Measuring the Impact of Primary Care Team Composition on Patient Activation Utilizing Electronic Health Record Big Data Analytics

Kristen K. Will
Yue Liang
Chih-Lin Chi
Gerri Lamb
Michael Todd
Connie Delaney

Follow this and additional works at: https://aah.org/jpcrr

Part of the Health Information Technology Commons, Health Services Research Commons, Medical Education Commons, Nursing Commons, and the Primary Care Commons

Recommended Citation

Published quarterly by Midwest-based health system Advocate Aurora Health and indexed in PubMed Central, the Journal of Patient-Centered Research and Reviews (JPCRR) is an open access, peer-reviewed medical journal focused on disseminating scholarly works devoted to improving patient-centered care practices, health outcomes, and the patient experience.
Measuring the Impact of Primary Care Team Composition on Patient Activation Utilizing Electronic Health Record Big Data Analytics

Kristen K. Will, PhD, MHPE, PA-C,1 Yue Liang, MS,2 Chih-Lin Chi, PhD, MBA,2 Gerri Lamb, PhD, RN,1 Michael Todd, PhD,1 Connie Delaney, PhD, RN2

1Arizona State University, Phoenix, AZ; 2University of Minnesota, Minneapolis, MN

Purpose
Team-based care has been linked to key outcomes associated with the Quadruple Aim and a key driver of high-value patient-centered care. Use of the electronic health record (EHR) and machine learning have significant potential to overcome previous barriers to studying the impact of teams, including delays in accessing data to improve teamwork and optimize patient outcomes.

Methods
This study utilized a large EHR dataset (n=316,542) from an urban health system to explore the relationship between team composition and patient activation, a key driver of patient engagement. Teams were operationalized using consensus definitions of teamwork from the literature. Patient activation was measured using the Patient Activation Measure (PAM). Results from multilevel regression analyses were compared to machine learning analyses using multinomial logistic regression to calculate propensity scores for the effect of team composition on PAM scores. Under the machine learning approach, a causal inference model with generalized overlap weighting was used to calculate the average treatment effect of teamwork.

Results
Seventeen different team types were observed in the data from the analyzed sample (n=12,448). Team sizes ranged from 2 to 5 members. After controlling for confounding variables in both analyses, more diverse, multidisciplinary teams (team size of 4 or more) were observed to have improved patient activation scores.

Conclusions
This is the first study to explore the relationship between team composition and patient activation using the EHR and big data analytics. Implications for further research using EHR data and machine learning to study teams and other patient-centered care are promising and could be used to advance team science. (J Patient Cent Res Rev. 2024;11:18-28.)

Keywords
health care teams; patient engagement; big data; machine learning

Despite this demonstrated impact, health services researchers studying teams face substantial challenges in advancing team science and contributing evidence to improve team performance. The lack of consistent definitions and frameworks for teamwork and collaboration impedes knowledge development and application.1,8 Traditional qualitative and descriptive approaches to team research often are labor-intensive, time-consuming and expensive.9 The move to quasi-experimental and experimental study designs, while yielding promising results, is still associated with delays in translation into practice.1 This movement also has focused more on team processes than team composition, a missing component in team research. Studies that rely on the use of claims data and billable encounters with the potential to close the time gap in application are unable to capture all team members who contribute to outcomes.10 Collectively, these issues limit drawing conclusions about the impact of teams on outcomes and our ability to design and implement optimal team interventions.

The electronic health record (EHR) is an important source of comprehensive, real-time data to advance team science.
and discern effective team interventions. Exploring the use of the EHR to study teams is particularly opportune as the Centers for Medicare and Medicaid Services increases focus on digital measurement and patient reported outcomes for performance evaluation and payment incentives.11 The use of the EHR provides the potential for use of large data sets and new analytic techniques, including machine learning. Further, EHR data are an optimal environment to look at team structure and composition, a vital component less studied in the field of team science.11

Based upon this background, a cause-and-effect relationship between health care teams and patient outcomes is yet undefined, at least for patients with chronic diseases, such as type 2 diabetes. This study provides a systematic approach to research this issue. As a first step, we hypothesize that the size and composition of health care teams will be associated with patient activation measures, a critical component of patient engagement. We also hypothesize that analysis of EHR data will be an improved approach to investigate our hypothesis rather than traditional approaches (ie, claims data) given the volume and complexity of EHR data. Last, we propose that a big data/machine learning analysis of the data will be a reasonable approach to assist in the exploration of these associations.

Background

Team-based care has been shown to improve the quality of patient care, lower costs, and enhance both patient and provider experience. Improved quality outcomes include lowering readmission rates and visits to the emergency department with enhanced clinical outcomes, particularly for specific populations, such as patients with chronic, comorbid diseases.12-16 Improved metrics of quality outcomes have led to lower health care costs as a result of team-based care, particularly for patients with high-cost, high-need conditions.5,17,18 Promising data reveal that team-based care may improve the patient experience, as measured primarily by patient satisfaction.2,19 Teamwork also has been shown to improve the provider experience through reducing feelings of burnout. Early research suggests that teamwork may mitigate anxiety and depression during prolonged provider stress, as with COVID-19.20-22

Although there is a robust body of research linking teamwork and outcomes, key gaps in knowledge limit the current ability to match team characteristics to desired outcomes. As noted earlier, there has been little standardization of core team characteristics in operational definitions and measurement of teamwork. Further, although team composition has been identified by well known team theorists as contributors to team performance, little attention within team research has focused on team structures and their impact on patient outcomes.23-28

Along with team membership, team size may also play a role in team performance. Early research suggests that larger, multidisciplinary teams (team size of 3 or more) may have an increased impact on patient outcomes, which include quality measures and patient satisfaction.2,29,30 More research is needed to examine team membership and size to determine optimal team structures based on patient characteristics and desired outcomes.

Leveraging existing resources of data, such as the EHR, may provide improved ways to study and link team composition to team processes and outcomes. Work by Everett and colleagues demonstrates the utility of using the EHR to study teams, including team composition. Their work connects claims data with EHR data points to look at provider dyad teams, specifically physicians and physician assistants, and their impact on patients with diabetes mellitus.10,31 Despite being pivotal research, Everett et al were unable to include additional members of the team not captured in billable encounters and may have missed important team members. With a focus on team composition, this study strives to build upon the work of Everett and colleagues to assemble health care teams utilizing readily available EHR data.

Conceptual Framework

The conceptual framework guiding this research is adapted from SEIPS 2.0, an integration of human factors and systems theories grounded in Donabedian’s classic structure-process-outcome model.32,33 Core constructs from SEIPS 2.0 are used here to frame the relationship between team composition, the primary predictor variable, and patient activation, the primary outcomes variable, at the conceptual level (Figure 1). The moderating variable, the diagnosis of diabetes mellitus, is included, as it may impact the relationship between the team and the patient. Type 2 diabetes mellitus (DM2) was chosen as a potential moderator for teams, as a diagnosis of DM2 requires increased team-based care in patient-centered care and could change the team composition required. Last, confounding variables, such as age and gender, are included in the model, as they may impact patient activation levels.34

METHODS

Study Design

This study used retrospective, exploratory secondary data analyses drawing on EHR data stored within a data repository of a large urban health system comprising 8 hospital systems and over 41 ambulatory care clinics.
Most primary care clinics (Family Medicine and Internal Medicine) include both physician and advanced practice providers who work together to care for a panel of patients, a common care model. These de-identified data were housed within a health informatics exchange (HIE) data shelter. Institutional review board approval was obtained from the urban health system and partnering academic institution (Arizona State University, STUDY00000984).

**Sample Population**
From within the data repository, medical records were selected from the data repository if they met the following criteria: patient was 18 years of age and older at the time of the visit; visit was for ambulatory, primary care only; and the patient had at least 1 Patient Activation Measurement (PAM©) score available from at least 1 ambulatory care visit between the dates of July 1, 2016, to December 31, 2019, using the most recent PAM score for each patient.

**Measures**

**Outcome.** The primary outcome for this study is each patient’s raw score on the PAM, a widely validated 13-question survey (short version) used to assess the level of patient activation. PAM has been validated in numerous settings, particularly in primary care for adults. PAM scores can range from 0 to 100. Hibbard and colleagues categorize PAM scores by 4 levels with corresponding raw scores: Level 1, Disengaged and Overwhelmed (0–47.0); Level 2, Becoming Aware but Still Struggling (47.1–55.1); Level 3, Taking Action and Gaining Control (55.2–67.0); Level 4, Maintaining Behaviors and Pushing Further (67.1–100). Our data set housed PAM scores from 2011 to 2020, which were collected on all primary care patients in the health system by the primary care teams. Focal predictor. Team composition, the focal predictor variable, was created through a series of decision rules in the EHR driven by team definition and theory. A detailed description of the team variable creation is described in earlier work by Will and Lam. This work focused on utilizing a widely accepted definition for teamwork, Interprofessional Teamwork, dissecting the definition to identify operational constructs and using these constructs as decision points in the EHR data.

This process yielded a total of 17 team compositions, ranging in size from 2 team members to 5 team members (Table 1). Medical assistant (MA) and physician (Phy) were the most common disciplines found in the team matrices, included in all but 2 team composition variables. Advanced practice providers (nurse practitioner [NP] or physician assistant [PA]) were the next most common providers observed in the team matrices, occurring in all but 3 team composition variables.

**Covariates.** Correlates of patient activation identified in the literature, including age, gender, and race/ethnicity, were included as background covariates in all analyses. A diagnosis of DM2, examined as a potential moderator of the association between team composition and PAM scores in multilevel regression models (described below), was used as a background covariate in machine learning.
analyses, and International Classification of Diseases 9 and 10 (ICD-9 and ICD-10) codes (ICD-9: 250.1–250.9; ICD-10: E11.2–E11.9) were used in the EHR data to retrieve the correct diagnosis.

Cluster identifier. A “center” variable was defined for each participant using the unique center identification (ID) variable for the patient’s primary care location (family and internal medicine) within the EHR associated with PAM collection and patient encounter visits during the designated time period. Each center ID was then linked with individual patient IDs associated with the encounters at the corresponding center. If a patient ID was linked to more than 1 center ID, the most common (modal) center ID for that patient was selected as their medical home. Provider types associated with each encounter were also linked to the corresponding center ID. In total, 38 centers were identified in the data.

Data Analysis

Initial data preparation and cleaning were performed in Structured Queried Language (SQL), prior to transferring the data for analysis. Descriptive statistics were calculated to describe the study population including age, gender, race and ethnicity. Additional descriptive statistics were used to describe the team composition variables derived from the EHR. Associations between team composition and patient activation were first examined with multilevel regression models and then with machine learning with causal inference modeling.

Because the data analyzed have an inherently multilevel structure, with individual patient encounters nested within centers, multilevel linear regression models were used to examine the relationships between the team composition variables and PAM scores, as these models can account for nonindependence (or clustering) of observations within centers and adjust for background covariates. The multilevel models estimated here accounted for between-center variation in PAM scores via random (center-level) intercept components. Models were constructed in a hierarchical fashion, beginning with a random intercept-only (or unconditional random means) model (Step 1) to obtain unadjusted between- and within-center variance components for PAM scores, followed by a model with terms for the random intercept and for the fixed effects of background covariates (Step 2); then, fixed effect terms for dummy vectors coding for team composition were added (Step 3). Model parameters were estimated along with fit statistics and a likelihood ratio test, separately for each of 4 subsamples comprising records with teams of size 2, 3, 4, and 5. Finally, the interaction of a DM2 diagnosis and team composition was also examined within each team size subsample. Random effects of team composition were examined, but due to model non-convergence, these terms were not included in the final models. Multilevel regression models were estimated using the lme4 package in R version 4.0.2.

Machine learning analysis with causal inference modeling was utilized as a confirmatory and comparison modality to the multilevel model for the exploration of optimal team composition across all team sizes and compositions and the relationship to PAM. Mehta and colleagues support the use of machine learning analysis using big data and the EHR, finding that machine learning methods have the potential to replicate high-powered randomized controlled trials. Using a multinominal logistic regression in R (“nnet” package), propensity scores were calculated for all team compositions. Generalized overlap weighting method for multiple treatments was utilized to control for the confounding variables (age, gender, race/ethnicity and diagnosis of DM2). In this analysis, DM2 was utilized as a covariate after the findings of the initial analysis did not show statistically significant moderation of the relationship between team composition and PAM for all team sizes. Overlap weights were then utilized to calculate the average treatment effect (ATE) for each team composition in relationship to PAM. A pairwise comparison of the team composition ATE was performed.

### Table 1. Team Composition, Including Size and Frequency

<table>
<thead>
<tr>
<th>Team Size 2</th>
<th>Team Size 3</th>
<th>Team Size 4</th>
<th>Team Size 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA.PA (622)</td>
<td>MA.Phy.NP (1701)</td>
<td>MA.Phy.NRS.NP (290)</td>
<td>MA.Phy.PA.NP.Od (158)</td>
</tr>
<tr>
<td>Phy.NRS (439)</td>
<td>MA.Phy.NRS (325)</td>
<td>MA.Phy.PA.NRS (246)</td>
<td>MA.Phy.PA.NP.Clinic (69)</td>
</tr>
<tr>
<td>MA.NP (416)</td>
<td>Phy.PA.NP (279)</td>
<td>MA.Phy.PA.Od (135)</td>
<td>MA.Phy.NP.Od (120)</td>
</tr>
</tbody>
</table>

Clinic, front office (referrals); MA, medical assistant; NP, nurse practitioner; NRS, nurse (RN); OD, optometry; PA, physician assistant; Phy, physician; SW, social worker.
To find statistical significance for the ATE scores, the bootstrapping (x100) method was utilized to calculate confidence intervals (95%). Team compositions found to be statistically significant were systematically compared to one another, taking each team composition and placing it in the position of the team of interest vs. all other team compositions. If ATE was positive for team composition in the team 1 position, it was considered superior to the opposing team composition. Table 2 provides an example of this procedure. The teams were then ranked according to average ATE (if occurring more than once in the sample) and frequency of occurrence within the sample to determine optimal team compositions.

### Table 2. Example of Pairwise Comparison for Team Compositions

<table>
<thead>
<tr>
<th>TEAM 1</th>
<th>TEAM 2</th>
<th>ATE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phy,PA,NRS,NP</td>
<td>MA,Phy,NP,OD</td>
<td>6.56</td>
</tr>
<tr>
<td>Phy,PA,NRS,NP</td>
<td>MA,Phy,NP</td>
<td>8.12</td>
</tr>
<tr>
<td>Phy,PA,NRS,NP</td>
<td>MA,NP</td>
<td>7.17</td>
</tr>
<tr>
<td>Phy,PA,NRS,NP</td>
<td>Phy,NRS</td>
<td>10.04</td>
</tr>
<tr>
<td>Phy,PA,NRS,NP</td>
<td>MA,Phy,SW,NP</td>
<td>8.11</td>
</tr>
<tr>
<td>Phy,PA,NRS,NP</td>
<td>MA,Phy,NRS,NP</td>
<td>17.17</td>
</tr>
</tbody>
</table>

ATE, average treatment effect.

### RESULTS

A total of 12,448 patients with PAM scores recorded from July 1, 2016, to December 31, 2019, were included in the sample, with an overall mean PAM score of 74.2 (standard deviation: 18.41), in the low level 4 range. The majority of the sample (58%) was female. The racial and ethnic composition of the sample was consistent with regional demographics (Hispanic or Latino: 0.9%; Black or African American: 8.2%; Asian: 6.2%; Native American: 0.4%; non-Hispanic White: 84.6%; those of unknown race or multiple races comprised less than 0.6% of the sample). Mean patient age was 45.8 years (standard deviation: 17.3). Final team composition variables included 17 teams comprising team sizes ranging from 2 to 5 members. Team size 2 was the most common (n=5315; 42.7%), followed by team size 3 (n=4307; 34.6%), team size 4 (n=2373; 19.1%) and team size 5 (n=453; 3.6%) (Table 1). Approximately 729 patients in the sample population possessed a diabetes diagnosis (n=729; 5.9%).

### Multilevel Model Analysis

The results of the multilevel regression analyses are summarized in Table 3. The unconditional means model (Step 1) for each team size revealed that the between-center variance was overall less than the within-center variance. Substantial non-independence at the within-center level (interclass coefficient [ICC]: 0.13, team size 2; ICC: 0.13, team size 3; ICC: 0.15, team size 4; ICC: 0.25, team size 5) was also observed. This indicates that center (location) accounted for a nontrivial proportion of the variance in PAM scores, especially in the subsample with 5-member teams.

Associations between the covariates introduced into the models at Step 2 (age, gender and race/ethnicity) and PAM score were mixed across team size subsamples. Across all the team sizes, age was generally negatively related to PAM score, with relatively older patients having relatively lower PAM scores, although this association was not significant across all team sizes. On average, men had lower PAM scores than women, and this difference was significant for all team sizes. Race and ethnicity (non-Hispanic/Latino vs Hispanic/Latino) were generally not significantly related to PAM scores, except in team size 5, where White patients had significantly higher PAM scores than the reference category.

Introduction of the team composition variable for each team size model, step 3, demonstrated overall that team members most associated with a significantly positive relationship with PAM were MAs, physicians, PAs, and NPs. Teams including a social worker had a significantly negative relationship with PAM, which could be indicative of other patient factors not accounted for, such as negative social determinants of health. Likelihood ratio testing for the fixed effects of team composition demonstrated significant findings for team sizes 2-4, indicating that inclusion of team composition indicators improved model fit.

Model-estimated marginal means (EMMs) with 95% confidence intervals for PAM scores were calculated for all selected team compositions, adjusting for background covariates. EMMs for PAM scores ranged from 61.7 (for physician+PA+NP and MA+physician+NP teams) to 78.0 (for MA+physician+PA+nurse teams; see Figure 2).

Interactions of DM2 diagnosis with team composition variables (moderating effects) were added to each model (Step 5). Across almost all team composition size models, these effects were not significant. The only significant interaction to emerge was the DM2 x MA+physician+social worker+NP effect, with the difference between PAM scores in these teams and MA+physician+nurse+NP (the reference team composition) being, on average, 1.27 points higher among patients with DM2 diagnoses compared to those with no DM2 diagnosis. Likelihood ratio testing for the fixed effects of team composition x DM2 diagnosis
demonstrated non-significant findings for team sizes 2–5, indicating no improvements in the model fit for the integration of the interaction between team composition and DM2 diagnosis.

### Machine Learning Analysis

After calculating propensity scores for each team composition using multinominal logistic regression, the ATE was calculated for each team composition after applying overlap weights to the PAM scores for each team composition variable. After a pairwise comparison of all ATE values was performed, a total of 136 (“17 choose 2” = 136 pairs) team composition comparisons emerged. To analyze for statistical significance, bootstrapping analysis yielded a total of 37 statistically significant team compositions. After weighting was applied, the final ranking of the teams yielded eleven teams with averaged weighted ATE scores greater than

#### Table 3. Multilevel Model Results: Model-estimated Marginal Means (EMMs) for PAM Scores and Regression Coefficients (bs) for Team Composition (Step 3) and Team Composition x DM2 Diagnosis (Step 5) Model Terms by Team Size

<table>
<thead>
<tr>
<th>Team Composition</th>
<th>Step 3 EMM (SE)</th>
<th>Step 3 b (SE)</th>
<th>Step 5 b (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Team Size 2</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA+PA</td>
<td>69.9 (5.75)</td>
<td>5.03 (0.00)***</td>
<td>-1.70 (9.05)</td>
</tr>
<tr>
<td>MA+Phy</td>
<td>66.8 (5.71)</td>
<td>2.75 (0.01)</td>
<td>-6.98 (7.36)</td>
</tr>
<tr>
<td>Phy+NRS</td>
<td>66.2 (5.75)</td>
<td>1.40 (0.16)</td>
<td>-9.16 (7.79)</td>
</tr>
<tr>
<td>MA+NPa</td>
<td>64.6 (5.71)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>-2LL</strong></td>
<td></td>
<td>49347</td>
<td>49332</td>
</tr>
<tr>
<td><strong>∆ -2LL (df)</strong></td>
<td></td>
<td>25.94 (3)***</td>
<td>2.45 (3)</td>
</tr>
<tr>
<td><strong>Team Size 3</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA+Phy+NRS</td>
<td>62.2 (6.07)</td>
<td>0.53 (1.00)</td>
<td>-2.22 (3.34)</td>
</tr>
<tr>
<td>MA+Phy+PA</td>
<td>63.7 (6.05)</td>
<td>2.01 (0.62)**</td>
<td>-0.42 (2.13)</td>
</tr>
<tr>
<td>Phy+PA+NP</td>
<td>61.7 (6.05)</td>
<td>2.41 (1.1)*</td>
<td>-7.88 (4.81)</td>
</tr>
<tr>
<td>MA+Phy+NPa</td>
<td>61.7 (6.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>-2LL</strong></td>
<td></td>
<td>39656</td>
<td>39650</td>
</tr>
<tr>
<td><strong>∆ -2LL (df)</strong></td>
<td></td>
<td>12.65 (3)**</td>
<td>2.98 (3)</td>
</tr>
<tr>
<td><strong>Team Size 4</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA+Phy+PA+NP</td>
<td>76.1 (3.33)</td>
<td>5.13 (1.23)**</td>
<td>1.56 (3.52)</td>
</tr>
<tr>
<td>MA+Phy+PA+NRS</td>
<td>78.0 (3.43)</td>
<td>7.03 (1.58)**</td>
<td>3.12 (4.12)</td>
</tr>
<tr>
<td>MA+Phy+SW+NP</td>
<td>63.2 (3.58)</td>
<td>-7.74 (1.79)**</td>
<td>1.27 (5.1)*</td>
</tr>
<tr>
<td>MA+Phy+NP+OD</td>
<td>75.6 (3.6)</td>
<td>4.66 (1.81)**</td>
<td>8.46 (4.69)</td>
</tr>
<tr>
<td>MA+Phy+PA+OD</td>
<td>76.7 (3.57)</td>
<td>5.74 (1.82)**</td>
<td>2.38 (4.73)</td>
</tr>
<tr>
<td>MA+Phy+NRS+NPa</td>
<td>70.9 (3.46)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>-2LL</strong></td>
<td></td>
<td>21530</td>
<td>21517</td>
</tr>
<tr>
<td><strong>∆ -2LL (df)</strong></td>
<td></td>
<td>65.50 (6)**</td>
<td>10.50 (6)</td>
</tr>
<tr>
<td><strong>Team Size 5</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA+Phy+PA+NRS+NP</td>
<td>71.4 (5.22)</td>
<td>-0.46 (2.23)</td>
<td>5.11 (8.6)</td>
</tr>
<tr>
<td>MA+Phy+PA+NP+OD</td>
<td>74.5 (5.22)</td>
<td>2.64 (2.49)</td>
<td>-1.40 (8.83)</td>
</tr>
<tr>
<td>Clinic+MA+Phy+PA+NP</td>
<td>71.9 (5.45)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>-2LL</strong></td>
<td></td>
<td>3994</td>
<td>3990</td>
</tr>
<tr>
<td><strong>∆ -2LL (df)</strong></td>
<td></td>
<td>2.25 (2)</td>
<td>1.41 (2)</td>
</tr>
</tbody>
</table>

*Reference category.

*Model -2 log likelihood (deviance) value.

*Reduction in -2 log likelihood and degrees of freedom vs. preceding model step.

*P<0.05; **P<0.01; ***P<0.001.
Figure 3 shows the team rankings with applied 95% confidence intervals. Teams ranked lower with higher ATE were due to a lower frequency within the statistically significant team composition group. Team compositions of physician, PA, nurse and NP ranked the highest of the teams, with a weighted ATE of 0.77 and a mean ATE of 9.53 (Table 4). This indicates that, on average, this team composition was associated with 9.53 points higher PAM score than all other statistically significant team compositions after accounting for the confounding variables. Similar to the initial analysis, MA, physician, PA and NP provider types continued to remain in the top ranked team composition variables. However, in the machine learning with causal inference analysis, additional provider types were observed including nurse and optometrist (Table 4).

### DISCUSSION

This study examined the relationship between a key aspect of team-based care, team composition, and a central patient-centered outcome, patient activation. Additional aims included exploring the ability of utilizing EHR data to construct and analyze the team composition variable. Last, big data analytics and machine learning,

<table>
<thead>
<tr>
<th>Team composition variable</th>
<th>Average ATE</th>
<th>Weighted mean ATE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phy.PA.NRS.NP</td>
<td>9.53</td>
<td>0.77</td>
</tr>
<tr>
<td>OD.MA.Ph.PA</td>
<td>11.78</td>
<td>0.63</td>
</tr>
<tr>
<td>OD.MA.Ph.PA.NP</td>
<td>11.56</td>
<td>0.62</td>
</tr>
<tr>
<td>MA.PA</td>
<td>9.56</td>
<td>0.51</td>
</tr>
<tr>
<td>MA.Ph</td>
<td>7.85</td>
<td>0.41</td>
</tr>
<tr>
<td>MA.Ph.PA.NP</td>
<td>10.17</td>
<td>0.41</td>
</tr>
<tr>
<td>MA.Ph.PA</td>
<td>10.1</td>
<td>0.41</td>
</tr>
<tr>
<td>Phy.PA.NP</td>
<td>12.32</td>
<td>0.17</td>
</tr>
<tr>
<td>MA.Ph.NRS</td>
<td>12.3</td>
<td>0.17</td>
</tr>
<tr>
<td>MA.Ph.PA.NRS.NP</td>
<td>12.25</td>
<td>0.17</td>
</tr>
<tr>
<td>MA.Ph.PA.NRS.NP</td>
<td>12.1</td>
<td>0.16</td>
</tr>
</tbody>
</table>

**ATE, average treatment effect.**
in comparison with traditional statistical analysis, were utilized to further examine the relationship between team composition and patient activation.

The key findings of this study were significant associations between primary care team compositions and patient activation. Overall, larger, more diverse teams were associated with improved PAM scores. In this study, a team size of 4 or more was observed to have overall better PAM scores and ranked the highest in the machine learning analysis, over smaller teams. This finding contrasts with Bodenheimer et al’s results that found significant relationships with 2-member teams and patient activation and is more consistent with the results of a recently performed systematic review, which found that multidisciplinary teams (3 or more team members) were associated with improved patient satisfaction.2,47

Larger, more diverse teams may have a greater impact on activation for several reasons. Members of these teams may use different strategies for engaging patients with synergistic effects. Research on motivational interviewing, often performed by expanded members of the team, suggests improved patient outcomes in high-risk patient groups such as those with heart failure and uncontrolled diabetes.48 Larger teams may be necessary to design meaningful interventions to address social determinants of health and other aspects of patient needs central to activation. Care coordination, an essential function performed usually by registered nurses (RNs) and other providers, has been directly associated with decreased emergency department visits for patients who have uncontrolled DM2.49 Further examination of team size holds promise and warrants further research.

In addition to team size, the diversity of disciplines represented by team members also may play a role on the impact that team composition has on patient activation. In this study, more diverse teams were found to be associated with improved PAM scores. Specifically, other provider types not usually considered part of the primary care core team were found in some of the highest ranking teams, including both nursing (RN) and optometry (OD). There is a national push to integrate RNs back into primary care, performing care coordination for complex patient populations, with promising outcomes for high-risk patients.50 Integration of social work onto the primary care team may improve patient activation and patient clinical outcomes. In this study, social work was initially observed to decrease PAM scores, but when coupled with DM2 diagnosis as a moderator, improved PAM scores were observed. Similarly, integration of social work on the health care team in the machine learning analysis was observed with a higher performing team. Recent literature supports this study finding, indicating that incorporation of social work onto the primary care team improves self-efficacy, a closely linked attribute of patient activation.51 Overall, this study identified key trends in...
team composition, including team size and diversity, that could be studied further to assess optimal team structures for various patient outcomes.

This study demonstrated the ability of using EHR data vs. traditional methods for identifying additional members of the team who are usually hidden. Many other studies focus on claims data or billable encounters, which miss important members of the team and their contribution. Compared to previous work by Everett et al, who studied dyad physician-advanced practice provider teams using EHR data coupled with claims data, this study included all providers associated with the patient population. In particular, this study identified all provider types linked to each unique patient identification number and then grouped providers with their patient population based on the primary care location most associated with each patient. Using unique provider identification numbers as data points in the EHR, provider types for both billable and non-billable providers on the health care team were able to be identified. In the age of team member attribution and value-based payment discussions, being able to identify all members of the team will be important in examining incentive-based payment structures for team-based care.

Last, this study is one of the first to utilize EHR data and compare analyses between traditional hierarchal regression and machine learning. It demonstrates the vital need to couple clinician scientists with informaticists and big data scientists to fully leverage the use of EHR data. The collaboration between clinician, with knowledge of the clinical environment, and the informaticist, with knowledge of information technology, is a powerful partnership that can harness the full power of the EHR data source and beyond.

One major limitation of this study was the availability of team data in the EHR platform used for analysis. The dearth of descriptive data about teams limited the operationalization of the team variable to providers who had contact with the same patient, either on the same day or in a specified time range. Data were not available to capture other characteristics linked to team composition and performance such as known collective identity, communication patterns and shared mental models. In future studies, proxy variables to examine these variables need to be explored as EHR data evolve. Similarly, EHR data did not include confounding variables regarding the relationship between team composition and patient activation, specifically literacy. Therefore, this study does not offer a causal model. In a study by Nijman et al (2014), health care literacy and education level were shown to be significant antecedents to patient activation. In future studies, controlling for literacy level as a confounding variable would be important to include to examine causal relationships.

CONCLUSIONS
This study explored the relationship between primary care team composition and patient activation, an important component of patient engagement. Further, it demonstrated the ease of using EHR data to study this relationship, capturing the “hidden” members of the team often lost in traditional analytical approaches. The results have promising implications for optimizing team structures in the future. The use of machine learning to analyze teams and their impact on patient outcomes has extensive applicability and is a powerful tool to include in future analyses. Future implications for this work include measuring the attribution of team members that are often hidden using traditional methods, which could support reimbursement models for team-based care and help examine other critical measures of the Quadruple Aim impacted by health care teams.

© 2024 Advocate Aurora Research Institute