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Real-World Nonmedical Support Data and Medicare Advantage Star Ratings

A METHODOLOGICAL FRAMEWORK AND ILLUSTRATIVE DATASET

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The relationship between nonmedical support services and Medicare Advantage (MA) Star Ratings performance is well-supported by clinical and health services evidence. What remains under-explored is the methodological question:

What does a real-world, operational nonmedical support dataset look like, and how can it be used to demonstrate and track the connection between service delivery and Star measure performance?

This paper addresses that question directly.

Drawing on a 12-month administrative dataset of **3,332,918 nonmedical support task instances** delivered across geographically dispersed MA health plan partnerships — spanning large national plans, regional Blue Cross Blue Shield affiliates, and specialty care organizations — this paper presents a methodological framework for connecting nonmedical support delivery data to the eight 2026 MA Star measures most directly influenced by nonmedical interventions. The dataset described is not proprietary to any single service model; its structure, variables, and linkage methodology are generalizable to any nonmedical support provider operating at sufficient scale.

The analysis indicates that real-world operational data from nonmedical support providers represents an underutilized asset for MA plans seeking data-driven quality improvement strategies — and that the infrastructure to collect, aggregate, and apply this data already exists in the field.

Keywords: nonmedical support, Medicare Advantage, Star Ratings, real-world data, administrative data, care coordination, quality improvement, health equity, sociodemographic risk adjustment

INTRODUCTION

Medicare Advantage (MA) Star Ratings are determined by data. Claims data, pharmacy fill data, Consumer Assessment of Healthcare Providers and Systems (CAHPS) survey responses, and administrative records combine to produce the annual ratings that determine Quality Bonus Payment (QBP) eligibility for the **$12.7 billion federal quality incentive program**.[1] Plans that earn four or more stars receive a 5% QBP bonus — **approximately $600 per member per year** for a plan at an average benchmark rate.[2] The incentive to identify, measure, and improve the behavioral and environmental determinants of Star measure performance is substantial and growing.

The scale of supplemental benefit investment in MA has grown dramatically. In 2026, CMS is projected to pay MA plans an average of **$2,660 per enrollee in rebates** to provide supplemental benefits — roughly 15% of total Medicare payments to MA plans.[3] Plans project allocating approximately 38% of those rebate funds to non-Medicare services — supplemental benefits such as in-home personal care, nutrition support, transportation, and environmental modifications that address the social and functional needs traditional Medicare does not cover. Despite this scale, the MedPAC Commission has documented a fundamental lack of transparency about how often enrollees use these benefits and what outcomes they produce, concluding that encounter data for most supplemental benefits are insufficient for characterizing enrollees' use.[4] This data gap is precisely what the framework described in this paper addresses.

1 KFF, 2025
2 Healthscape Advisors, 2025
3 MedPAC, 2026
4 Ibid

Clinical and health services evidence supports the relationship between nonmedical support services — personal care, homemaking, nutrition support, transportation, medication reminders, companionship, and environmental modifications — and the clinical outcomes and member experience measures that Star Ratings capture (see companion paper: 'Nonmedical Support and Medicare Advantage Star Ratings'.)[5]

What that evidence base has not yet addressed is the operational question:

What does a real-world nonmedical support dataset look like, and how can it be structured and applied to demonstrate this connection in practice?

This paper takes a methodological approach to that question. It describes the structure of a real-world administrative dataset drawn from 12 months of nonmedical support delivery across a geographically dispersed set of MA health plan partnerships. It presents a framework for linking service delivery variables to the eight Star measures with the strongest evidence of nonmedical influence. And it argues that the infrastructure to collect and apply this data — which already exists in the field among established nonmedical support providers — **represents a significant and underutilized asset for MA quality improvement strategies.**

The dataset described in this paper is drawn from one provider's operational records and is used as an illustrative example of what this kind of data can look like at scale. The methodological framework, however, is generalizable. **Any nonmedical support provider with sufficient operational scale, geographic dispersion, and documentation infrastructure can apply this framework to their own data** — and any MA plan can request it from their nonmedical support partners as a quality management tool.

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5 Katabaro & Co, LLC, 2026

SECTION 1

The Case for Real-World Data in Nonmedical Support

Limitations of the Current Evidence Base

The existing evidence base for nonmedical support and MA Star Ratings is largely derived from randomized controlled trials, prospective cohort studies, and secondary analyses of administrative claims data (see companion literature review). While this evidence is methodologically rigorous, it has three limitations that constrain its practical application to MA quality strategy.

First, most studies examine a single service type — homemaking, or transportation, or meal delivery — rather than an integrated ecosystem of nonmedical support delivered across multiple bundle types simultaneously. **The real-world experience** of a member receiving personal care, food as medicine support, and technology assistance in the same week **is not captured by studies that examine each service in isolation.**

Second, most studies are conducted in controlled or quasi-experimental settings with defined populations, fixed intervention protocols, and prospective data collection. Operational nonmedical support delivery — which is adaptive, member-directed, and embedded in real health plan relationships — differs substantially from these research conditions.

Third, few studies connect nonmedical support delivery data directly to the specific Star measure variables that CMS uses for rating calculations. Demonstrating that home-based care reduces 30-day readmissions is not the same as demonstrating that a specific pattern of nonmedical support delivery is associated with movement in the Plan All-Cause Readmissions Star measure for a specific health plan.

Real-world operational data from nonmedical support providers addresses each of these limitations. It captures multi-bundle, integrated service delivery across diverse member populations. It reflects actual operational conditions rather than controlled research settings. And it can be linked — through claims data matching, Proportion of Days Covered (PDC) calculation, and member-level longitudinal tracking — to the specific Star measure variables that matter to MA plans.

The Value of Administrative Dataset Analysis

Administrative datasets derived from operational nonmedical support delivery have several characteristics that make them particularly valuable for MA quality improvement purposes. First, they are large: A provider operating at meaningful scale generates hundreds of thousands to millions of service task records per year, providing the statistical power to detect associations between service patterns and quality outcomes that smaller studies cannot. The dataset described in this paper contains **3,332,918 task instances across 394,260 member visits** — a sample size that substantially exceeds most published studies in this area.

Second, they are geographically dispersed: Operational datasets that span multiple health plan partnerships across multiple states capture the demographic, clinical, and social diversity of the MA population in ways that single-market studies cannot. Geographic dispersion is particularly important for sociodemographic risk adjustment analysis, as the Sociodemographic Status (SDS) adjustment methodology introduced in the 2026 CMS Final Rule **requires understanding of how member characteristics vary across market contexts**.[6]

Third, they are longitudinal: Administrative records of recurring service delivery capture the frequency, intensity, and continuity of nonmedical support over time — the variables that are most likely to be associated with sustained improvement in chronic disease measures like Controlling Blood Pressure and Diabetes Care – HbA1c Control, which require sustained behavioral and environmental change rather than episodic intervention.

Fourth, they are linkable: With appropriate data sharing agreements and member consent frameworks, nonmedical support administrative data can be linked to plan-level claims data, pharmacy fill records, and CMS Star measure performance data **to enable direct analysis of the relationship between service delivery patterns and measure outcomes.**

6 AdhereHealth, 2025

SECTION 2

Dataset Description and Methodological Validity

Dataset Overview

The illustrative dataset described in this paper is drawn from 12 months of operational service delivery records — April 2025 through March 2026 — from a single nonmedical support provider operating across multiple MA health plan partnerships. The dataset comprises:

3,332,918
total service task instances across 24+ task types

1,582,775
activities of daily living (ADL) task instances across six core task categories

394,260
unique member visits with documented service delivery

1,725,143
instrumental activities of daily living (IADL) task instances across 24+ task categories

1,755,346
total home care hours

170,574
health plan touchpoints (132,720 inbound, 37,854 outbound) across MA health plan partners

The dataset spans partnerships with large national MA plans, regional Blue Cross Blue Shield affiliates, specialty care organizations, and Dual-Eligible Special Needs Plans (D-SNPs) — reflecting the demographic and clinical heterogeneity of the broader MA population.

Data Structure and Variables

Each service delivery record in the dataset contains the following primary variables: member identifier (de-identified), service date, service category (ADL or IADL), specific task type, task duration, caregiver identifier (de-identified), health plan partner identifier, and geographic market code. Secondary variables captured through the care coordination infrastructure include visit completion status, caregiver observation flags, appointment management outcomes, and medication management interaction type.

This variable structure enables several categories of analysis relevant to Star measure performance. Task type and frequency variables can be mapped to the specific Star measure domains they address — for example, medication management task instances map to medication adherence PDC calculations, while transportation task instances map to Transitions of Care follow-up appointment compliance. Task duration and continuity variables enable analysis of intensity-response relationships — the question of whether more frequent or longer-duration service delivery is associated with greater Star measure impact. Caregiver observation flags enable identification of early deterioration signals that predict readmission risk.

Geographic Dispersion and Representativeness

A key methodological strength of operational administrative datasets from established nonmedical support providers is their geographic dispersion. The dataset described in this paper spans health plan partnerships across multiple states and market types — urban, suburban, and rural — reflecting the geographic diversity of the MA population. This dispersion is methodologically important for two reasons.

First, it reduces the risk of market-specific confounding that affects single-market studies. The association between nonmedical support delivery and Star measure performance observed across geographically diverse markets is more likely to reflect a generalizable relationship than one observed in a single market with specific demographic or clinical characteristics.

Second, it enables analysis of geographic variation in service delivery patterns and outcomes — a dimension that has gained regulatory significance with the introduction of SDS risk adjustment in the 2026 Star Ratings. Understanding how the relationship between nonmedical support and Star measures varies across markets with different sociodemographic profiles is **essential for designing equity-responsive quality improvement strategies**.[7]

7 Yang et al., 2024

Health Plan Partnership Diversity

The dataset spans partnerships with MA health plan partners of varying organizational types, sizes, and member population characteristics. This diversity is methodologically valuable because it enables analysis of whether the observed associations between nonmedical support delivery and Star measure performance are consistent across plan types — an important validity check for any claim of generalizability.

The partnership structure also reflects a real-world care coordination model in which nonmedical support delivery is embedded in ongoing health plan relationships rather than delivered as a standalone intervention. The 170,574 health plan touchpoints documented in the dataset — inbound and outbound calls facilitating appointment scheduling, post-discharge coordination, medication management support, and care manager communication — represent the connective tissue through which nonmedical support data is integrated into health plan quality management workflows.

Data Validity and Reliability

Administrative data from operational nonmedical support delivery has known validity strengths and limitations. On the strength side, task-level records are generated at the point of service through electronic documentation systems, reducing the retrospective recall bias that affects survey-based data. Visit completion records are auditable against payroll and billing records, providing a cross-validation mechanism for service delivery data. Caregiver observation flags are entered contemporaneously with service delivery, reducing the temporal gap between observation and documentation.

On the limitation side, administrative data captures what was delivered and documented — not necessarily what was needed or what the member experienced.

Member-reported outcomes, functional status assessments, and quality-of-life measures are not routinely captured in operational administrative records and require supplementary data collection to enable comprehensive outcome analysis. Additionally, the linkage of administrative service delivery data to Star measure performance data requires data sharing agreements and member-level matching methodologies that are not universally available across health plan partnerships.

These limitations are addressable through data infrastructure investment that is increasingly feasible as nonmedical support providers develop more sophisticated care coordination platforms. The methodological framework described in this paper assumes a baseline of operational administrative data and identifies the supplementary data elements and linkage methodologies needed to enable direct Star measure analysis.

SECTION 3

Linking Nonmedical Support Data to Star Measure Performance

Conceptual Framework

The conceptual framework for linking nonmedical support data to Star measure performance rests on three propositions grounded in clinical and health services evidence (see companion paper: 'Nonmedical Support and Medicare Advantage Star Ratings').[8] First, specific categories of nonmedical support delivery address specific behavioral, social, and environmental determinants of Star measure performance. Second, the frequency and intensity of nonmedical support delivery are associated with the magnitude of Star measure impact — more sustained delivery produces more sustained improvement. Third, the data generated by nonmedical support delivery can be structured to enable direct linkage to the Star measure variables that CMS uses for rating calculations.

The framework organizes this linkage across the eight Star measures with the strongest evidence of nonmedical influence, grouping them by the primary nonmedical support mechanism through which they are affected.

8 Katabaro & Co, LLC

Medication Adherence Measures

The three medication adherence measures — for diabetes, hypertension (RAS Antagonists), and statins — are calculated by CMS using the Proportion of Days Covered (PDC) methodology. PDC is derived from pharmacy fill records and measures the proportion of days in the measurement period during which a member has prescription coverage for the relevant drug class, with 80% coverage defining the adherence threshold and **92-93% coverage required for five-star performance**.[9]

Nonmedical support data relevant to adherence analysis includes: medication management task instance frequency and dates (mapping to the specific days on which medication reminders were provided), errand and transportation task instances associated with pharmacy visits (mapping to prescription fill dates), and technology support task instances associated with pharmacy platform navigation (mapping to mail-order fill patterns). A nonmedical support provider with sufficient data infrastructure can generate a medication management interaction record for each member that can be compared against pharmacy fill dates to analyze the association between reminder frequency and PDC scores.

The illustrative dataset described in this paper contains **27,541 medication management task instances and 29,812 transportation task instances** — the two service categories most directly linked to PDC performance. Analysis of the temporal relationship between these task instances and pharmacy fill dates represents a tractable methodological approach to quantifying the adherence impact of nonmedical support delivery.

Chronic Disease Outcome Measures

Controlling Blood Pressure and Diabetes Care – HbA1c Control are intermediate clinical outcome measures that reflect the cumulative effect of sustained medication adherence, dietary management, physical activity, and social connection. Nonmedical support data relevant to these measures includes meal preparation task instances (mapping to dietary quality and therapeutic diet adherence), mobility and walking assistance task instances (mapping to physical activity), companionship task instances (mapping to social connection and depression mitigation), and errands and shopping task instances (mapping to food access and therapeutic diet support).

The methodological challenge for these measures is that the data linkage requires clinical outcome data — blood pressure readings and HbA1c laboratory values — that are not routinely available in nonmedical support administrative records. Enabling this linkage requires data sharing arrangements with health plan partners that include access to clinical claims data. However, the frequency and category distributions of nonmedical support task types can be analyzed as predictors of clinical outcome measure performance using regression-based methods that have been applied in comparable administrative data studies.[10]

9 AnewHealth, 2025
10 Kumar, 2024; Shearer et al., 2023

Plan All-Cause Readmissions

Plan All-Cause Readmissions is a **3x-weighted outcome measure** calculated from inpatient claims data. Nonmedical support data relevant to readmissions analysis includes: visit frequency and continuity in the 30-day post-discharge window (mapping to the transitional care support that reduces readmission risk), ADL task completion rates during post-discharge periods (mapping to functional stability and fall prevention), medication management task instances in the post-discharge window (mapping to medication reconciliation and adherence), and caregiver observation flags indicating early deterioration signals (mapping to proactive intervention that prevents readmission).

The illustrative dataset contains **59,152 safety and supervision task instances** — a category with particular relevance to fall prevention and post-discharge monitoring. Analysis of the association between safety and supervision task frequency in the post-discharge window and 30-day readmission rates represents a methodologically tractable approach that has analogues in the home health literature.[11]

Transitions of Care and Care Coordination

The Transitions of Care measure assesses post-discharge follow-up visit compliance. Nonmedical support data relevant to this measure includes transportation task instances associated with follow-up appointments and outbound call records documenting appointment scheduling support. The care coordination call volume data in the illustrative dataset — **37,854 outbound calls across health plan partners** — represents a documented record of post-discharge coordination activity that can be analyzed in relation to follow-up visit compliance rates.

The Care Coordination CAHPS composite is derived from member survey responses and is therefore not directly linkable to nonmedical support administrative data without supplementary survey collection. However, the frequency and continuity of nonmedical support delivery — particularly companionship and care coordination touchpoints — can be analyzed as predictors of CAHPS response patterns using plan-level aggregate data.

11 Siclovan et al., 2021

Data Integration Requirements

Realizing the full analytical potential of nonmedical support administrative data for Star measure analysis requires integration with three external data sources. First, **pharmacy fill data** — available through plan pharmacy benefit manager (PBM) partners — enables PDC calculation and the direct linkage of medication management task instances to adherence outcomes. Second, **inpatient claims data** — available through plan administrative data sharing agreements — enables readmissions analysis and the identification of post-discharge windows for transitional care analysis. Third, **CMS Star measure performance data** — available through plan quality reporting systems — enables the direct correlation of service delivery patterns with measure-level ratings.

The infrastructure for this integration exists in increasingly sophisticated care coordination platforms operated by established nonmedical support providers.

The data sharing agreements, member consent frameworks, and technical integration standards required to enable it are areas of active development in the MA supplemental benefits market — accelerated by CMS's increasing emphasis on data-driven quality improvement and the introduction of SDS risk adjustment methodology that requires member-level data linkage.[12]

12 CMS Final Rule, 2026

SECTION 4

Implications for Nonmedical Support Providers and MA Plans

For Nonmedical Support Providers

The methodological framework described in this paper has direct implications for nonmedical support providers seeking to demonstrate their value to MA health plan partners.

Providers that invest in the data infrastructure required to generate, structure, and link their operational administrative data to Star measure performance variables will be able to offer a qualitatively different value proposition than providers that can only offer service delivery records without outcome linkage.

The minimum data infrastructure requirements for this capability include: electronic point-of-service documentation systems that capture task-level records with the variable structure described in Section 2; care coordination platforms that log health plan touchpoints with dates, call types, and outcomes; member-level identifiers that enable longitudinal tracking and external data linkage; and data sharing agreement templates that establish the legal and technical framework for plan-level data integration.

Providers that have already invested in this infrastructure — and that operate at the geographic scale and health plan partnership diversity needed to generate statistically meaningful datasets — **are positioned to lead the development** of the evidence base described in this paper. The dataset characteristics described here — scale, geographic dispersion, health plan diversity, task-level granularity — represent the methodological standards against which nonmedical support data will increasingly be evaluated by MA plan quality and analytics teams.

For Medicare Advantage Health Plans

For MA health plans, the implication of this framework is equally direct: Nonmedical support partners who generate and share operational administrative data are qualitatively more valuable than those who do not. A nonmedical support partner whose data can be integrated into a plan's quality analytics infrastructure — enabling analysis of the association between service delivery patterns and Star measure performance — is a quality improvement partner in a meaningful sense that extends beyond service delivery volume.

Research on MA plan decision-making found that evidence and return on investment were the primary factors limiting social determinants of health (SDOH) supplemental benefit implementation — making the data infrastructure described in this paper not merely a quality management tool but the answer to the question plans have been asking.[13] Plans seeking to maximize the Star Ratings value of their nonmedical support supplemental benefits should require, as a condition of partnership, the data infrastructure described in this paper. The data sharing agreements, technical integration standards, and reporting formats that enable this integration should be specified in partner contracts — **not treated as aspirational.**

The 2026 CMS Star Ratings environment, in which clinical outcome measures carry proportionally greater weight following the removal of 11 administrative process measures under the 2027 Final Rule, makes the evidence-based management of nonmedical support partnerships a strategic priority rather than an operational nicety.

13 Thomas et al., 2019

The Equity Dimension

The SDS risk adjustment methodology introduced in the 2026 Star Ratings for the three medication adherence measures acknowledges what the nonmedical support literature has long established: **that sociodemographic factors create differential barriers to medication adherence that are not addressable through clinical interventions alone**.[14] Nonmedical support administrative data has a particular contribution to make in this context.

Because nonmedical support is delivered disproportionately to dual-eligible, low-income, and disabled members — the populations subject to SDS adjustment — the administrative data generated by nonmedical support delivery is inherently rich in sociodemographic signals. Research documenting the differential whole health and social needs across MA subpopulations establishes the depth and specificity of these barriers — and why standard clinical interventions are insufficient to address them.[15] Analysis of how service delivery patterns and outcomes vary across SDS-adjusted populations can inform equity-responsive quality improvement strategies that are directly aligned with CMS's stated regulatory priorities. This analysis requires the member-level sociodemographic data that is available through plan eligibility files, making it another dimension of the data integration framework described in Section 3.

14 AdhereHealth
15 McNamara & Rudy, 2023

DISCUSSION

This paper has made the case that real-world operational data from nonmedical support providers represents a methodologically valid and practically valuable resource for MA quality improvement — one that is underutilized relative to its potential. The case rests on three arguments: that the dataset characteristics available from established nonmedical support providers (scale, dispersion, longitudinality, linkability) address the key limitations of the existing experimental evidence base, that a generalizable framework exists for linking specific nonmedical support data variables to specific Star measure performance outcomes, and that the data infrastructure required to enable this linkage is increasingly available in the field.

The regulatory context for this work is significant. In June 2025, the Medicare Payment Advisory Commission documented **a fundamental lack of transparency in how MA supplemental benefits are used and administered,** concluding that encounter data for most supplemental benefits other than vision and hearing are insufficient for characterizing enrollees use, and that plans frequently administer nonmedical supplemental benefits through third-party vendors with limited data reporting.[16] The framework described in this paper is a direct response to this documented gap. As plans expand their supplemental benefit portfolios and as **policymakers scrutinize the ROI of the billions in annual rebates Medicare pays to fund those benefits**, the challenge of demonstrating value from nonmedical support investments will only become more pronounced. A platform-based approach to benefit administration, with the data infrastructure described here, is the mechanism through which that demonstration becomes possible.

Several important limitations of this framework merit acknowledgment. First, the dataset described in this paper is from a single provider operating in a specific set of market contexts.

16 MedPAC, 2025

While its characteristics are used as an illustration of what generalizable dataset standards look like, the specific findings from this dataset should not be treated as externally valid without replication across other providers and market contexts.

Second, the linkage methodology described requires data sharing arrangements that are not universally available and that raise legitimate privacy and data governance considerations that must be addressed in implementation. Third, the causal interpretation of associations observed in administrative data is inherently limited — the framework described enables correlation analysis, not causal inference, and the experimental evidence base in the companion literature review remains the appropriate foundation for causal claims about nonmedical support impact.

Despite these limitations, the framework described here represents a meaningful advance over the current state of evidence for nonmedical support and Star Ratings.

The development of shared data standards, linkage methodologies, and reporting frameworks for nonmedical support administrative data — analogous to the HEDIS measurement standards that have enabled systematic quality improvement in clinical care — is an important direction for the field.

CONCLUSION

The connection between nonmedical support services and MA Star Ratings performance is established in the peer-reviewed literature. The methodological infrastructure to demonstrate and track this connection in real-world operational data is increasingly available. What remains is the deliberate development of data standards, sharing agreements, and analytical frameworks that enable nonmedical support providers and MA health plans to realize the quality improvement value of the data that operational service delivery already generates. The MedPAC Commission finding that encounter data for most supplemental benefits are insufficient for characterizing enrollees' use (MedPAC, 2025) makes this development a regulatory imperative — the data infrastructure described in this paper is what responsible stewardship of the billions in annual MA supplemental benefit rebates requires.

The dataset and framework described in this paper are offered as a contribution to that development — not as a definitive answer, but as a demonstration that the data exists, that it is methodologically tractable, and that the field is ready for a more systematic approach to evidence generation from real-world nonmedical support delivery.

Any nonmedical support provider operating at scale, across diverse health plan partnerships, with the data infrastructure described here, can apply this framework to their own data.

And any MA health plan can ask their nonmedical support partners whether they can.

The companion paper to this document — 'Nonmedical Support and Medicare Advantage Star Ratings: An Evidence-Based Policy Analysis' (2026) — provides the full clinical and health services evidence base for the service-to-measure relationships described here. This paper provides the methodological framework for operationalizing that evidence in real-world data. Together, they constitute a research agenda as much as a set of conclusions — an invitation to the field to develop the data infrastructure that will enable the next generation of evidence on nonmedical support and MA quality.

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