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Mental illness-related disparities in length of stay: Algorithm choice influences results

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Abstract—Methodological challenges arise when one uses various Veterans Health Administration (VHA) data sources, each created for distinct purposes, to characterize length of stay (LOS). To illustrate this issue, we examined how algorithm choice affects conclusions about mental health condition (MHC)-related differences in LOS for VHA patients with diabetes nationally (*n* = 784,321). We assembled a record-level database of all fiscal year (FY) 2003 inpatient care. In 10 steps, we sequentially added instances of inpatient care from various VHA sources. We processed databases in three stages, truncating stays at the beginning and end of FY03 and consolidating overlapping stays. For patients with MHCs versus those without MHCs, mean LOS was 17.7 versus 13.6 days, respectively (*p* < 0.001), for the crudest algorithm and 37.2 versus 21.7 days, respectively (*p* < 0.001), for the most refined algorithm. Researchers can improve the quality of data applied to VHA systems redesign by applying methodological considerations raised by this study to inform LOS algorithm choice.

Key words: algorithms, databases, Department of Veterans Affairs, episode of care, healthcare disparities, health services research, human, length of stay, mental disorders, outcome and process assessment, patient discharge, physician's practice patterns, rehabilitation, reproducibility of results, veterans, veterans hospitals.

INTRODUCTION

Health services researchers often use administrative data for characterizing length of stay (LOS) to address a range of objectives. For example, they may examine how LOS (as a dependent variable) varies as a function of patient characteristics (e.g., age, race, insurance status, presence of comorbidity), processes of care (e.g., speed of emergency department response, types of medications administered or interventions applied, discharge protocols, etc.), or institutional characteristics (e.g., teaching hospital, mental health facility, etc.) [1–7]. Alternatively,

they may examine LOS as a potential explanatory variable for predicting other outcomes [8] or they may restrict their cohort to patients meeting specific LOS criteria [9]. Furthermore, accurate identification of intervals of inpatient care is required for studies using an episodes-of-care approach [10].

The concept of LOS is simple: time from admission to discharge. However, a number of methodological considerations arise when Veterans Health Administration (VHA) data are used for calculating LOS. First, goals of the project must be carefully considered, because this will influence the algorithm selected. Is the focus on acute or long-term care, on medical-surgical or mental health stays? Is the objective to examine total LOS across multiple years or LOS during a particular interval of study? Second, the algorithm must account for technical, data-quality issues. These include duplicate records, overlapping or sequential inpatient stays, transfers between different inpatient units, and inpatient stays that are recorded in a subsequent year.

Despite that numerous studies focus on LOS, these subtleties of LOS calculation have received little attention. This oversight could have serious implications: algorithm choice can influence conclusions in health services studies [11–13], although to our knowledge this possibility has not been studied in the specific case of LOS. As VHA leadership increasingly seeks to obtain accurate estimates of healthcare costs and use evidence to guide strategic planning decisions, it is critical that the evidence base supporting those decisions be as accurate as possible.

One example of a clinical scenario wherein LOS algorithm choice could influence conclusions is mental health condition (MHC)-related differences in inpatient care use. Prior studies both within and outside the VHA have documented that, compared with patients without MHCs, patients with MHCs tend to use more inpatient care [6,14–19]. Thus, patients with MHCs represent a particularly high-intensity, high-cost group likely to merit special attention by VHA policy makers. However, some characteristics of the way patients with MHC receive inpatient care may make their VHA records disproportionately susceptible to variation in algorithm choice. For example, patients with MHC might be more likely to experience more complex patterns of inpatient care (e.g., transferring between a medical unit and a psychiatric unit during the course of a single hospitalization episode), or to receive care in extended-care settings, where stays can be long and can span multiple fiscal years (FYs). Such factors could potentially influence LOS calculations differently for patients with MHC versus those without MHC.

We used VHA administrative data to examine how application of incrementally more refined algorithms for calculating LOS during 1 year of care affected conclusions about mean LOS in a national cohort of VHA patients with diabetes. Then, as an illustrative example of the practical implications of such methodological decisions, we examined whether the magnitude of observed mental illness-related disparities in mean LOS varied as a function of LOS algorithm applied.

METHODS

Study Context

This work is part of a larger study examining the effect of MHC on processes of outpatient diabetes care in FY03. Because the focus of that study is on outpatient care, we wished to identify (and ultimately exclude from the larger study) patients who were institutionalized (i.e., on inpatient status) for the majority of FY03. Therefore, our goal was to identify, for each patient in our cohort, all days in FY03 during which the patient was on inpatient status (acute care or extended care). We were not seeking to characterize total LOS for the patients in our cohort (which could have spanned multiple years), but only those inpatient days that occurred during FY03. The process of creating our LOS variable and the effect of algorithm choice on conclusions about MHC-related differences in LOS is the focus of the present study.

Subjects

The cohort was drawn from the FY02 Diabetes Epidemiology Cohort (DEpiC), a census of patients with diabetes in VHA nationally. DEpiC is used extensively for VHA epidemiological and health services research [20]. DEpiC identifies patients with diabetes based on the presence of at least one instance of an antiglycemic prescription or at least two instances of a diabetes International Classification of Diseases-9th Revision (ICD-9) code in inpatient or outpatient records. Among the 911,451 FY02 DEpiC members who were veterans, used VHA outpatient care at least once in FY02, and were alive as of the first day of FY03, we selected the 784,321 whose MHC status could be verified, as described next (in subsidiary analyses, we included the full 911,451 subjects, including those with "MHC Possible" status).

711

FRAYNE et al. Algorithm choice for length of stay

Steps to Assemble Raw Record-Level Database of Inpatient Stays

We started by creating a record-level file containing every instance of inpatient care recorded in any inpatient database available in centralized VHA files. We selected only records that contained at least 1 day of inpatient care in FY03. We also deleted duplicate records. In 10 sequential "steps," we pulled all nonduplicate inpatient records containing any FY03 inpatient care for patients in our cohort from the following FY03 files:

Step 1. Bedsection file, which represents acute care hospital stays.

Step 2. OBS (Observation) file, which represents short (e.g., overnight) acute care stays during which the patient is observed regarding the potential need for admission to an acute care bed.

Step 3. EXT (Extended Care) file, which represents long-term care stays (such as rehabilitation stays or nursing home stays).

Step 4. Census file (for Bedsection, OBS, and EXT), which include records for all patients who still held inpatient status on the last day of the FY, and thus for whom a discharge date was not available when the files for that FY were created.

Step 5. Non-VHA file.

Step 6. Fee basis file.

(These latter two files reflect care received outside of VHA but with funding for the care provided by VHA.)

We then searched FY04 and FY05 files for any records that included some FY03 care:

Step 7. Sources 1 through 5, FY04.

Step 8. Fee basis FY04 file (presented separately from other FY04 files to emphasize that fee basis files are more likely to contain "late entry" records from prior years).

Step 9. Sources 1 through 5, FY05.

Step 10. Fee basis FY05 file.

Stages of Processing Record-Level Database of Inpatient Stays

Next, we processed this raw database in sequential "stages." Stage A represented the raw file at any given step. In stage B, we deleted pre-FY03 and post-FY03 care. Specifically, for records with an admission date earlier than the first day of FY03, we deleted any days preceding FY03 (i.e., we modified the record to begin on the first day of FY03), because we were interested in days of care during FY03, not total LOS for the patient across multiple years.

Similarly, for records with a discharge date later than the last day of FY03, we modified the record to end on the last day of FY03.

In stage C, we addressed overlapping stays. Several types of overlap were observed, as illustrated in **Figure 1**. In some cases, the entire stay (admission date through discharge date) was contained within the time interval of another record. This might happen, for example, if a patient in a rehabilitation unit was temporarily transferred to an acute care observation bed for an intercurrent illness like pneumonia. If the patient was not formally discharged from the rehabilitation facility prior to the transfer, then the time interval of the short-term stay (appearing in the OBS file) could be bracketed by the interval of the long-term stay (appearing in the EXT file). In other cases an overlap occurred (e.g., the admission date of one record fell between the admission and discharge dates of a subsequent record, or the discharge date of a record fell between the admission and discharge date of a subsequent record). In other cases, contiguous admissions occurred (i.e., the discharge date of one record was the same as the admission date of a subsequent record). For all these overlap cases (which could involve a pair of records or even three or more records), we created a single contiguous episode of FY03 inpatient care by assigning the admission date to be the first admission date in FY03 among the overlapping records and the discharge date to be the last discharge date in FY03 among the overlapping records. The resulting file at step 10, stage C, was our final record-level file of inpatient stays.

Variables

We calculated LOS for each record as the number of days from its start through end dates. At each step/stage, we calculated a cumulative LOS for each patient by adding the record-level LOS for all records included in that step/stage.

To identify patients with MHC, we used the Agency for Health Research and Quality's Clinical Classifications Software (with minor modifications) to generate a list of ICD-9 codes indicating the presence of MHC [21]. A patient was assigned a "Yes" for MHC status if he/she had at least one instance of an MHC ICD-9 code in any inpatient record or outpatient face-to-face clinic visit at baseline (FY01–02) and at least one confirmatory ICD-9 in the study period (FY03). If he/she had no instance of an MHC ICD-9 in FY01 through 03, then he/she was assigned MHC status "No." Otherwise, MHC status was

considered "Possible." That is, the MHC Possible group represents those patients who had an MHC diagnosis in the baseline period or in the study period, but not both.
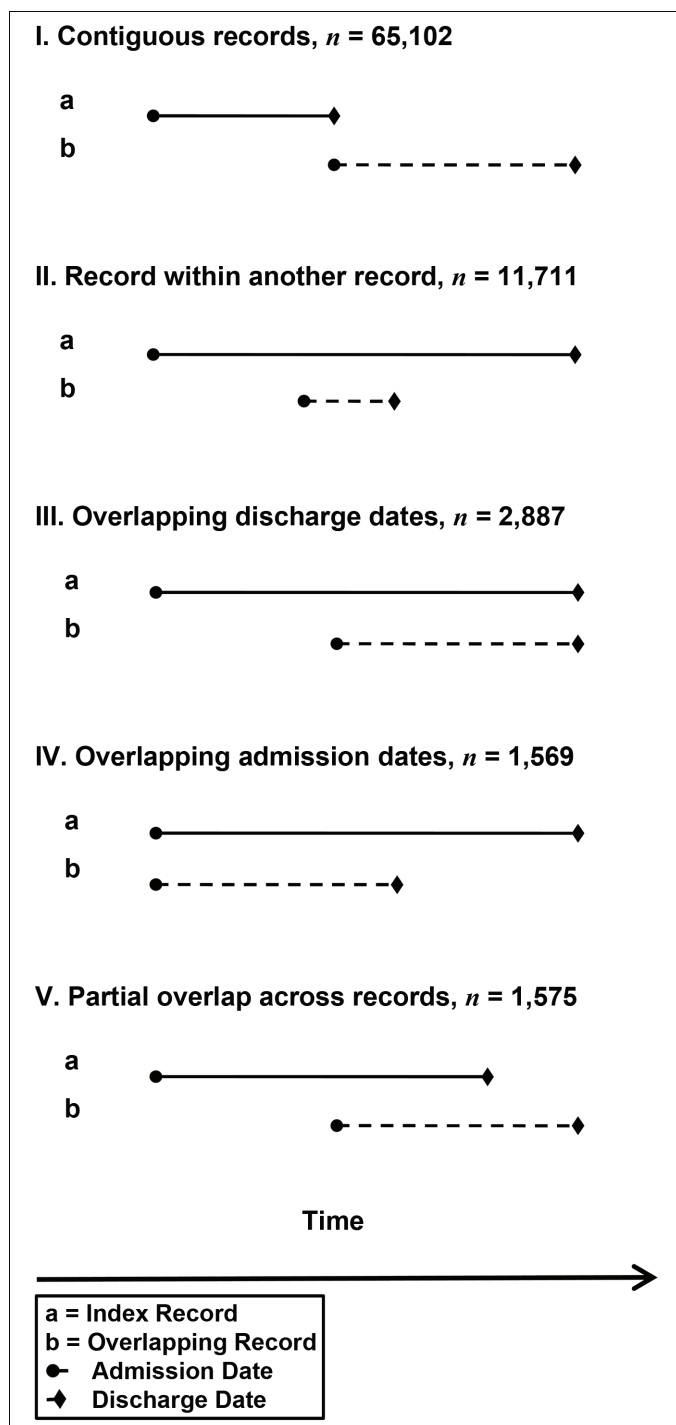

Figure 1.
Patterns I–V of overlap between pairwise records of an individual patient and record-level frequency of each pattern at step 10, stage C.

Cases with MHC Possible status were excluded from main analyses; this allowed us to compare LOS in two more sharply defined groups (MHC Yes vs MHC No).

Analysis

We tabulated the number of records and calculated mean LOS within each cell of a 10×3 matrix representing the steps and stages of database development. Next, in each cell, we calculated mean LOS as a function of MHC status. We then calculated the difference (Δ) in mean LOS among patients with MHC versus those without MHC and compared mean LOS for the MHC Yes versus MHC No groups using a two-sample t-test. We applied Bonferroni correction for compounding of Type I error across multiple comparisons. Results of hypothesis tests are declared statistically significant for $p < 0.05$ after Bonferroni correction.

RESULTS

Among the 784,321 patients with diabetes in the full cohort, 152,591 were identified as having evidence of an MHC diagnosis (MHC Yes). Among the subset of 92,255 patients who received any inpatient care in FY03 (based on step 10, stage C), 39,452 had MHC Yes. **Table 1** presents the age, sex, Physical Comorbidity Index score (a count from 0–35, developed for case mix adjustment in VHA patients [22–23]), and primary care use in the full cohort and in the subset who used inpatient care, by MHC status.

Table 2 catalogs the number of records and LOS at each step/stage in the database assembly process. The cumulative number of patients who are identified as having received inpatient care in FY03 (based on stage C) increases progressively from step 1 to step 10 (as do the number of records). For example, when the OBS file was added to the Bedsection file, an additional 10,660 records were added for stays that did not perfectly duplicate a Bedsection file stay for that patient. This is expected, because additional evidence of inpatient care is added at each step. More noteworthy is that some steps contribute more records than others.

The number of records does not change at stage B (compared with stage A), because this processing step truncates records (to include only inpatient days during FY03) but does not delete records. However, at stage C (record consolidation), the number of records drops substantially, because overlapping stays are merged into a single, longer stay.

713

FRAYNE et al. Algorithm choice for length of stay

Table 1.
Characteristics of cohort by mental health condition (MHC) status (full cohort and subset who used Veterans Health Administration inpatient care).

Characteristic	Full Cohort, *n* = 784,321		Inpatient Users,[*] *n* = 92,255	
	MHC Yes	**MHC No**	**MHC Yes**	**MHC No**
n	152,591	631,730	39,452	52,803
Age (years, mean ± SD)	62.1 ± 11.6	69.6 ± 10.3	61.4 ± 11.9	69.1 ± 10.5
Male (%)	96.4	98.5	96.1	98.4
Physical Comorbidity Index (mean ± SD)	3.6 ± 2.4	2.8 ± 2.0	4.6 ± 2.8	4.5 ± 2.7
Used Primary Care in FY03 (%)	93.6	86.8	90.6	91.7

[*]Inpatient user cohort selected from step 10, stage C.
FY = fiscal year, SD = standard deviation.

Table 2.
Effect of sequential data assembly steps and data cleaning stages on number of patients identified as having received inpatient care and on count of inpatient records and mean length of stay (LOS).

Step	Patients[*] (*n*)	Records Added in Step (*n*)	Number of Records			LOS (days), Mean ± SD		
			Stage A	**Stage B**	**Stage C**	**Stage A**	**Stage B**	**Stage C**
1. Bedsection FY03	77,817	173,707	173,690	173,690	127,566	15.3 ± 21.1	14.8 ± 20.1	14.2 ± 19.4
2. OBS FY03	81,489	10,660	184,350	184,350	135,398	14.9 ± 22.8	14.4 ± 19.8	13.8 ± 19.2
3. EXT FY03	85,198	14,844	199,194	199,194	140,283	27.3 ± 103.8	21.7 ± 37.8	20.7 ± 36.1
4. Census FY03	86,990	6,990	206,184	206,184	143,193	37.6 ± 198.4	26.7 ± 53.1	25.6 ± 51.2
5. Non-VHA FY03	89,135	5,438	211,622	211,622	146,723	37.2 ± 196.2	26.5 ± 52.8	25.4 ± 50.9
6. Fee FY03	90,558	15,107	226,729	226,729	148,721	40.4 ± 198.8	29.8 ± 61.9	27.7 ± 56.2
7. FY04 Records	90,689	5,898	232,627	232,627	148,905	58.3 ± 370.4	35.7 ± 91.2	28.0 ± 57.4
8. Fee FY04	92,068	6,829	239,456	239,456	151,891	58.4 ± 368.5	36.1 ± 93.0	28.3 ± 58.9
9. FY05 Records	92,181	1,569	241,025	241,025	151,980	74.9 ± 518.8	39.4 ± 113.4	28.4 ± 59.3
10. Fee FY05	92,255	293	241,318	241,318	152,157	74.8 ± 518.6	39.4 ± 113.4	28.4 ± 59.3

Note: To create table, we started with step 1 and completed cells across each stage sequentially. Then, for the step 2 analyses, we started with records from steps 1 and 2 and completed cells across each stage sequentially. Analyses for each subsequent step similarly included records from all prior steps. Stages were stage A (original record), stage B (delete days prior to first day of FY03 and after last day of FY03), and stage C (consolidate overlapping stays).
[*]Reflects cumulative number of patients who received inpatient care in FY03 at each step at stage C. Inpatient records were drawn from patients in analytical cohort (*n* = 784,321).
EXT = extended care, FY = fiscal year, OBS = observation, SD = standard deviation, VHA = Veterans Health Administration.

Consistent with these observations, mean LOS at stage C increased progressively with sequential steps (i.e., as more sources of data were added), except at step 2 (where patients with short OBS stays were added) and at step 5 (where patients with non-VHA stays were added). Similarly, mean LOS decreased progressively with sequential stages. That is, mean LOS decreased from stage A to stage B as non-FY03 days were deleted (which would be relevant to a study like ours that focuses on care received in a single FY). Mean LOS also decreased from stage B to stage C as overlapping days were deleted (which would be relevant to the accuracy of the LOS estimate in any study design). Across the 10 × 3 matrix, mean LOS ranged from 13.8 to 74.9 days.

Table 3 presents LOS by MHC status at every step/stage in the database assembly process. The calculated difference (Δ) in mean LOS between the MHC Yes and the MHC No groups varied markedly by algorithm and was statistically significant ($p < 0.001$) at every step/stage. Correction for multiple comparisons did not statistically affect any findings significantly. As illustrated in **Figure 2**, step 1, Δ = 4.1 at stage A and 3.8 at stage C. In contrast, at step 10, Δ = 57.8 at stage A and 15.5 at stage C ($p < 0.01$ for both between-algorithm comparisons of the values of Δ).

To obtain the LOS in stage C, for each pair of overlapping records, we generated a single record by setting the FY03 admission date as the earliest of the two admission dates and the FY03 discharge date as the latest of the two

Table 3.
Effect of sequential data assembly steps/data cleaning stages on fiscal year (FY) 2003 length of stay (LOS) calculations by mental health condition (MHC) status.

Step	Stage A			Stage B			Stage C		
	MHC Yes	MHC No	Δ	MHC Yes	MHC No	Δ	MHC Yes	MHC No	Δ
1. Bedsection FY03	17.7	13.6	4.1	17.0	13.2	3.8	16.4	12.6	3.8
2. OBS FY03	17.3	13.1	4.2	16.6	12.8	3.8	16.0	12.2	3.8
3. EXT FY03	36.6	20.4	16.2	27.5	17.4	10.1	26.4	16.5	9.9
4. Census FY03	51.6	27.2	24.4	34.0	21.3	12.7	32.7	20.3	12.4
5. Non-VHA FY03	51.0	26.9	24.1	33.7	21.1	12.6	32.4	20.1	12.3
6. Fee FY03	56.1	28.6	27.5	39.1	22.9	16.2	36.2	21.3	14.9
7. FY04 Records	82.1	40.5	41.6	47.1	27.3	19.8	36.7	21.5	15.2
8. Fee FY04	82.3	40.5	41.8	47.8	27.4	20.4	37.1	21.6	15.5
9. FY05 Records	108.0	50.2	57.8	52.5	29.6	22.9	37.3	21.7	15.6
10. Fee FY05	107.9	50.1	57.8	52.4	29.6	22.8	37.2	21.7	15.5

Note: Every difference (Δ) between mean LOS for MHC Yes vs MHC No in this table is statistically significant at $p < 0.001$. Stages were stage A (original record), stage B (delete days prior to first day of FY03 and after last day of FY03), and stage C (consolidate overlapping stays). Two sample t-tests were conducted for two key comparisons in this table: comparing within step 1 for stage A vs stage C and within step 10 for stage A vs stage C ($p < 0.01$ for both comparisons).
Δ = mean LOS (MHC Yes) minus mean LOS (MHC No), EXT = extended care, OBS = observation, VHA = Veterans Health Administration.
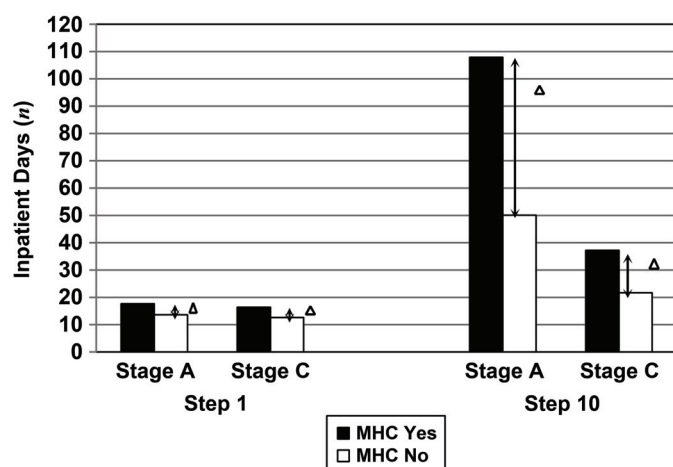
Figure 2.
Effect of sequential data assembly steps and data cleaning stages on fiscal year 2003 number of inpatient days. MHC = mental health condition, Δ = mean length of stay (LOS) (MHC Yes) – mean LOS (MHC No).

discharge dates. We repeated this process iteratively until all pairwise overlaps were addressed. This data processing stage was the most involved, because it needed to account for multiple potential overlap patterns, as illustrated schematically in **Figure 1**. The most common overlap pattern (pattern I) was contiguous records, i.e., where the discharge date of one record was the admission date of the following record. This pattern would happen, for example,

if a patient were admitted to one bed section (e.g., to the Psychiatry Department for suicidal ideation) and then transferred to another bed section (e.g., to General Medicine for a hospital-acquired infection). Of note, we used the Bedsection files for these analyses. VA Bedsection files create a new record each time a patient transfers to a different clinical service ("bedsection") during a hospital stay. This is in contrast to the VA Main files, which create a new record for each stay; all contiguous bedsection stays are combined in a single record. Had we used the Main file instead of the Bedsection file, we expect that we would not have encountered this particular form of overlap. Other overlap patterns were also observed, as **Figure 1** shows. Of note, step 10, stage B, yielded LOSs of more than 365 days for 3.2 percent of the MHC Yes group and 1.4 percent of the MHC No group, clearly representing a residual problem with the algorithm; in contrast, no patient had LOS greater than 365 days at stage C. This finding supports the importance of the stage C processing.

In a subsidiary analysis, we found that both the admission and discharge dates fell within FY03 for 91 percent of records at step 10, stage A. In those instances, the full LOS for that episode of care was captured and no truncation was required.

Our main analyses excluded patients who had MHC Possible status (i.e., those patients who had an MHC diagnosis in the baseline period or in the study period, but not both). In another subsidiary analysis (see online **Appendix**), we repeated the main analysis in the initial cohort

715

FRAYNE et al. Algorithm choice for length of stay

(n = 911,451), calculating mean LOS as a function of MHC as a three-way variable (MHC Yes, MHC Possible, MHC No). Mean LOS for the MHC Possible group was consistently intermediate between that for the MHC Yes and MHC No groups. For example, for the MHC Possible group, mean LOS was 16.2 at step 1, stage A; 15.1 at step 1, stage C; 90.3 at step 10, stage A; and 34.4 at step 10, stage C.

DISCUSSION

Choices about what algorithm to use when identifying episodes of inpatient care substantially alter conclusions about the overall intensity of inpatient use and about MHC-related disparities in LOS. Not searching across all appropriate sources of data can lead to failure to capture a substantial amount of inpatient care, thus leading to underestimates of LOS. Decisions about how to process records can likewise influence calculated LOS. While other studies have documented that algorithm choice can influence conclusions drawn from VHA data [11–13], we are not aware of this result having been previously documented for LOS.

Researchers have access to many sources of data about VHA patients' nonambulatory care. Indeed, the large number of sources can bewilder investigators new to VHA administrative data, who may be unsure which files to select. Fortunately, the technical manuals developed by the Department of Veterans Affairs Information Resource Center (available at http://www.virec.research.va.gov/) and the Department of Veterans Affairs Health Economics Resource Center (available at http://www.herc.research.va.gov/) explain these files in detail. Our data provide further empiric information to help guide these decisions. First, our results confirm that adding more data sources identifies more inpatient days. Second, our results indicate that the EXT and Census files are especially important sources of incremental days of inpatient care. Third, our results indicate that adding more data sources also changes conclusions about the magnitude of effect (though not the direction of effect) of MHC on LOS. The step at which this has a particularly pronounced effect is the addition of EXT files, indicating that, compared with patients with no MHC, patients with MHC have disproportionately more frequent or prolonged stays in the long-term care setting.

Investigators using any VHA database need to examine data closely to determine whether data processing steps

are necessary. In the case of inpatient files, our data indicate that in addition to the standard procedure of deleting pure duplicate records, investigators must account for overlapping stays (wherein a single day can be counted twice) and, for studies such as ours that focus on a single year of care, to truncate days falling before or after the FY of interest. Such pitfalls could, in some cases, reflect data quality problems, such as a data-entry error in admission or discharge date. However, in many cases, they may not represent deficits in the quality of VHA administrative data, but instead may reflect VHA clinical/administrative record-keeping practices. For example, a single stay could legitimately be recorded in more than one file if these files are used differently. Similarly, a fee basis stay (with the correct admission and discharge dates) could be filed in a subsequent year's records if a delay occurred in receipt of the bill from the outside vendor. Regardless of whether some of these factors represent data quality problems, investigators need to account for them; if not, some patients will have inflated estimates of LOS. Indeed, without such corrections, some patients will appear to be on inpatient status for more than 365 days in a single FY.

While the focus of this study is on the issue of algorithm choice for calculation of LOS, we use MHC-related disparities in LOS as a case study to illustrate what can happen if such issues are not considered. Health services researchers frequently examine disparities in processes and outcomes of care. Historically, interest in disparities related to characteristics like race, sex, and age has been great, but emerging evidence suggests that disparities related to MHC status are also common [9,24]. We demonstrated that the magnitude of MHC-related differences in LOS varied markedly as a function of LOS algorithm. Thus, the methodological issues raised here are not just theoretical: algorithm choice can have marked effects on conclusions in healthcare disparities research.

In the course of conducting analyses for this illustrative example, a subsidiary benefit was that informative findings about associations between MHC status and LOS emerged. Patients with MHC spent more of FY03 on inpatient status than did patients with no MHC; this was a consistent and robust finding across every algorithm examined. This finding is consistent with other studies that have shown heavier use of inpatient services by patients with MHC [6,14–19]. Our study also shows that some types of care (e.g., EXT) are associated with a disproportionately greater MHC effect. Another strength of our approach is that we distinguished between patients

with stronger evidence of MHC (i.e., at least one MHC diagnosis at baseline in FY01–02 and at least one confirmatory MHC diagnosis in the study period, FY03) and patients with less certain (Possible) MHC status (i.e., presence of an MHC diagnosis either at baseline or in the study period, but not both). Our subsidiary analyses provide information about MHC Possible patients, a group that has not been well characterized in prior work. The MHC Possible group is likely heterogeneous and includes patients with an erroneous MHC diagnosis, with transient or resolved MHC, or with less severe MHC, as well as patients who receive part of their care outside the VHA system. Mean LOS for the MHC Possible group consistently fell between the mean LOS observed for the MHC Yes and the MHC No groups.

Interpretation of our findings is subject to several caveats. First, our aim was to calculate total number of days spent on inpatient status during FY03; values should not be interpreted as indicating total LOS across years. However, for 91 percent of records, the patient's complete stay was contained within FY03. Second, we did not use the VHA Decision Support System (DSS) Outpatient (OPAT) file as a data assembly step. In the OPAT file, Stay Type 42, Bedsection 80 refers to nursing home care reimbursed by VHA in any particular month. However, dates of admission and discharge could not be accurately generated from that source. Third, our focus was on VHA use. Depending on an investigator's study question, capturing inpatient days spent in other settings might also be important, such as days identified from Medicare claims data, which can be linked to VHA administrative data [25]. Fourth, because the purpose of our study was to identify periods during which the patient was on nonoutpatient status, our LOS calculations included both acute care and long-term care days. Studies focusing on one or the other setting might need to consider other methodological issues. For example, a patient's stay in a skilled nursing facility could have short gaps (e.g., for a brief acute care stay), which might not be captured with the databases used. Fifth, our main analyses excluded patients whose MHC status could not be ascertained with certainty (MHC Possible), so LOS estimates cannot be generalized to all VHA patients. Subsidiary analyses suggested that these excluded patients had intermediate LOS and that algorithm choice similarly affected LOS calculations for them. Sixth, MHC diagnoses came from ICD-9 diagnosis codes in VHA administrative data rather than from direct assessment of patients' MHC.

Given the known problem of underdiagnosis of MHC [26–27], some patients with MHC are likely included in the MHC No group. This would be expected to bias results toward the null.

This study examines methods that should be considered when an algorithm is developed that uses VHA data to calculate LOS. The specific algorithm selected will depend on the research question, such as—

- What types of inpatient care are of interest? For example, is the focus on acute care, extended care, care received on a fee basis outside of VHA or some combination of these sources? If rehabilitative/extended care is the focus, will additional sources (e.g., VHA EXT, fee basis, non-VHA and DSS OPAT files, as well as Medicare or Medicaid files) be queried, and how will multiyear stays be addressed?

- Is the focus on care received in a particular time interval (such as one FY) or on a full episode of inpatient care? If the former, will subsequent years' files be searched for stays recorded in a subsequent FY, and what is the expected incremental benefit versus cost of pulling data from multiple years? If the latter, how many years of data will be searched to identify the complete LOS, which could potentially span many years?

- Is the objective to characterize private sector inpatient care received as well, and if so, should other sources (such as Medicare claims data) be queried?

Careful consideration of these study design issues should yield an algorithm tailored to a particular study's objectives.

CONCLUSIONS

Accounting for the methodological issues raised here should help VHA health services researchers avoid pitfalls in calculation of VHA LOS, such as failure to capture care recorded in more obscure data sources (leading to underestimates of LOS) or duplicate counting of some days of care (leading to overestimates of LOS). This result is expected to support more robust estimates for economic analyses, since inpatient costs contribute disproportionately to total cost of VHA care. This result is also expected to enhance the accuracy of data VHA uses in its evidence-based efforts to redesign its healthcare delivery systems, which aim to improve the quality of care provided to veterans.

717

FRAYNE et al. Algorithm choice for length of stay

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