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Outpatient Provider Staffing Ratios: Binary Recursive Models Associated With Quality, Access, and Satisfaction

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Veterans Health Administration (VHA) continues to expand the mental health (MH) workforce to meet increasing demand for services. In the present study, longitudinal unbiased recursive partitioning models (conditional inference trees) were created to identify optimal cutoffs for outpatient staffing ratios associated with success on VHA's measures of quality, access, and satisfaction. Quarterly Staff-to-Patient Ratios (SPRs), defined as the number of full-time equivalent providers per 1,000 veterans receiving outpatient mental health care, were calculated for 12 quarters from fiscal years 2016–2018. Associations between VHA metrics associated with quality, access, and satisfaction were evaluated in relation to the overall outpatient SPR. The root node identified an overall outpatient SPR of 7.39 as the split for optimal MH performance. Root nodes associated with metrics addressing population coverage, continuity of care, and experience of care identified SPRs of 7.87, 6.81, and 7.42, respectively. In all analyses, the lowest SPRs were associated with the lowest performance on VHA MH metrics, while the highest SPRs were associated with the highest performance. Analyses support VHA's current recommended minimum outpatient SPR of 7.72 as a reasonable target to provide high-quality care, access, and satisfaction.

Impact Statement
Determination of appropriate mental health staffing is critical to meet quality, cost, and satisfaction expectations. Since 2012, Veterans Health Administration has advocated for a recommended minimum outpatient staffing level. The present study supports ongoing prioritization of mental health staffing to meet ongoing demand increases.

Keywords: Staffing model, staffing ratio, supply-and-demand

It is well-known that across the American health care system, there is an insufficient supply of mental health providers necessary to meet growing demand (Beck et al., 2018). In the last decade, demand for Veterans Health Administration (VHA) mental health (MH) services has grown significantly (e.g., the number of MH treatment visits increased from 10.5 to 21.3 million from fiscal years [FY] 2006–2018). In response to increasing demand for MH services, VHA increased MH staffing from 6,923 to 15,746 full-time equivalents (FTE) from 2006 to 2018. Despite the workforce expansion, a subset of local VHA healthcare facilities have been unable to keep pace with increasing demand, leading to ongoing challenges and concerns with access, quality, and satisfaction (Shulkin, 2016).

Currently, there is no single industry standard to determine optimal or even appropriate MH provider staffing levels in private or public integrated healthcare systems. To date, MH staffing models have focused on the simple availability of the psychiatry workforce, on caseload calculations, on known or theoretical workloads, on demand projections, and/or on mathematical needs-based calculations (Bhaskara, 1999; Burke et al., 2013; Morrison, 1998; Scheffler & Ivey, 1998). With no industry MH staffing standard, VHA developed a recommended minimum outpatient MH staffing ratio after a U.S. Department of Veterans Affairs, Office of Inspector General (2012) Office of the Inspector General report suggested that many VHA facilities did not have sufficient MH services to meet demand in a timely manner. In conjunction with a hiring initiative undertaken to bolster staffing at facilities with access concerns, the VHA Office of Mental Health Operations (OMHO; now Office of Mental Health and Suicide Prevention) developed an outpatient MH staffing model focusing on the FTE needed to treat a defined population. Prior to the initiative, the average MH staff FTE per 1,000 veterans treated in outpatient MH settings was 7.72, which was then set as the *minimum* recommended target value for all facilities. For program monitoring, OMHO established processes to (a) rigorously track overall staffing ratios across the enterprise and

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(b) through program oversight, formally demonstrated associations between outpatient MH staffing ratio and measures of access to, quality of, and satisfaction with MH care (Boden et al., 2019).

Suicide prevention is considered the top clinical priority for VHA (U. S. Department of Veterans Affairs, Veterans Health Administration, 2018), and while higher levels of MH staffing have been associated with decreased suicidal behavior (Atkinson et al., 2019, Katz et al., 2013), the available fiscal resources and provider supply are not limitless. Ongoing research evaluating which staffing models optimally meet patient demand given fiscal limitations remains critical. To date, while Boden et al. (2019) demonstrated an association between outpatient staffing ratios and performance on measures of quality, access, and satisfaction, the associations between optimal outpatient staffing ratio cutoffs that distinguish higher performing from lower performing VHA facilities have not been evaluated. To evaluate VHA staffing ratio recommendations, we conducted a series of exploratory analyses using longitudinal binary recursive modeling to determine the optimal ratio associated with overall quality, access, and satisfaction. In the first series of models, the overall outpatient staff-to-patient ratio (SPR) was entered as the variable of interest for performance on the VHA's core metrics assessing MH quality, access, and satisfaction. Optimal SPR cutoffs have not been systematically evaluated, and this analytic approach can tell us whether current VHA recommendations established in 2012 are in-line with statistically derived cutoffs for enhancing quality, access, and satisfaction.

Method

Data for the analyses reported in this paper below were obtained from each VA Medical Center ($n = 140$) for the 1st quarter (Q1) of fiscal year (FY) 2016 (beginning October, 2015) through the 4th quarter (Q4) of FY 2018 (ending September, 2018).

Measures

Staff-to-Patient Ratio

For each of the 12 quarters from FY2016 thru FY2018 outpatient, MH staffing ratios were calculated for total mental health staff using the standardized SPR calculation method detailed in Boden et al. (2019).

MH Strategic Analytics for Improvement and Learning Domain Score

The Mental Health Strategic Analytics for Improvement and Learning (MH SAIL) Domain score is a metacomposite of three mental health specific composite measures created by the VHA for internal quality evaluation, and described in detail by Lemke et al. (2017) and Schmidt et al. (2017). Briefly, the MH SAIL metric consists of a single overall metric (MH SAIL Domain), which is a composite of three summary metrics each consisting of multiple measures considered to assess (a) *Population Coverage* representing the proportion of veterans who receive MH services whose availability is required by the U. S. Department of Veterans Affairs, Veterans Health Administration (2008) Uniform Mental Health Service Handbook, (b) *Continuity of Care* representing the proportion of treated mental health patients who successfully engage in an evidence-based course of care, and (c) *Experience of Care* representing veteran and provider satisfaction with access, quality, and coordination of care. MH SAIL Domain and the three composite scores are restandardized ($M = 0$, standard deviation = 1) at the start of each performance year (Quarter 4) to allow for cross facility comparison and to assess individual facility change through the performance year. For this study, analyses focused on MH SAIL Domain and the three composite measures, Population Coverage, Continuity of Care, and Experience of Care.

Data Analysis

Binary recursive partitioning (BRP), also known as classification and regression trees (CART), are computationally intensive, nonparametric statistical methods that have been shown to be advantageous when relationships are not necessarily linear (Merkle & Shaffer, 2011). Often attributed to Breiman et al. (1984), the statistical methods have been extended to include mixed and random effects models associated with longitudinal data (Fu & Simonoff, 2015; Kundu & Harezlak, 2019; Sela & Simonoff, 2012).

To evaluate the longitudinal relationship between outpatient SPR and MH SAIL performance, we developed a series of BRP trees, which relies upon CART-type tree building algorithms (Breiman et al., 1984) and were extended to longitudinal data using random effect expectation maximization (REEM; Sela & Simonoff, 2012). While CART-based algorithms function by maximizing a statistical criterion over all possible predictors and split points simultaneously, the algorithms have been criticized for variable selection bias where the machine learning algorithm artificially prefers variables with certain characteristics (Strobl et al., 2009). To address variable selection bias within the automated algorithm, tree algorithm models developed by Hothorn et al. (2006) correct for splitting bias based upon a series of tests identifying statistically significant associations between responses and predictors using a conditional inference tree (cTree) framework. Fu and Simonoff (2015) later extended the work with conditional inference models by combining the REEM tree algorithm with the cTree (REEMcTree). The use of the automated BRP tree modeling analytic approach will tell us which SPR cutoffs are associated with statistically significant group differences in MH SAIL performance.

Analyses were completed in R 3.5.2 (R Core Team, 2019) using party (Hothorn et al., 2019), REEMtree (Sela & Simonoff, 2011), and ggplot2 (Wickham, 2016) packages. REEMctree coding by Fu and Simonoff (2015) is available at http://people.stern.nyu.edu/jsimonof/unbiasedREEM/.

Results

Overall Outpatient Staffing

Between FY16Q1 and FY18Q4, the total outpatient FTE increased from 11,454 to 11,857, while the number of veterans receiving services increased from 1.65 million to over 1.70 million. For each quarter (Table 1), outpatient MH SPRs varied widely across the VHA. In FY16 Q1, the average outpatient MH FTE per 1,000 patients was 7.41 (range = 3.96–17.44). In FY18Q4, the

Table 1
Descriptive Statistics by Quarter

Variable	Time	*M* (*SD*)	Min	Max	Median
SPR_all	FY16Q1	7.41 (1.72)	3.96	17.44	7.29
	FY16Q2	7.47 (1.64)	4.38	16.66	7.39
	FY16Q3	7.35 (1.62)	3.88	15.47	7.37
	FY16Q4	7.20 (1.56)	4.02	15.08	7.06
	FY17Q1	7.30 (1.55)	4.25	13.80	7.12
	FY17Q2	7.36 (1.52)	4.61	13.72	7.33
	FY17Q3	7.35 (1.49)	4.66	13.97	7.21
	FY17Q4	7.19 (1.46)	4.25	14.23	7.05
	FY18Q1	7.40 (1.52)	4.21	14.64	7.30
	FY18Q2	7.38 (1.47)	4.64	13.71	7.31
	FY18Q3	7.43 (1.50)	4.92	14.26	7.25
	FY18Q4	7.29 (1.44)	4.73	13.56	7.07
SAIL_MHDom	FY16Q1	0.17 (1.00)	−2.30	3.45	0.12
	FY16Q2	0.24 (0.98)	−2.47	3.15	0.23
	FY16Q3	0.34 (0.93)	−1.81	2.84	0.32
	FY16Q4	0.00 (1.00)	−2.34	3.03	−0.18
	FY17Q1	0.10 (0.99)	−2.39	3.17	0.01
	FY17Q2	0.12 (1.01)	−2.48	3.48	0.08
	FY17Q3	0.19 (0.98)	−2.31	3.32	0.17
	FY17Q4	0.00 (1.00)	−2.18	2.48	−0.09
	FY18Q1	0.16 (0.99)	−2.04	2.70	0.07
	FY18Q2	0.18 (0.98)	−2.18	2.46	0.01
	FY18Q3	0.40 (0.96)	−2.21	2.68	0.33
	FY18Q4	0.00 (1.00)	−2.15	2.37	−0.18
SAIL_PopCov	FY16Q1	0.17 (0.98)	−1.85	3.33	0.13
	FY16Q2	0.27 (0.97)	−1.68	3.31	0.23
	FY16Q3	0.35 (0.97)	−1.62	3.21	0.27
	FY16Q4	0.00 (1.00)	−2.09	2.69	−0.08
	FY17Q1	−0.01 (0.99)	−2.24	2.55	−0.11
	FY17Q2	−0.02 (0.98)	−2.30	2.50	−0.12
	FY17Q3	−0.04 (0.96)	−2.32	2.44	−0.17
	FY17Q4	0.00 (1.00)	−2.36	2.52	−0.12
	FY18Q1	−0.02 (1.00)	−2.35	2.69	−0.14
	FY18Q2	−0.05 (0.97)	−2.34	2.73	−0.19
	FY18Q3	−0.05 (0.97)	−2.65	2.83	−0.19
	FY18Q4	0.00 (1.00)	−2.43	2.58	−0.15
SAIL_ContCare	FY16Q1	0.04 (1.06)	−2.30	2.82	0.04
	FY16Q2	0.09 (1.06)	−2.52	2.69	0.21
	FY16Q3	0.13 (0.96)	−1.88	2.64	0.19
	FY16Q4	0.00 (1.00)	−2.38	2.70	−0.09
	FY17Q1	0.20 (1.01)	−2.16	2.84	0.17
	FY17Q2	0.27 (1.04)	−3.05	2.94	0.30
	FY17Q3	0.30 (1.06)	−4.31	2.92	0.42
	FY17Q4	0.00 (1.00)	−2.46	2.42	0.10
	FY18Q1	0.38 (0.98)	−1.88	2.84	0.40
	FY18Q2	0.47 (0.98)	−1.94	2.85	0.43
	FY18Q3	0.94 (0.99)	−2.09	3.34	0.92
	FY18Q4	0.00 (1.00)	−2.11	2.70	−0.06
SAIL_ExpCare	FY16Q1	0.15 (0.95)	−2.62	3.49	0.14
	FY16Q2	0.15 (0.95)	−2.62	3.49	0.14
	FY16Q3	0.25 (0.94)	−2.46	3.30	0.32
	FY16Q4	0.00 (1.00)	−2.90	3.27	0.06
	FY17Q1	0.02 (1.00)	−3.32	3.05	0.05
	FY17Q2	0.02 (1.00)	−3.32	3.05	0.05
	FY17Q3	0.14 (0.99)	−2.48	2.94	0.19
	FY17Q4	0.00 (1.00)	−2.67	2.82	0.03
	FY18Q1	−0.01 (0.96)	−2.30	3.04	−0.01
	FY18Q2	−0.01 (0.96)	−2.30	3.04	−0.01
	FY18Q3	−0.01 (0.95)	−2.70	3.02	−0.09
	FY18Q4	0.00 (1.00)	−2.70	3.02	−0.12

Note. FY = Fiscal year; Q = quarter; SPR_all = staff–patient ratio all outpatient providers; SAIL = strategic analytics for improvement and learning.

average outpatient MH SPR decreased to 7.29 with a range of 4.73–13.56. At the end of FY18Q4, 39.3% of VA Medical Centers were at or above the recommended minimum outpatient SPR of 7.72.

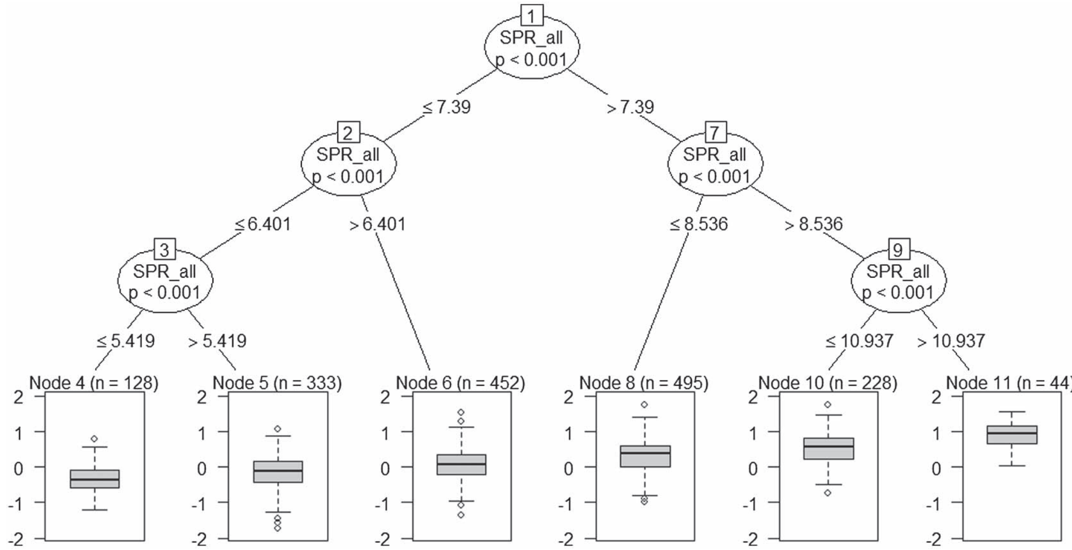
As obtained through longitudinal REEMcTree modeling, Figure 1 highlights the optimal outpatient staffing level for predicting MH SAIL Domain performance. The root node separates MH SAIL Domain performance associated with an outpatient MH total SPR of 7.39. Among those sites with a staffing ratio lower than 7.39, the final node is associated with an SPR of 5.42. The leaf nodes associated with these splits (Node 4 and Node 5) are associated with average MH SAIL Domain score of −0.32 and −0.14, respectively. For total staffing ratio greater than 7.39, the next significant split is associated with total staffing ratios below or above 8.54. The final split occurred at SPR of 10.94 with the mean MH SAIL Domain performance of 0.53 (Node 8) and 0.88 (Node 9), respectively. Compared to facilities averaging an SPR below 5.42, facilities with SPR over 10.94 averaged over one standard deviation higher performance on the MH SAIL Domain.

Among the three MH SAIL components, for Population Coverage, as shown in Figure 2, an SPR of 7.87 was associated with the initial REEMcTree root node. Higher staffing ratios were associated with overall increased performance. The highest performance was associated with a staffing ratio above 11.39 (Node 7: $M = 2$), while the lowest performance was associated with SPR below 6.97 (Node 3: $M = -0.32$). Optimal Continuity of Care domain was associated with an initial staffing ratio split of 6.81 (Figure 3). Optimal performance on Continuity of Care was noted with an SPR greater than 8.58 (Node 7: $M = 0.68$), with poorest performance associated with SPR below 5.42 (Node 3: $M = -0.32$). For performance on the Experience of Care domain (Figure 4), the initial split was associated with SPR of 7.42. Among facilities with lower staffing ratios, the additional split at SPR 6.02 was associated with mean Experience of Care performance −0.26 (SPR < 6.02) versus a mean of −0.03 for sites with SPR greater than 6.02.

Discussion

Recognizing the critical need for MH staff and the clear relationship between MH staffing supply and veteran demand, Congress in the Further Consolidated Appropriations Act, 2020, expressed ongoing interest in the VHA staffing model and the ratio of MH providers to veterans receiving care in the VHA. In the present study, we identified optimal outpatient MH staffing ratios associated with VHA-specific measures of MH quality, access, and satisfaction using binary recursive modeling. Overall, the present study found that higher outpatient MH SPRs are associated with increased MH SAIL performance. Specifically, for the overall MH SAIL Domain performance, the initial split (i.e., root node) identified an outpatient MH SPR of 7.39. Root nodes identifying the outpatient MH SPR associated with specific MH SAIL composite measures varied from 7.87 (Population Coverage), to 6.81 (Continuity of Care), to 7.4 (Experience of Care). The variability across the MH SAIL Domain composite measures for the overall SPR is not unexpected. As noted by Lemke et al. (2017) and Schmidt et al. (2017), Population Coverage is specifically designed to assess overall access to care using a population health approach (i.e., engagement of known population in care), whereas the Continuity of Care domain assesses

Figure 1
Optimal Staff-to-Patient Ratio for MH SAIL Domain Performance

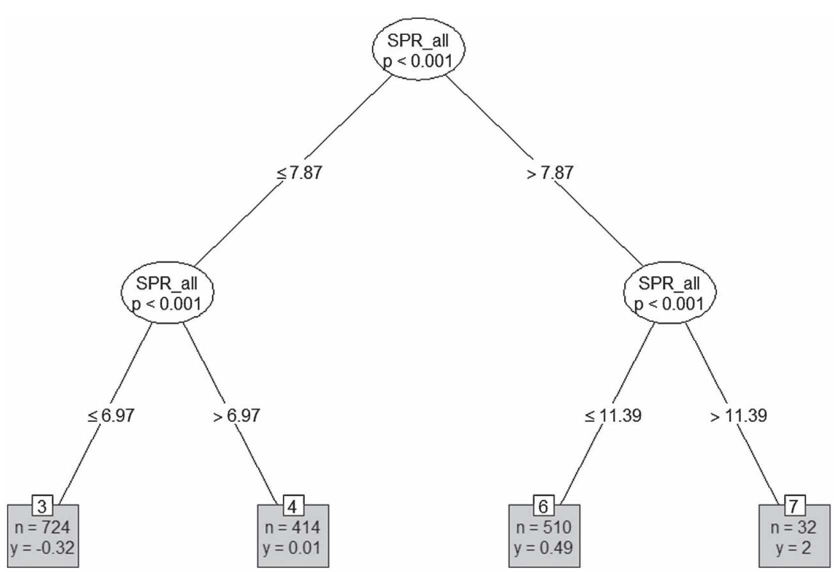


Note. Longitudinal REEM conditional inference tree for staff-to-patient ratio with MH Overall SAIL performance. For each inner node, the Bonferroni-adjusted *P* values are given, the average performance on MH SAIL Domain is displayed for each node. Each box in the terminal nodes shows the number of observations falling in the branch and boxplot of performance values.

the ongoing ability of those engaged in care to receive care. Given the complementary, but unique demands of care within each domain, the staffing levels needed to meet those demands are unique to each domain.

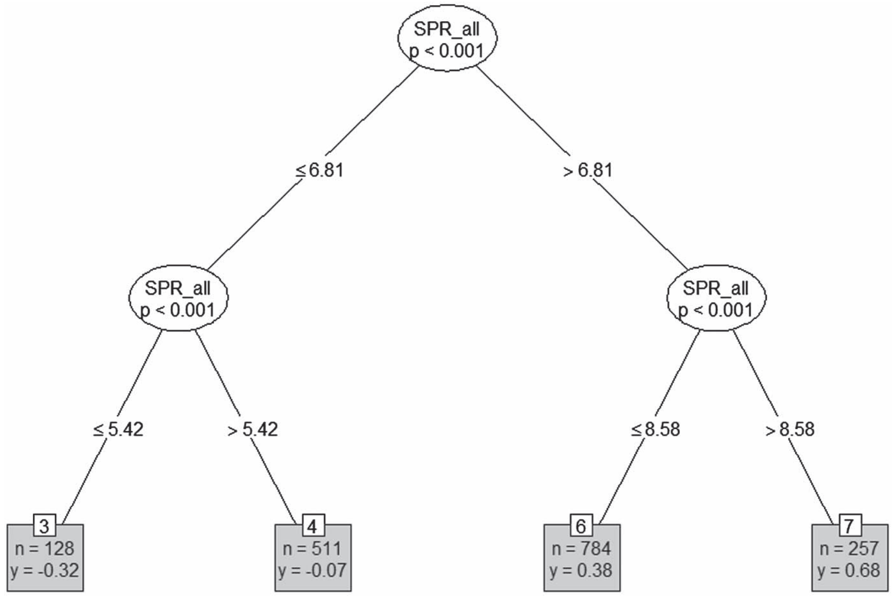
Historically, one approach to ensure access to health care has been to apply the economic principle of supply and demand. Simply stated, if one can define the demand of a service, such as patient requests for care, one can calculate the needed supply or number of

Figure 2
Optimal Staff-to-Patient Ratio for MH SAIL Population Coverage



Note. Longitudinal REEM conditional inference tree for staff-to-patient ratio associated with MH SAIL Population Coverage performance. For each inner node, the Bonferroni-adjusted *P* values are given, the average performance on MH SAIL Population Coverage is displayed for each leaf node. Each box in the terminal nodes shows two figures, the first (*n*) stating the number of observations falling in the branch and the second (*y*) giving the mean value of the observations in the branch.

Figure 3
Optimal Staff-to-Patient Ratio for MH SAIL Continuity of Care



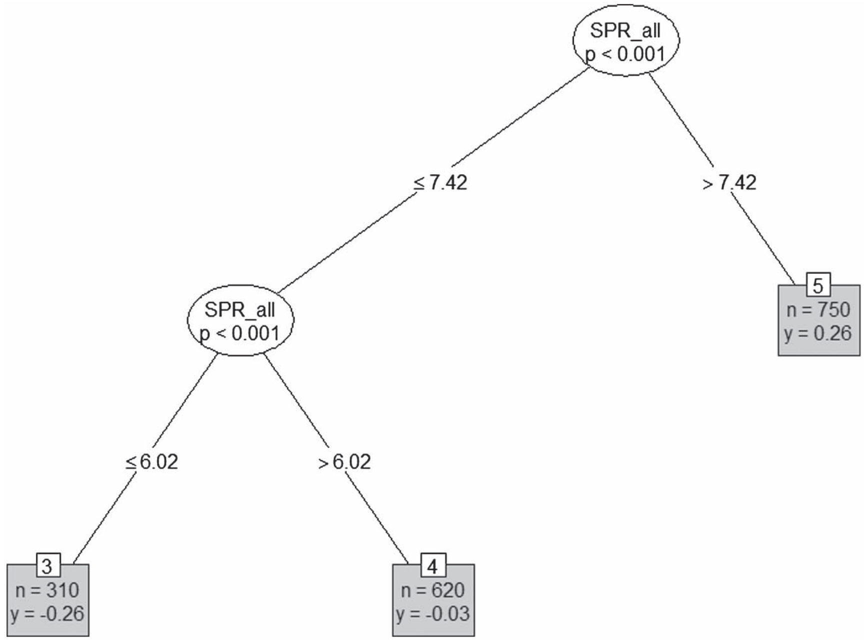
Note. Longitudinal REEM conditional inference tree for staff-to-patient ratio associated with MH SAIL Continuity of Care performance. For each inner node, the Bonferroni-adjusted *P* values are given, the average performance on MH SAIL Continuity of Care is displayed for each leaf node.

providers necessary to meet that demand. Pertaining to MH services specifically, this simple formulation is problematic. While one can calculate the number of providers necessary to meet a defined demand, fiscal resources and supply availability are not limitless. Additionally, in response to growing demand, VHA's efforts to increase supply (i.e., hiring additional providers, increasing daily productivity expectations, increasing scheduling utilization efficiency, etc.) has resulted, paradoxically, in further demand increases with more veterans requesting care. This paradox is not unexpected, as the paradoxical decrease in access despite increased VHA hiring and efficiency efforts is consistent with the MH service supply and demand dilemma outlined by Riessman (1970). In evaluating community MH services, Riessman noted the following three key propositions pertaining to the utilization of community MH services: (a) if the MH service is underutilized, there is either something wrong with the service or the way it is being offered; (b) if an MH service is overutilized, the program is successful; and (c) if the supply of an MH service is increased to meet the growing demand, this will in turn lead to even further increase in demand. Proposition 3 offered by Riessman is consistent with the recent experience of VHA where efforts to increase the supply of staffing and appointment availability have been associated with a corresponding increase in demand which has often outpaced the capacity of the increased supply of newly hired providers.

This exploratory analysis using binary recursive modeling is not without limitation. First, performance on MH SAIL metrics is variable across the SPR spectrum. There are low performing facilities with high SPR levels and high performing facilities with low SPR levels. Staff availability is important for treatment engagement, but not sufficient for success. Factors, such as administrative decisions, program alignment, team-based collaboration, provider burnout, among others, likely contribute to MH SAIL variety. Second, MH SAIL is specifically designed to be fluid in that new metrics are added and stable metrics are removed upon yearly review. Optimal SPR for any given year, therefore, may vary, as measures of quality, access, and satisfaction are added or removed. Finally, the current analyses did not evaluate staff-mix considerations to distinguish specialty contributions to overall performance. While Boden et al. (2019) noted that total staffing ratios predicted MH access and quality to a stronger degree than psychiatrist staffing ratios separately, the unique roles served by MH staff of various types (e.g., psychiatrist, psychologist, social worker, etc.) may be important to providing the diverse range of treatments needed to address the clinical needs of persons with MH conditions.

The outpatient SPR used in the VHA could certainly be applied to non-VHA settings. While the VHA healthcare system includes a broad array of integrated physical, social, and mental health resources not common to private healthcare systems, the core principle of calculating the necessary resources (supply) needed to meet a known clinical need (demand) is universal—the provision of MH care is dependent upon staff availability to meet the patient demand. The challenge, however, is true demand which may be unknown, as not all individuals who may need or benefit from mental health services seek out such care. VHA methodology integrates caseload calculations (Greenwood et al., 2000; King et al., 2004), needs-based calculations (Konrad et al., 2009), and ratio calculations (Scheffler & Ivey, 1998). In contrast to previous studies where ratios are reported as providers per 100,000 health organization members (Scheffler and Ivey) or per 100,000 population (Mulhausen & McGee, 1989), the VHA SPR currently reported focuses on providers needed to treated MH outpatients (per 1,000),

Figure 4
Optimal Staff-to-Patient Ratio for MH SAIL Experience of Care



Note. Longitudinal REEM conditional inference tree for staff-to-patient ratio associated with MH SAIL Experience of Care performance. For each inner node, the Bonferroni-adjusted *P* values are given; the average performance on MH SAIL Experience of Care is displayed for each leaf node.

which is more conducive to facility-level planning and supports efforts to ensure adequacy of mental health services for patients who engage services. Additional research is needed to evaluate demand models that incorporate population-based need considerations. While non-VHA systems may not have the volume, care complexity, or resources of the VHA, all systems must work to optimize supply limitations and demand expectations. Future research using non-VHA healthcare systems would need to confirm or refute this assertion.

Conclusion

Exploratory recursive modeling identified optimal outpatient SPRs associated with MH SAIL Domain, SAIL Population Coverage, SAIL Continuity of Care, and SAIL Experience of Care performance. SPRs identified by root and leaf nodes can serve as hiring targets for staffing decisions and understanding the influence of SPR on performance. One approach in determining an appropriate SPR target would be to consider the SPR associated with optimal leaf node for overall MH SAIL Domain success, as an outpatient SPR greater than 10.94 was associated with a one standard deviation increase in performance. However, to attain this SPR, approximately 6,000 additional providers such would be required. Such an increase in FTE would require a significant increase in VHA budget, as well as in the national supply of providers available for hiring. A second approach would be to consider the initial root node associated with optimal MH SAIL composite performance. The outpatient SPR identified by the root node for SAIL Population Coverage (7.87) would exceed the root notes for MH SAIL Domain, Continuity of Coverage, and Experience of care. A final more conservative approach would be to consider the root node for outpatient SPR (7.39) associated with overall MH SAIL Domain. Currently, the VHA recommendation of a minimum 7.72 outpatient SPR identifies an SPR target between these two conservative approaches. Until further research is completed identifying contributors to performance variability associated with SPR, the current VHA recommendations for the minimum appear to be an appropriate compromise between fiscal demands, supply resources, and the quality of MH services.

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