versions offering modest improvements.

Introduction

The growing prevalence of multimorbidity [1], particularly in individuals aged 65 and older in developed countries [2], places a heavy financial burden on healthcare systems, increasing demand for primary care, emergency services, hospitalizations, and medications [3–5]. Multimorbidity complicates care through complex disease interactions, polypharmacy, and coordination challenges across different care levels [6, 7].

Poorly managed multimorbidity leads to worse outcomes and reduced quality of life. Integrated, patient-centred care models are needed to ensure continuity and adapt to evolving needs [7, 8]. Their effectiveness depends on identifying patients with high clinical complexity through robust statistical tools capable of measuring and stratifying multimorbidity [9]. These multimorbidity indices support evidence-based policies, resource allocation, and equitable care.

The Multisource Comorbidity Score (MCS), developed in Italy using healthcare utilization data (inpatient diagnoses, outpatient drug prescriptions), was internally and externally validated in three Italian regions [10], outperforming conventional tools (Elixhauser [11], Charlson comorbidity index [12], Chronic Disease Score [13]) and showing reproducibility across regions. The MCS is widely used in Italy, is open-source, and has been adopted by the Ministry of Health for risk adjustment in analyses examining the association between process and outcome indicators of quality of care [14, 15]. MCS was conceived to provide a comparable measure of clinical complexity, although not yet used nationally [16]. Its simplicity and reliance on routinely collected data make it suitable for adoption in similar systems.

Given its regional origins, external validation is needed to assess the generalizability and reliability of the MCS, thus providing information on its potential transferability and adaptation to other settings [17]. The Catalan healthcare system offers a robust data infrastructure facilitating the development of sophisticated morbidity metrics, such as the Adjusted Morbidity Groups (AMG) algorithm [18–20], and, prior collaborations with Italy [21, 22], represents an ideal setting for testing MCS transferability.

This study aimed to externally validate and adapt the MCS within the Catalan healthcare system, assessing its predictive capability beyond its original Italian context. Ultimately, this validation seeks to determine whether the MCS can serve as a reliable and transferable tool for health systems with other organizational characteristics and data availability.

Methods

This observational study was conducted and reported according to STROBE guidelines [23].

Study design and population

This observational longitudinal study included the residents of the Barcelona-Esquerra health district (AISBE) [24] aged 50 years or older. This age threshold was selected to ensure comparability with the original MCS development study [10] and to reflect the age at which chronic conditions typically increase in prevalence and contribute substantially to clinical complexity and healthcare use [25]. AISBE is a representative urban area within the Catalan healthcare system, with demographic and utilization patterns comparable to the broader population of Catalonia. Integrated care models have been widely implemented in the district, making it an ideal setting for validating and adapting multimorbidity assessment tools like the MCS [24].

The study cohort was selected on 1 January 2016 (index date) and followed until 31 December 2019. This approach provides a comprehensive longitudinal perspective, intentionally excluding the COVID-19 pandemic period. Individuals were excluded if they were not residents or had not been continuously insured by the Catalan healthcare system during the 2 years preceding the index date. The cohort selection flowchart is available in Supplementary Fig. S1.

Data sources

Data were extracted from the Catalan Health Surveillance System (CHSS) [26] which gathers demographic, clinical, and resource utilization information from several healthcare databases [27], including:

(1) *Catalan healthcare system beneficiary's database*: This database records the start and end dates of an individual's beneficiary status within the CHSS, along with demographic information such as age, gender, and current status (active, migrated, or deceased).
(2) *Minimum Basic Dataset (CMBD, from its Catalan acronym)*: A structured health information system that compiles and standardizes data on healthcare activity across multiple levels of care, including acute hospital care, emergency care, primary care, socio-healthcare services, and mental health and addiction services. Each dataset contains administrative, clinical, and resource utilization data, including patient demographics, diagnoses, medical procedures, visit or admission dates, and length of stay. Diagnoses are coded using the International Classification of Diseases, 10th Revision, Clinical Modification (ICD-10-CM) [28]. Since the conditions identified by MCS were coded using ICD-9-CM system, these conditions were converted to ICD-10 following [29]. Full details are available in Supplementary Table S1.
(3) *Pharmacy dispensation records*: This dataset captures information on prescriptions reimbursed by the CHSS, classified according to the Anatomical Therapeutic Chemical (ATC) classification system [30].

Records were linked between databases using unique identification codes assigned to each CHSS beneficiary. To ensure confidentiality, identification codes were anonymized, and the mapping table was not provided to the research team.

Outcomes

The primary outcome was 1-year all-cause mortality. Secondary outcomes included 4-year all-cause mortality, hospital admissions at 1 and 4 years, and high-frequency primary care utilization (defined as ≥10 visits per year) at 1 and 4 years.

MCS calculation

The MCS scores were calculated for each individual within the study cohort following the methodology described in [10], and using three different approaches to evaluate both its validity and adaptability to the Catalan healthcare context (for more information, see Supplementary Material):

(1) MCS original: This version was computed based on hospital discharge records and pharmacy dispensation data, applying the original weights reported in [10]. It served as the external validation of the MCS in the Catalan setting, ensuring comparability with previous applications of the score in the Italian healthcare system.

Additionally, to assess the adaptability of the MCS to the Catalan healthcare system and improve its predictive performance within this new context, two modified versions were developed by recalculating the condition weights based on local data sources. A training set comprising 60% of the study cohort, with individuals followed until death or 31 December 2016, was randomly selected to estimate weights using the same methodology reported in [10] with the following approaches:

(2) MCS recalibrated: This version was adapted by recalibrating the original weights using hospital discharge and pharmacy dispensation data specific to the Catalan healthcare system. Following the methodology in Corrao et al. [10], weights were estimated using a Cox proportional hazards regression to model the association between 1-year all-cause mortality and 46 preselected conditions. This approach aimed to capture potential differences in disease prevalence, coding practices, and healthcare utilization patterns between the Italian and Catalan populations, ensuring a more contextually relevant risk stratification tool.

(3) MCS with enhanced data sources: Given that in Catalonia a significant proportion of chronic disease management and multimorbidity care occurs in primary care settings, this version incorporated all the diagnoses available in the CMBD, in addition to hospital discharge and pharmacy dispensation records.

MCS scores were stratified using two complementary approaches to facilitate risk categorization. First, we applied the five fixed risk categories defined in the original study (0–4, 5–9, 10–14, 15–19, and ≥20). Second, we performed a population-based stratification by dividing the scores into five percentile-based groups (<50th, 50–80th, 80–95th, 95–99th, and >99th), thus contextualizing individual risk within the local distribution. In both schemes, the five resulting levels were mapped to equivalent qualitative risk strata: very low, low, moderate, high, and very high risk. A Sankey diagram was used to display the distribution of the study population according to the MCS categories for the three different versions.

Categorical variables were reported as absolute and relative frequencies (%). Continuous variables were described using median and interquartile range (IQR) as their distribution was not normal. Differences in age across MCS risk categories were assessed using Kruskal–Wallis tests. Post-hoc comparisons were performed using the Bonferroni method.

MCS assessment

The performance of the three MCS scores was evaluated using the remaining 40% of the cohort, the test set.

To evaluate the performance of the different MCS versions, generalized linear models (GLMs) with binomial distribution were constructed using the primary and each of the secondary outcomes as dependent variables. These models served as the basis for estimating receiver operating characteristic (ROC) curves, from which the area under the curve (AUC) and corresponding 95% confidence intervals (95% CIs) were calculated to assess the discriminatory ability of each MCS version. Model goodness-of-fit was evaluated using the likelihood ratio test. The agreement between the three MCS scores in the classification within five categories and percentiles was measured using the weighted Cohen's kappa. The NRI was calculated to assess the improvement of risk classification of MCS scores versions [31]. Finally, the Kaplan-Meier curves were used to estimate 1-year survival probabilities according to MCS categories and percentiles and the comparison between the curves of three different MCS types was performed using the log-rank test.

Furthermore, the distribution of annual health care utilization in terms of primary care contacts and drug consumption costs was evaluated using the categorical and percentile MCS scores calculated with improved data sources.

The significance level for all the analyses was set at a probability level lower than .05. Statistical analyses were performed using R, version 4.4.0 [32].

Ethics approval and consent to participate

The study received approval from the Ethical Committee for Human Research at Hospital Clínic de Barcelona on 8 September 2021 (reference HCB/2021/0768), as part of the EU project 'Joint Action on Implementation of Digitally Enabled Integrated Person-Centered Care' (JADECARE). Data handling adhered to the General Data Protection Regulation (GDPR) 2016/679, ensuring the protection of personal data and privacy for all individuals within the European Union. Although the study did not involve interventions beyond routine care, it complied with all applicable legal frameworks, including the Biomedical Research Act 14/2007 of 3rd July.

The Ethical Committee waived the requirement for informed consent, given the retrospective nature of the study and the use of fully anonymized data. This exemption applied to data collection, analysis, and publication, as the study was non-interventional and posed no additional risks to participants.

Results

As of 1 January 2016, a total of 440 790 individuals had been residing in the AISBE health district for at least 2 years. Of these, 198 753 (45%) were aged 50 years or older, comprising the study cohort (Supplementary Fig. S1). Most cohort members were females 113 708 (57%) and the median age was 66 years (IQR: 57–76).

MCS calculation

The proportion of individuals classified as having good or fair health (MCS score 0–4) was 58.6% with the original MCS, 83.5% with the recalibrated version, and 80.3% with the enhanced data sources version. In the mild-risk group (MCS 5–9), the corresponding proportions were 23.7%, 9.0%, and 10.9%, respectively. For the moderate-risk group (MCS 10–14), the values were 11.0%, 4.6%, and 5.2%. In the high-risk group (MCS 15–19), the cohort distribution was 3.6%, 1.6%, and 1.9%, while individuals classified in the highest risk category (MCS ≥20) accounted for 3.1%, 1.1%, and 1.6%. Most individuals classified in the mild-risk group (MCS 5–9) by the original version were classified as having a good or fair health (MCS score 0–4) in the adopted MCS versions (Supplementary Fig. S2).

All versions of the MCS showed a consistency in advancing age with increasing health risk scores (Fig. 1). Older adults were more frequently classified into higher-risk categories compared to younger individuals, reflecting the greater clinical complexity associated with aging (significant differences in age were observed between all MCS categories, $P < .001$, except for: MCS—original: 15–19 vs ≥20, $P = .304$; MCS—recalibrated: 5–9 vs 15–19, $P = .175$; MCS—with enhanced data sources: 10–14 vs ≥20, $P = .275$).

The set of conditions contributing to the MCS varied between versions: 34, 32, and 28 conditions were significant in the original, recalibrated and enhanced data sources versions, respectively. While metastatic cancer was consistently the strongest predictor, some conditions lost relevance and others emerged as important in the Catalan context. Full details are available in Supplementary Table S2.

MCS predictions assessment

Figure 2 illustrates the predictive performance of the three MCS versions in estimating 1-year mortality. Panel A shows the performance of the original MCS in the AISBE cohort, with an AUC of 0.742 (95% CI: 0.734–0.750), which is comparable to the AUC reported in the original Italian validation study [0.78 (95% CI: 0.77–0.79)]. Panels B and C display the performance of the remaining versions, showing similar levels of discrimination. The recalibrated MCS achieved an AUC of 0.756 (95% CI: 0.744–0.768) (Panel B), while the enhanced data sources version (Panel C) showed the highest performance, with an AUC of 0.771 (95% CI: 0.760–0.783), indicating a slight but consistent improvement over the original model.

The adapted versions of MCS significantly improved the net 1-year mortality reclassification with respect to the original MCS. In particular, the NRI increased by 0.63% (95% CI: 0.14–1.17) and 2.17% (95% CI: 1.39–2.97) for the recalibrated MCS and for the enhanced data sources MCS, respectively.

Table 1 shows the discriminative performance of the three MCS versions in predicting secondary outcomes, including 1-year and 4-year all-cause mortality, hospitalization, and primary care hyperfrequency. Overall, the three versions showed comparable performance across outcomes and timeframes. The MCS with enhanced data sources achieved slightly higher AUC values for 4-year mortality prediction. Conversely, the original MCS performed marginally better in forecasting hospitalization over 4 years, as well as primary care hyperfrequency at both 1 and 4 years.

Across all versions, survival probability decreased progressively with increasing MCS risk, confirming the expected gradient of worsening prognosis. This pattern was consistent whether risk was expressed using categories or percentiles, although survival probabilities were slightly lower among individuals in the highest percentiles groups compared to those in the highest score categories (Supplementary Fig. S3).

Agreement between the two adapted MCS versions was high when using score categories (weighted $\kappa = 0.78$, 95% CI: 0.78–0.79) and moderate when using percentiles ($\kappa = 0.53$,95% CI: 0.52–0.53). In contrast, agreement between the original MCS and the Catalan versions was low. For categories, the weighted kappa was 0.26 (CI 95%: 0.25–0.26) and 0.25 (CI 95%:0.25–0.26) for the recalibrated and enhanced data sources versions, respectively. For percentiles, agreement was slightly higher, with κ values of 0.45 (CI 95%:0.44–0.45) and 0.32 (95% CI: 0.31–0.32), respectively for the recalibrated and enhanced data sources versions.

The average annual distribution of healthcare resources use, specifically primary care contacts and pharmacy expenditures (€) by MCS categories and percentiles based on the enhanced data sources version is reported in Supplementary Table S3. A clear gradient was observed: as MCS scores increased, so did the average number of primary care

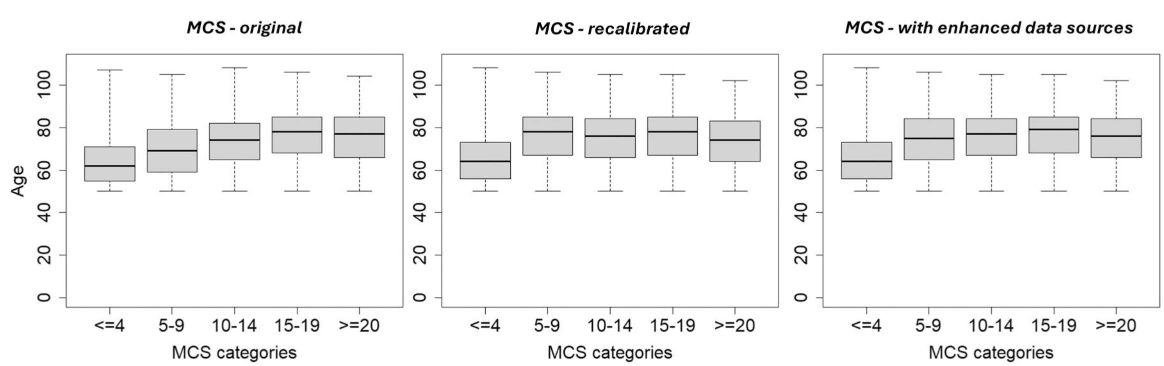

Figure 1. Distribution of age according to MCS categories in the three different scores in the study cohort.

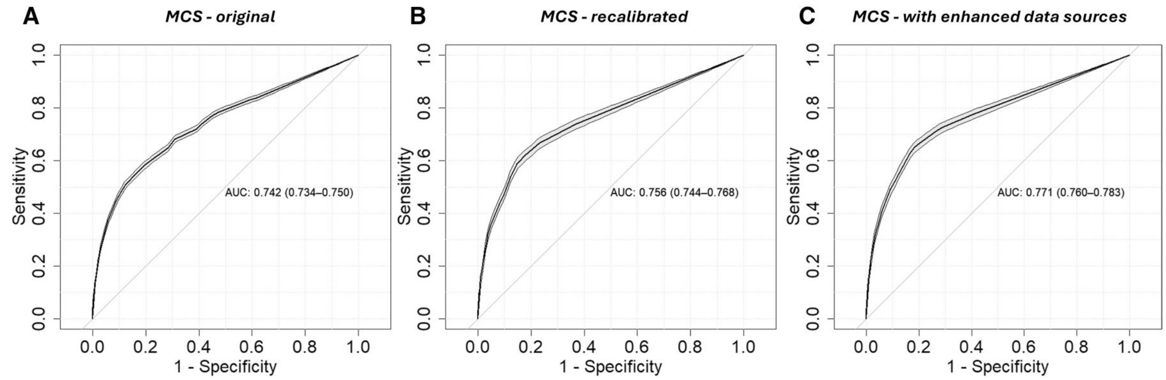

Figure 2. Discriminant power of the MCS original, MCS with Catalan weights, and MCS-enhanced data source in predicting 1-year survival in AISBE population: result of the receiver operating characteristic (ROC) curve.

Table 1. Comparison of discriminant power of MCS scores modalities in predicting in mortality, hospitalization, and primary care hyperfrequency: AUC and 95% confidence intervals

	AUC (95%CI)					
	Mortality		All-cause hospitalization		Primary care hyperfrequency[a]	
	1 years	4 years	1 year	4 years	1 year	4 years
MCS—original	0.742 (0.734–0.750)	0.732 (0.728–0.736)	0.705 (0.701–0.708)	0.681 (0.678–0.683)	0.749 (0.747–0.751)	0.767 (0.754–0.769)
MCS–recalibrated	0.756 (0.744–0.768)	0.742 (0.735–0.748)	0.689 (0.684–0.695)	0.661 (0.658–0.665)	0.717 (0.713–0.721)	0.734 (0.731–0.738)
MCS—with enhanced data sources	0.771 (0.760–0.783)	0.757 (0.750–0.763)	0.700 (0.695–0.706)	0.670 (0.667–0.674)	0.729 (0.725–0.733)	0.747 (0.743–0.751)

a: ≥10 visits per year. AUC: area under the curve; CI: confidence intervals.

visits and pharmacy cost. The greatest increase occurred between the first and second classes (good health-average health), with more than a two-fold increase in primary care contacts, and more than a three-fold increase in pharmacy expense across both categorizations. The increase in primary care use decreased in the subsequent MCS categories and then stabilized in the highest risk classes.

Discussion

Main findings

This study tested and validated the performance and generalizability of the MCS in a new setting, using real-world data from Catalonia's publicly funded healthcare system, and represents the first cross-national application of the MCS. The validation was conducted using a large population-based cohort of individuals aged 50 years and older, leveraging routinely collected data on hospital discharges and outpatient pharmacy dispensation. The original MCS version demonstrated robust performance in predicting both 1- and 4-year all-cause mortality, as well as moderate discriminatory capacity for hospital admissions and high primary care utilization. These findings are consistent with the results from the original Italian study [10].

Importantly, the adaptation of the MCS using local data sources and recalibrated weights led to only marginal improvements in mortality prediction and did not substantially enhance performance for healthcare utilization outcomes. These results suggest that the core structure and variables of the original MCS remain broadly valid across settings, and that the inclusion of additional data sources or reweighting may offer limited incremental benefit when applied to regions with similar health systems and demographics.

Insights from MCS adaptation in Catalonia

However, some differences were observed between the original and adapted versions of the MCS, particularly in the selection and weighting of specific conditions, that might be explained for the following factors: (i) In Catalonia, the central role of primary care in chronic disease management may lead to earlier detection and more comprehensive registration of health conditions, including cases in less severe stages. As a result, the presence of certain diagnoses may be less strongly associated with adverse short-term outcomes, such as mortality, because the spectrum of disease severity is broader than that typically captured in hospital-based datasets. (ii) Also, regional differences in prescribing behaviour, driven by clinical practice guidelines, pharmaceutical availability, or professional culture, can alter the weight of medication-based predictors. (iii) And finally, the transition from ICD-9, used in the original MCS development, to ICD-10-CM in the Catalan dataset adds another layer of complexity.

The recalibrated MCS improved prediction of 1-year mortality, its primary target outcome, but showed no notable gains for secondary endpoints such as hospital admissions or high primary care utilization. This suggests that future adaptations of the score could consider tailoring condition weights to specific outcomes of interest. For example, optimizing the score for healthcare utilization, cost prediction, or patient-reported measures might enhance its relevance in different decision-making contexts. Aligning the recalibration process with the intended application could help improve the score's performance across diverse healthcare objectives [17].

Implications for future opportunities for MCS

With the aim of using standardized tools for the population health risk assessment (HRA), evidence from both internal and external validation study suggests that MCS can be considered a good starting point to develop a tool to be used at national level. Recently, based on MCS as a primary driver for stratifying patients' clinical complexity, a national tool for classification and stratification of the Italian population, identifying homogeneous population groups according to the type and intensity of social healthcare need, to which different types of prevention, health promotion, and care can correspond, is being developed to support healthcare planning decisions [33].

On the other hand, the flexibility and adaptability of this tool based on the use of secondary health data is strongly related to the data availability and accessibility. The new European Health Data Space (EHDS) regulation on secondary health data usage is set to significantly influence the management of health data within Italy's NHS databases [34]. This initiative could overcome barriers related to privacy issues that hinder the transferability of HRA tools such as MCS [35] and could represent an opportunity for the tool to refine its predictive capabilities by integrating vertically aligned data, spanning primary and specialist care.

Strengths and limitations

This study has several strengths that enhance the robustness and generalizability of its findings. It represents one of the few external validations of a multimorbidity-based risk stratification tool in a setting outside its original development context [36–38]. The study also evaluated multiple score configurations, original, recalibrated, and enriched, enabling a nuanced understanding of how data sources and local adaptation influence predictive performance. Furthermore, the use of routinely collected healthcare data mirrors the real-world conditions in which such tools would be applied, supporting the feasibility of future implementation.

Nonetheless, the study has some limitations that should be acknowledged. First, the validation was restricted to individuals aged 50 years and older, to ensure the comparability of the results with previous studies [10], which limits the generalizability of the findings to younger populations. Although preliminary analyses suggest that the MCS can also stratify healthcare use in the broader adult population, further research is needed to assess its performance and refine its components in younger age groups. Second, the original MCS was developed using ICD-9-CM diagnostic codes, whereas the Catalan dataset uses ICD-10-CM, which may have introduced discrepancies in disease classification. Additionally, although both the Italian and Catalan systems are publicly funded and universal, differences in data completeness, coding practices, and the role of private care may affect the comparability of predictors and outcomes.

Overall, the study provides strong evidence supporting the external validity of the MCS while also highlighting the importance of contextual adaptation. These findings lay the groundwork for further applications and refinements of the score across diverse health systems and population segments.

Supplementary data

Supplementary data are available at *EURPUB* online.

Conflict of interest: The authors have no competing interests to declare.

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This study received no funding.

Data availability

The raw data accessed belong to the Catalan Health System and are not publicly accessible, whereas the scripts and the anonymized datasets generated and used for the modelling are available from the corresponding author upon reasonable request.

Key points

- First external validation and adaptation of MCS in the Catalan healthcare system.
- Original MCS showed a robust performance in predicting mortality in Catalonia.
- Adapted MCS versions showed marginal improvements in mortality prediction.
- Results can help refine MCS in other healthcare and population segments.

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