

MDGuidelines' Medical Cost and Treatment Utilization Tool

Introduction

Health care costs and treatment utilization have high variability, including significant waste or ineffective treatments that do not produce better health outcomes, which threatens the solvency of private and public insurers.¹⁻³ Without the ability to measure spending and treatment utilization, there is limited ability to improve savings and related patient outcomes. To address this dynamic, MDGuidelines offers the Medical Cost and Treatment Utilization Tool, which provides users with the following capabilities:

- Predict medical costs for a case
- Compare medical costs to national benchmarks
- Review treatment and diagnosis statistics
- Estimate service-specific cost

This tool aims to inform Actuaries, Utilization Review Nurses, and Nurse Case Managers; the treatment utilization estimates aim to inform Physicians, Utilization Review Nurses, and Nurse Case Managers.

Methods

Conditions Covered

Using millions of disability claims and billions of medical transactions, MDGuidelines' provides medical cost and treatment utilization statistics for 15,900 unique medical diagnoses (ICD-10-CMs) for 380 medical topics.

Tool Inputs

The model uses the following inputs to produce the statistics generated in the Medical Cost and Treatment Utilization Tool:

- Reason for Disability. MDGuidelines' topics were used for the reason for disability. These topics have diagnostic and procedure medical codes attached to them.
- Principal Procedure. The user may select the most significant procedure in the patient's claim (see definition below).
- Age. The patient's age at the date of injury or illness.
- Inpatient Stay. This determines whether the patient had an inpatient stay as part of their treatment, as defined by being admitted to an inpatient unit of a hospital.
- Inpatient/Outpatient. Claims may be identified as being for inpatient or outpatient treatment.
- Reason for Inpatient Stay. If an inpatient stay occurred, the user can select the reason for inpatient stay.
- Zip Code. The postal code of where the majority of treatment is performed.
- Program Type. The claim may be for an occupational injury covered by Workers' Compensation or for a non-occupational injury covered by a Short-Term Disability program.

- Comorbidities. Up to five comorbidities may be entered using Quan et. al's comorbidity mappings.⁴

Geographic Cost Estimates

The geographic variation in medical costs and treatment utilization is well documented, but the underlying reasons for these differences remain unsolved.⁵ Therefore, this tool accounts for, but cannot statistically control, variables within the dataset including age and industry. The effect of geographic variability in medical costs is addressed by using Medicare's Geographic Practice Cost Index (GPCI), which is mapped to zip code by the Department of Labor.⁶ The GPCI provides payment indices for work performed, practice expense, and malpractice by geographic location. While the GPCI is typically multiplied to the corresponding relative value units (RVUs) of a procedure, a weighted average of the GPCI per zip code was used and multiplied so that the medical cost was associated with the disability claim. The weighted average used the distribution of work (52.5%), practice expense (43.7%), and malpractice (3.9%) percentages reported by the Government Accountability Office.⁷

Non-Occupational Claims

Non-occupational cost and treatment statistics were estimated using two of IBM Watson's MarketScan databases: Commercial Claims and Encounters (CCAЕ), and Health and Productivity Management (HPM). Short-term disability claims from the past 10 years with medical insurance eligibility during, and at least 180 days after the return to work (RTW) date, were included in this analysis. The HPM databases' primary diagnosis was used for the claim's reason for disability. All procedures, prescriptions, and diagnoses noted between 7 days prior to disability and 180 days after the disability end date were collected from the CCAЕ database. In the CCAЕ database, procedures have an associated diagnosis, and therefore only procedures related to the reason for disability were included. The single-level category from Healthcare Cost and Utilization Project's multi-level Clinical Classification Software (CCS) was used to link procedures to the reason for disability.⁸ In the CCAЕ database, prescriptions are not linked to a diagnosis and therefore were linked to new prescriptions dated within 2 days of the date of diagnosis in outpatient and inpatient claims. All prescriptions up to 180 days after disability in the therapeutic class of the prescriptions were matched to the date of diagnosis.

Workers' Compensation Claims

Workers' Compensation (WC) cost and treatment statistics were estimated using state-specific WC cost combined with claim level WC data from California's Workers Compensation Information System (WCIS). California's WC data includes records in the past 10 years from medium to large employers required to report to the Department of Industrial Relations. The primary reason for disability was determined by matching the nature of injury (e.g., "strain or sprain") and body part injured (e.g., "low back") fields provided by WCIS with the medical codes in the medical claim data. An algorithm was used to match the medical code description to the information noted in the first report of injury by WCIS and weight the frequency in which the medical code appeared in the claim. In addition to collecting medical costs at the billing level, the models include lump sum medical payments in the total outpatient and prescription costs according to the empirical distribution.

To make state-specific estimates of medical costs, a literature search was conducted for information on cost differences across states. The main references included: 1) Workers Compensation Research Institute's (WCRI) 19th Edition of the CompScope™ Benchmark Reports;⁹ 2) Oregon's Department of Consumer and Business Services (ODCBS) Worker's Compensation Premium Rate Ranking for Calendar Year 2016;¹⁰ 3) WC average costs calculated using the IBM Watson HPM database by state; and 4) the National Academy of Social Insurance (NASI)'s 2016 report on *Workers' Compensation: Benefits, Costs, and Coverage*.¹¹ The WCRI CompScope™ Benchmark Reports present the average medical costs on all paid claims at 36 months' average maturity for 18 states. The ODCBS rate is reported as a state's cost of workers compensation claims per \$100 of payroll in all 50 states. NASI's report provided the total benefits paid per \$100 of covered payroll by state and percent of benefits attributed to medical payments by state. We combined NASI's benefits paid with the percent attributed to medical to make a state specific medical benefits paid per \$100 of covered payroll.

When comparing WCRI's average costs per claim to the premium rate of ODCBS, it was found to have a moderate correlation (Spearman's rho = 0.47, p-value = 0.05). Higher correlation was observed between IBM's average WC costs and WCRI's average medical costs (Spearman's rho = 0.65, p-value = 0.004), whereas lower correlation was observed between IBM's average WC costs and ODCBS rates (Spearman's rho = 0.35, p-value = 0.02). NASI's medical benefits per \$100 of covered payroll had a high correlation with WCRI's average medical costs (Spearman's rho = 0.62, p-value = 0.007).

Given that WCRI's estimates are widely used in the Workers' Compensation field, and NASI's rates were correlated with WCRI estimates and available for all 50 states, we used NASI's rates to estimate medical costs by state.¹² These estimates were combined with zip code specific Geographic Practice Cost Indices to account for the variation in medical costs by geographic location within a state.

Procedure and Prescription Groupings

For both non-occupational and occupational claims, procedures were coded using Current Procedural Terminology (CPT®) and/or Healthcare Common Procedure Coding System (HCPCS). Prescriptions were coded using the National Drug Code (NDC). CPT codes were grouped using SNOMED CT groupings derived from Observational Health Data Science and Informatics' ATHENA standardized vocabularies.¹³ SNOMED CT is one of a suite of designated standards for use in U.S. Federal Government systems for the electronic exchange of clinical health information, and is also a required standard in interoperability specifications of the U.S. Healthcare Information Technology Standards Panel. NDCs were grouped using the drug classes in MDGuidelines' Formulary or the therapeutic class defined by IBM Micromedex Red Book.

After combining all costs from the treatment group within a disability episode together, the principal procedure were identified by finding the most expensive procedure within a disability episode, and where that treatment was the most expensive procedure in at least 5% of the cases for that diagnosis group. Anesthesia procedures were not considered principal treatments, as they are typically part of a surgical procedure.

Inpatient Costs and Length of Stay

The 2016 National Inpatient Sample (NIS) database developed by the Healthcare Cost and Utilization Project (HCUP) was used to estimate inpatient cost and length of stay. The 2016 NIS provides all-payer

data (including persons covered by Medicare, Medicaid, private insurance, and the uninsured) on approximately 7 million inpatient stays from nearly 4,500 hospitals; approximating a 20% stratified sample of discharges from U.S. community hospitals.

Hospitalization statistics are presented by Diagnosis Related Groups (DRGs). DRGs were established by the Centers for Medicare and Medicaid Services as a patient classification scheme to account for the severity of illness, prognosis, treatment difficulty, need for intervention, and resource intensity. Since NIS data captures only charge data, we used their charge-to-cost ratio to produce cost estimates per DRG. To produce national estimates, the weighted cost and length of stay (LOS) predictive models used the *survey* package in R.¹⁴ Only DRGs present in 5% of the cases in the diagnosis group are included in the tool.

Comorbidities

Comorbid diagnoses noted in the STD/WC claim were grouped using the Comorbidity Grouper developed by Quan et al.¹⁵ In addition, nicotine dependence medical codes were grouped to indicate smoking as a comorbidity. For each diagnosis, the top five most frequent comorbidities were identified and used as inputs in the medical cost and treatment models.

Outpatient and Prescription Treatment Statistics

Outpatient statistics include frequency of the outpatient service, time to outpatient service, and a distribution of the number of times an individual received the outpatient service. Prescription statistics include frequency of filling the prescription class, time to filling the prescription class, and the total number of days' supply for that prescription class. Given the low number of claims with reported days' supply in our WC data set, these values are only derived using the non-occupational injury dataset. Outpatient and prescription treatment statistics do not utilize geographic location.

Predicting Costs and Treatment Variability Metrics

Outpatient costs, prescription costs, and treatment statistics were predicted using generalized linear models with explanatory variables selected using the Least Absolute Shrinkage and Selection (lasso) algorithm¹⁶ implemented using the *glmnet* function in R.¹⁷ Five-fold cross validation was used to protect against overfitting each model. Medical costs, treatment counts, and duration were log transformed to fit with a linear regression kernel within lasso, whereas frequency was predicted using a logistic regression kernel.

Cumulative Medical Costs versus Disability Duration Figure

The Medical Cost and Treatment Utilization tool presents the cumulative medical costs by disability duration. "Disability duration" represents calendar days from the start of disability to returning at full duty. The cumulative medical costs are modeled using disability duration and useful for benchmarking claim medical costs when the disability duration is known. It should be noted that total medical costs includes costs related to the disability for up to 180 days after the claimant returns to work to account for individuals who continue to receive treatment for their injury after they return to work.

Variability around Predicted Values

The variability of cost and treatment statistics was assessed using the standard deviation of the residuals (σ), which is the difference between the predicted (Y) and observed values.

Outcomes	Lower estimate equation	Predicted estimate equation	Upper estimate equation
Binomial (Frequency)	$100 * \exp(Y - \sigma) / (1 + \exp(Y - \sigma))$	$100 * \exp(Y) / (1 + \exp(Y))$	$100 * \exp(Y + \sigma) / (1 + \exp(Y + \sigma))$
Log normal	$\exp(Y - \sigma)$	$\exp(Y)$	$\exp(Y + \sigma)$

Cost Profile Builder

The Cost Profile Builder allows the user to create a unique cost profile by entering specific procedures, drugs, and inpatient stays related to a patient claim. The Cost Profile Builder does not depend on the inputs used to generate claim costs or treatment statistics. Instead, it is a summary of the 25th percentile, 50th percentile (median), and 75th percentile of costs associated with a treatment. The procedure, durable medical equipment, and drug summary statistics are calculated using distinct CPT, HCPCS, and NDC codes using the CCAE database. For the DRG codes, the NIS database was used to calculate nationwide estimates using the supplied survey weights.

Accuracy

In-Sample Accuracy

When specifying a principal procedure/treatment, the total cost models captured approximately 25% of the variability, as measured by the R^2 between the predicted and observed costs. The average mean squared error was 1.6. The maximum amount of variability captured was 63%. The reasons for variability in models include the variability in the care costs, the limited number of variables provided for the models, and limiting the models to either logistic or log-linear models.

Out-of-Sample Accuracy

Predicted costs were compared to IBM Watson's Workers' Compensation medical costs. Although the total amount of medical expenses for WC claims are available in IBM's HPM database, we do not have access to information at the medical billing level that corresponds to the type of procedures or prescriptions. Because we did not use this data in building our models, this is a true validation dataset to compare our predicted costs to an external data source. IBM's WC data includes diagnosis, age, and geographic location, but no other variables present in our predictive models, requiring this analysis to assume that IBM's WC population had similar characteristics as our population including the types of procedures performed for the specific diagnosis. For our population, we predicted the medical costs for WC claims by diagnosis not specifying a specific principal treatment, but averaging the costs across all principal treatments performed by condition with at least 100 records. For IBM, we took the median medical costs per diagnosis for those conditions with at least 100 records. Our WC claim predictions tended to be slightly lower than IBM's WC costs, especially in the higher range of estimates (Figure 1).

Nonetheless, the correlation is moderately strong (Spearman's rho = 0.71) and provides confidence in the accuracy of the model results.

Next, we compared state estimates to those reported by WCRI in their Benchmark Scope Reports.⁹ WCRI reports the 2015/2018 average medical payment per claim for all paid claims at 36 months' average maturity by state. Therefore, to compare, we calculated the average predicted medical costs across all diagnoses (not knowing the exact case mix in WCRI's reports) and applied our state medical price index factor to the estimate. In the 18 states WCRI provides estimates for, our estimates correlation was good (Spearman's rho = 0.64); however, our predictions are systematically lower due to WCRI reporting an average cost, whereas our predictions are the geometric mean.



Figure 1. Comparison of MDGuidelines predicted medical costs to IBM Watson's Medical Costs grouped by diagnosis (left plot) and WCRI's 2015/2018 Average medical payment per claim for all paid claims at 36 months average maturity grouped by state (right plot). The green line is the linear fit from a robust linear regression and the black line is the identity.

Finally, we compared our results to estimates found in the literature. When looking at "all diagnoses," our results are generally in line with external estimates (Table 1). For example, our estimates are within \$1,000 when comparing to estimates compiled by WCRI, WCIRB, IBI, and Pumkam et al. (2013). When we compared our estimates using specific chronic diagnoses like low back pain, our results fall within the large range reported (Table 2). For example, Shraim et al. (2015) reported a median medical cost for low back pain of \$3,786,¹⁸ which is approximately \$400 higher than our estimate. However, Owens et al. (2019) and Webster et al. (2007) reported low back pain cost estimates at \$770 (median) and \$12,188 (mean), respectively, which are outside our predictions. Our estimates for disabilities with surgeries are in general alignment with previous research (Table 3), likely due to our models being able to use the principal procedure variable to get a more accurate estimate.

Table 1. Comparison of MDGuidelines' predicted medical cost for "all diagnoses" to external estimates

Medical episode/procedure	MDGuidelines' Estimate	External Estimate	Reference to External Estimate
All diagnoses	\$2,889 (WC median) \$4,868 (WC mean)	\$4,631	WCRI's 18-state median of average medical costs. 2014/2017 all paid claims at 36 months average maturity. U.S.
All diagnoses	\$2,889 (WC median) \$4,868 (WC mean)	\$3,201 (18 months maturity) \$5,101 (30 months maturity)	WCIRB's average medical costs from 2009 to 2017 in California, U.S. ¹⁹
All diagnoses	\$2,889 (WC median) \$4,868 (WC mean)	\$10,896	WC estimates from White et al. (2012). Michigan, U.S. 2006 to 2011. Average costs. ²⁰
All diagnoses	\$2,889 (WC median) \$4,868 (WC mean)	\$3,841	Average costs for 418 claims reported at The Erickson Living Experience. Results presented by Shiner and Thorne at AOHC 2019. ²¹ U.S.
All diagnoses	\$2,889 (WC median) \$4,868 (WC mean)	\$2,718 (workers with persistent disabilities) \$1,797 (workers without persistent disabilities)	Expenditure per occupational injury. U.S. national estimate from Medical Expenditure Panel Survey data. 2004 – 2011. Shi et al. (2015) ²²
All diagnoses	\$2,889 (WC median) \$4,868 (WC mean)	\$5,566 (mean)	WorkSafeBC average medical expenditure for 2017. British Columbia, Canada. ²³ Converted from Canadian dollars using 1 CAD = 0.76 USD.
All diagnoses	\$2,889 (WC median) \$4,868 (WC mean)	\$3,498 (mean)	Average compensated WC claims in 2012/2013. Australia. ²⁴ Converted from Australian dollars using 1 AUD = 0.70 USD.
All Diagnoses	\$2,889 (WC median) \$4,868 (WC mean)	\$1,935 (median) \$3,696 (mean)	Integrated Benefits Institute's WC average medical paid costs. Weighted average across years 2014 to 2016. Claims closed within 36 months. ²⁵

Medical episode/procedure	MDGuidelines' Estimate	External Estimate	Reference to External Estimate
All diagnoses	\$2,195 (STD median) \$3,698 (STD mean)	With persistent disabilities: \$4,234 With temporary disabilities: \$1,612 No disabilities: \$748	Data from Medical Expenditure Panel Survey panel 12 (2007 to 2008). U.S. Pumkam et al. (2013). Median annual expenditures, self-reported. ²⁶

Table 2. Comparison of MDGuidelines' predicted medical cost to external estimates. Chronic conditions. MDGuidelines estimates are a weighted average of all STD or WC claims with and without inpatient stays.

Medical episode/procedure	MDGuidelines' Estimate	External Estimate	Reference to External Estimate
Low back pain	\$2,819 (WC median) \$3,429(WC mean)	\$3,786 (median) \$8,296 (mean)	Low back pain WC claims from 49 U.S. states, Shraim et al. (2015). ¹⁸
Low back pain	\$2,819 (WC median) \$3,429(WC mean)	\$770 (median)	Low back pain WC claims from Utah. U.S. Owens et al. (2019). ²⁷
Low back pain	\$2,819 (WC median) \$3,429(WC mean)	\$12,188 (mean)	Low back WC claims from Webster et al. (2007). 2002 to 2003, U.S. nationwide sample. ²⁸
Low back pain	\$1,093 (STD median) \$1,936 (STD mean)	\$655 (6-month mean cost) \$769 (12-month mean cost)	Kim et al. (2019) expenditures for low back pain. U.S. general population between 2008 to 2015. ²⁹
Major depressive disorder	\$1,172 (STD median) \$1,691 (STD mean)	\$1,730 (mean)	Gauthier et al. (2017) reported per-patient-per-year mean medical costs associated with MDD-related pharmacy costs and mental health related mental costs following first-line antidepressant treatment for patients with major depressive disorder. U.S. general population from 2003 to 2014. ³⁰
Major depressive disorder	\$1,172 (STD median) \$1,691 (STD mean)	\$487 (adjusted mean)	Mental health and addiction costs per person per year. Nationally weighted and covariate adjusted. Chiu et al. (2017). Canadian, general population in 2002. ³¹

Table 3. Comparison of MDGuidelines' *predicted* medical cost to external estimates. Surgeries. MDGuideline estimates use age = 45, no inpatient stay, and zip code = 80033.

Medical episode/procedure	MDGuidelines' Estimate	External Estimate	Reference to External Estimate
Cataract surgery	\$4,429 (STD no comorbidities) \$4,608 (STD with hypertension)	\$3,783 to \$6,898	https://www.allaboutvision.com/conditions/cataract-surgery-cost.htm . Accessed 10/12/2020.
Cataract surgery	\$4,429 (STD no comorbidities) \$4,608 (STD with hypertension)	\$5,351	Fair Health Consumer Episode of Care. Using zip code of 80033, in-network costs for primary procedure and related costs. Accessed 10/12/2020.
Total knee replacement	\$11,211 (STD no comorbidities) \$13,349 (STD with hypertension)	\$13,831	Fair Health Consumer Episode of Care. Using zip code of 80033, in-network costs for primary procedure and related costs. Accessed 10/12/2020. Assumes procedure was in outpatient setting.
Achilles tendon rupture – surgical repair	\$4,662 (STD no comorbidities) \$5,698 (STD with hypertension)	Surgical: €5007 or \$5,911	Direct costs of surgical vs. non-surgical treatment of Achilles rupture by Westin et al. (2018). ³² Sweden. Euro conversion made 10/12/2020.
Achilles tendon rupture – surgical repair	\$4,662 (STD no comorbidities) \$5,698 (STD with hypertension)	\$3,145	Initial surgical cost of surgical repair from a Markov cost-utility analysis. ³³
Carpal tunnel release	\$4,100 (STD no comorbidities) \$4,467 (STD with hypertension)	\$5,438	Fair Health Consumer Episode of Care. Using zip code of 80033, in-network costs for primary procedure and related costs. Accessed 10/12/2020.
Open treatment of fractured ankle	\$6,349 (STD no comorbidities) \$8,553 (STD with hypertension)	\$8,396	Fair Health Consumer Episode of Care. Using zip code of 80033, in-network costs for primary procedure and related costs. Accessed 10/12/2020.
Repair of umbilical hernia	\$5,389 (STD no comorbidities) \$5,892 (STD with hypertension)	\$5,257	Fair Health Consumer Episode of Care. Using zip code of 80033, in-network costs for primary procedure and related costs. Accessed 10/12/2020.
Nasal Septoplasty	\$8,244 (STD no comorbidities) \$9,090 (STD with hypertension)	\$7,521	Fair Health Consumer Episode of Care. Using zip code of 80033, in-network costs for primary procedure and related costs. Accessed 10/12/2020.
Fingertip amputation	\$8,404 (WC no comorbidities)	\$4,049	Ontario's WSIB claims from 2009 to 2018. Average healthcare costs for claims with 12-months maturity. N = 1,753.

	\$10,851 (WC with hypertension)		
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