Voice of the Publisher, 2023, 9, 354-364
https://www.scirp.org/journal/vp
ISSN Online: 2380-7598
ISSN Print: 2380-7571

Medicare Risk Adjustment Coding in U.S. Health Insurance

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How to cite this paper: Lekkala, L. R. (2023). Medicare Risk Adjustment Coding in U.S. Health Insurance. *Voice of the Publisher, 9,* 354-364.
https://doi.org/10.4236/vp.2023.94028

Received: October 23, 2023
Accepted: December 24, 2023
Published: December 27, 2023

Abstract

The Medicare Risk Adjustment system is an important feature of the U.S. public health arena that affects medical results, quality care, and medical bills. This study delves into complex issues associated with Medicare risk adjustment coding by applying sophisticated statistical techniques in an effort to understand relevant healthcare data science matters. **Background:** Healthcare relies on accurate risk assessment for patients, and the Medicare risk adjustment model plays an essential role. The program has ensured that insurers providing care for differing, disease-specific patient' demographics are properly remunerated. Nevertheless, accurate risk adjustment poses a serious challenge considering the numerous determinants that encompass diagnosis, treatment, and demographic elements. **Methods:** This paper explores the principles behind Medicare risk adjustment coding, focusing on risk scores, hierarchical condition categories, and historical data. To measure their effectiveness and accuracy, we use artificial intelligence, data analysis, as well as statistical methods. The paper also suggests new measures to enhance the risk adjustment process for the purposes of ensuring reliability as well as fairness. **Results:** The results demonstrate the strengths and weaknesses of modern Medicare risk adjustment coding methods. This involves finding areas in which more improvement should be added so as to make sure that the system is fair and responsive to the changing world of health. **Conclusions**: This study shows that in order for healthcare risk adjustment to be improved, data science and statistical methods must be employed. With the healthcare industry progressing, there is great importance in making sure that risk adjustment coding will be precise, credible, and just. This is where our work adds to these efforts and lends critical information to policymakers, healthcare providers, and machine learning professionals looking to enhance the Medicare risk adjustment system.

Keywords

Medicare, Medicaid, Coding, AI, Artificial Intelligence, Healthcare, Insurance, Health Cover, USA, U.S. Health Insurance, Policies, Policy Insurance

1. Introduction

Healthcare is one of the most significant sectors in any country. One would have to mention the United States healthcare system, which is probably the most complicated and innovative and caters to a range of people with different healthcare requirements. The Medicaid program constitutes a vital pillar of this model and comprises millions of Americans above 65, as well as some disabled citizens (Geruso & Layton, 2020). Medicare's success depends largely on whether its risk adjustment coding system is valid and reliable. The risk adjustment process ensures fair payments for the care provided by healthcare workers as it forms part of the health insurance management system. The approach understands that patients do not present equal risks and, hence, should not be reimbursed similarly. The attempt to account for these differences is made by employing a risk adjustment system that involves an assessment of the respective beneficiaries' health status and medical needs. The risk adjustment process plays an important role in controlling costs and preserving quality in a Medicare setting Markovitz, Hollingsworth, Ayanian, Norton, Moloci, Yan, & Ryan (2019). This creates monetary incentives for plans to recruit and appropriately take care of sicker people by providing a channel for Medicare on the transfer of funds among different programs based on the health status of beneficiaries. Nonetheless, risk adjustment within Medicare is not a simple procedure. This consists of complex components such as diagnostic coding, patient statistics, and healthcare resource usage statistics Dinh, Liao, & Navathe (2019). The financial viability of health plans depends on accurate risk adjustment. It should also be noted that individuals suffering from chronic and acute illnesses require proper care. The focus of this research is on Medicare risk adjustments through coding. This paper will look at the processes, problems, and possible outcomes associated with the process in trying to explore a better comprehension of its place in the wider U.S. healthcare setting.

2. Literature Review

Data science and machine learning in healthcare, in particular, in relation to recommender algorithms and disease prognostication software, has experienced rapid growth and is expected to have major ramifications on patient health outcomes as well as cost-effectiveness strategies in healthcare organizations. A number of researches examine whether using more sophisticated algorithm could improve performance of disease appraisal and prediction. Research undertaken by Dinh, Liao, & Navathe (2019) and Geruso & Layton (2020) aimed at developing an ML-based algorithm can forecast CVDs. Therefore, this work demonstrates how older historical health data can be utilized in training models that deliver improved risk predictions, consistent with the aim of this paper. Likewise, a study by Kocher (2021) discusses the role of recommendation systems in health care, highlighting the need to adopt customized procedures that will help deliver appropriate feedback for patients. The works of Irvin et al. (2020) and Jacobs & Kronick (2021) offer an intensive review of ML applications in diabetic diagnosis. This tool also considers historical data and sophisticated algorithms which help better understand factors contributing to diabetes among different populations per this article. Therefore, Krumholz et al. (2019) work offers a solution for adding support and appropriate literature on developmental science. Optimization of illness assessment by integrating data science techniques underscoring the continued development of health care methodology (Markovitz, Hollingsworth, Ayanian, Norton, Moloci, Yan, & Ryan, 2019; McGuire, Schillo, & Van Kleef, 2020). Such is consistent with the descriptive developmental characterization of this study, where refinement of algorithms leading more precise sickness ratings is an iterative procedure. The work of Li et al., 2019, on predictive modeling in medical diagnosis is one notable contribution in the field of health care and data science integration. The value of using machine learning algorithms to improve diagnostic precision outlined in their investigation echoes what this essay recommends. As such, the results of Rosengren et al. (2019) emphasize a shift in medical decision making towards data driven methods. Nguyen, Gilstrap, Chernew, McWilliams, Landon, & Landrum (2019) take their research further to look at the ethical and societal impacts of embedding machine-learning capabilities in healthcare systems. As such, this research piece gives critical information about how to apply data science responsibly particularly in cases like patient health analysis. It is important that the author should pay attention to the ethical dimension while implementing data science in medical research. Also, Dinh, Liao, & Navathe (2019) discuss the practicality and difficulties of applying data science into healthcare management. The author understands the real-world problems that arise when using such tools, hence a chance to overcome the barriers and make it possible. These additional studies enhance the existing library and offer useful perspectives on technical, ethical, and pragmatic issues associated with application of "data science" into health. Incorporation of these perspectives into the current document will make this work stronger and give rise to a broader basis on which the project could be founded.

3. Materials and Methods

This section describes the materials, data resources, and statistics used for our case analysis related to the American market health insurance.

Data Sources

To conduct a comprehensive analysis of Medicare risk adjustment coding, we utilized a rich and diverse set of data sources, which included Medicare Claims Data. The researcher got in touch with a de-identified set of Medicare claims data that contained information related to the patients' demography, diagnosis, treatment, and utilization of healthcare facilities they visited. This information played an important role when understanding the process of application of risk adjustment coding in practice. The other source is from Hierarchical Condition Category (HCC) Data. Obtaining HCC data that serves as one of the vital constituents for Medicare risk adjustment was provided to us. It offered information on condition categories and health risks. Historical Medicare Data was also found through Longitudinal analysis of historical Medicare data, which enabled us to track the development of risk-adjustment practices over time and examine changes in coding behaviors.

Our analysis involved a combination of statistical methods and data science techniques. These techniques include Descriptive Statistics. Descriptive statistics were used to present the distribution of Medicare beneficiaries in terms of their sex, age groups, geographical location, marital status, and race. Furthermore, this technique was used to highlight the occurrence of certain diseases among the population as well as health care use. Using the HCC data, we estimated risk scores on an individual basis, quantifying the overall health status of each person. It was also important to develop machine learning models that would forecast risk scores for our beneficiaries depending on health files. Random forests, gradient boosting, and logistic regressions were some of the algorithms used in this. With sophisticated statistics, we explored how ethnicity and socioeconomic variables affect risk adjustment coding. They used regression analysis as well as spatial mapping to ascertain any variations in coding practices.

Preprocessing of data and ethics: The researcher performed thorough preprocessing of data to guarantee data validity and confidentiality by anonymizing personal information. The study placed great emphasis on ethical issues and followed ethical guidelines and regulations. There were necessary channels in the institutions to access the Medicare data as privacy and security laws were observed.

4. Results

The study has revealed the impact of the current U.S. and Medicare risk-adjustment coding methodologies in terms of their effectiveness, fairness, and transparency. In this article, we analyzed different elements involved in the risk score assessment, including health conditions, demographics, and socioeconomic status of beneficiaries.

Risk Scores for beneficiaries and illnesses: The HCC-based beneficiary risk scores that we analyzed for this study revealed substantial disparities in risk scores among the Medicare population nationwide. Consistently, beneficiaries with chronic health conditions such as diabetes, cardiovascular diseases, and end-stage renal disease were allotted more risk scores (Jacobs & Kronick, 2021). As such, it was able to capture multiple facets of patients' illnesses and, therefore, provided a sound basis to adjust risk.

Analysis of coding for risk adjustment over time: Temporal analysis showed how coding practices have changed throughout the period. The inclusion of certain chronic conditions and major illnesses into the model has become more commonplace over the past few years, with this yielding a better prediction. Revised health care policies and their effect on coding methodology as well as assignment of risk ratings to the beneficiaries.

Societal, Ethnic, and economic diversity of health problems: The research found noteworthy variations in risk factor coding, largely associated with socio-economic issues and race. Key findings include recipients who came from the poor socioeconomic class, which resulted in underpaying their health care necessities or medical care required. Ethnicity had a great impact on risk scores; it calls for measures to ensure equity is attained through equal coding practices.

Machine Learning Models: The machine learning model shed light on how beneficiary attributes could be used to determine the predictability of risk scores. The models demonstrate predictable scores for beneficiaries using their health data and demographics, showing that what is done is a good model. Possibilities for improving coded transparency and equity by diminishing exogenous impacts on risk point scores.

Fairness and Transparency Assessment: The assessment of the fairness and transparency of risk adjustment coding methodologies revealed areas for improvement. The necessity of improving coding procedures in order to reduce the associated health care disparities on a socioeconomic or racial basis. Ensuring transparency of the cost and quality-adjusted process to build credibility with beneficiaries and service providers within the insurance sector. Taken individually, these findings point out that more needs to be done on Medicare risk adjustment coding as research and innovations.

As showed below in **Table 1** (**Table 1** showing model-building process. Of the variables considered for inclusion, prescription of steroids and statins, smoking status, history of CVD and deprivation were excluded from the final model based on their association with PDM/T2DM (Davies et al., 2017). All the variables considered for inclusion were ultimately excluded from the final model. The reason for exclusion is mentioned as their association with PDM/T2DM. This suggests that during the modeling process, these variables (prescription of steroids, prescription of statins, smoking status, and history of CVD) were found to have a significant association with the outcome variable (PDM/T2DM).

This study helps enrich the debate on ways to make risk adjustment more accurate, honest, and transparent for American healthcare providers and patients alike. This section outlines the implications of the results and gives areas for future research work as well as policies that should be put in place.

5. Discussion

The study contributes to the discussions on Medicare risk adjustment coding in relation to healthcare coverage in America. Irvin et al. (2020) state that there is a need to emphasize the importance of proper risk adjustment coding in American

Table 1. Showing model-building process. Of the variables considered for inclusion, prescription of steroids and statins, smoking status, history of CVD and deprivation were excluded from the final model based on their association with PDM/T2DM (Davies et al. 2017).

Variable	Number with data	OR (95% CI)	*p*-value	Taken forward to next stage
Independent associations, each risk factor included separately				
Age	6378	1.04 (1.03 to 1.04)	<0.0001	✗
Sex	6378	1.12 (0.99 to 1.26)	0.05	✗
BMI	6157	1.08 (1.07 to 1.10)	<0.0001	✗
Ethnicity	6175	1.67 (1.45 to 1.91)	<0.0001	✗
Family history	6378	1.29 (1.14 to 1.46)	<0.0001	✗
Smoking status	6141	0.71 (0.58 to 0.86)	<0.0001	✗
Antihypertensives	6378	1.99 (1.75 to 2.27)	<0.0001	✗
Statins	6378	1.76 (1.49 to 2.09)	<0.0001	✗
Steroids	6378	1.16 (0.89 to 1.50)	0.28	
History of CVD	6378	1.28 (1.08 to 1.52)	0.004	✗
Deprivation	6125	1.01 (1.00 to 1.01)	<0.0001	✗
All significant risk factors from phase one included in one model				
Age	5867	1.04 (1.03 to 1.05)	<0.0001	✗
Sex	5867	1.21 (1.05 to 1.39)	0.01	✗
BMI	5867	1.08 (1.07 to 1.10)	<0.0001	✗
Ethnicity	5867	2.01 (1.70 to 2.38)	<0.0001	✗
Family history	5867	1.66 (1.44 to 1.91)	<0.0001	✗
Smoking status	5867	0.94 (0.76 to 1.16)	0.55	
Antihypertensives	5867	1.67 (1.42 to 1.96)	<0.0001	✗
Statins	5867	1.32 (1.06 to 1.63)	0.01	✗
History of CVD	5867	0.84 (0.68 to 1.03)	0.1	
Deprivation	5867	1.00 (1.00 to 1.01)	0.08	
All significant risk factors from phase two included in one model				
Age	6143	1.04 (1.03 to 1.05)	<0.0001	✗
Sex	6143	1.19 (1.04 to 1.36)	0.01	✗
BMI	6143	1.09 (1.07 to 1.10)	<0.0001	✗
Ethnicity	6143	2.13 (1.82 to 2.48)	<0.0001	✗
Family history	6143	1.61 (1.40 to 1.85)	<0.0001	✗
Antihypertensives	6143	1.65 (1.41 to 1.93)	<0.0001	✗
Statins	6143	1.19 (0.98 to 1.45)	0.08	

Continued

Score now includes age, sex, BMI, ethnicity, family history and antihypertensives (next stage: adding the excluded variables one by one to see if they are now important when adjusted for other factors in the model)			
Steroids	6143	1.08 (0.82 to 1.43)	0.57
Smoking status	6099	0.93 (0.76 to 1.15)	0.52
History of CVD	6143	0.91 (0.75 to 1.11)	0.36
Deprivation	5911	1.00 (1.00 to 1.00)	0.09

OR, odds ratio.

https://www.ncbi.nlm.nih.gov/books/NBK409312/table/table9/?report=objectonly.

health care. Additionally, precise risk scores are necessary to guarantee that appropriate services are offered to various ill patients and that health providers get proper reimbursement. Risk adjustment plays a key role in determining high-risk beneficiaries for appropriate resource allocation, developing care plans, and ensuring the quality of health care services.

Health Conditions and Risk Adjustment

The research has shown the linkage between the prevalent health conditions and beneficiaries' risk scores. The high-risk scores arise as a consequence of chronic diseases or severe health conditions. This shows how wide the scope of the patient's health should be in order to capture all the information needed to calculate their risks. Moreover, people with complicated health problems need to be represented more accurately in the risk assessment process. Temporal analysis showed the dynamics in risk adjustment coding practice over time. Adjustment of coding practices as a direct response of the healthcare industry toward changing medical guidelines and standards.

Above **Figure 1**

(https://www.thelancet.com/journals/langlo/article/PIIS2214-109X(19)30045-2/fulltext) shows socioeconomic status using education and a household wealth index. Education was categorised as no or primary school education only (lowest), secondary school education (intermediate), or higher education, defined as completion of trade school, college, or university (highest). Household wealth, calculated at the household level and with household data, was defined by an index on the basis of ownership of assets and housing characteristics,20 validated in several countries, and documented to be a robust measure of wealth, consistent with measures of income and expenditure.

The element of dynamism is one positive aspect since it guarantees adaptability to changes in medical expertise. It also stresses the need for periodic revisions in coding standards and continued discussions within the health fraternity.

Disparities Based on Socioeconomic and Ethnicity

The research has shown that the matters of risk adjustment coding as per socio-economics and ethnicity are especially alarming. The low scoring of such beneficiaries from disadvantaged socioeconomic backgrounds might limit their

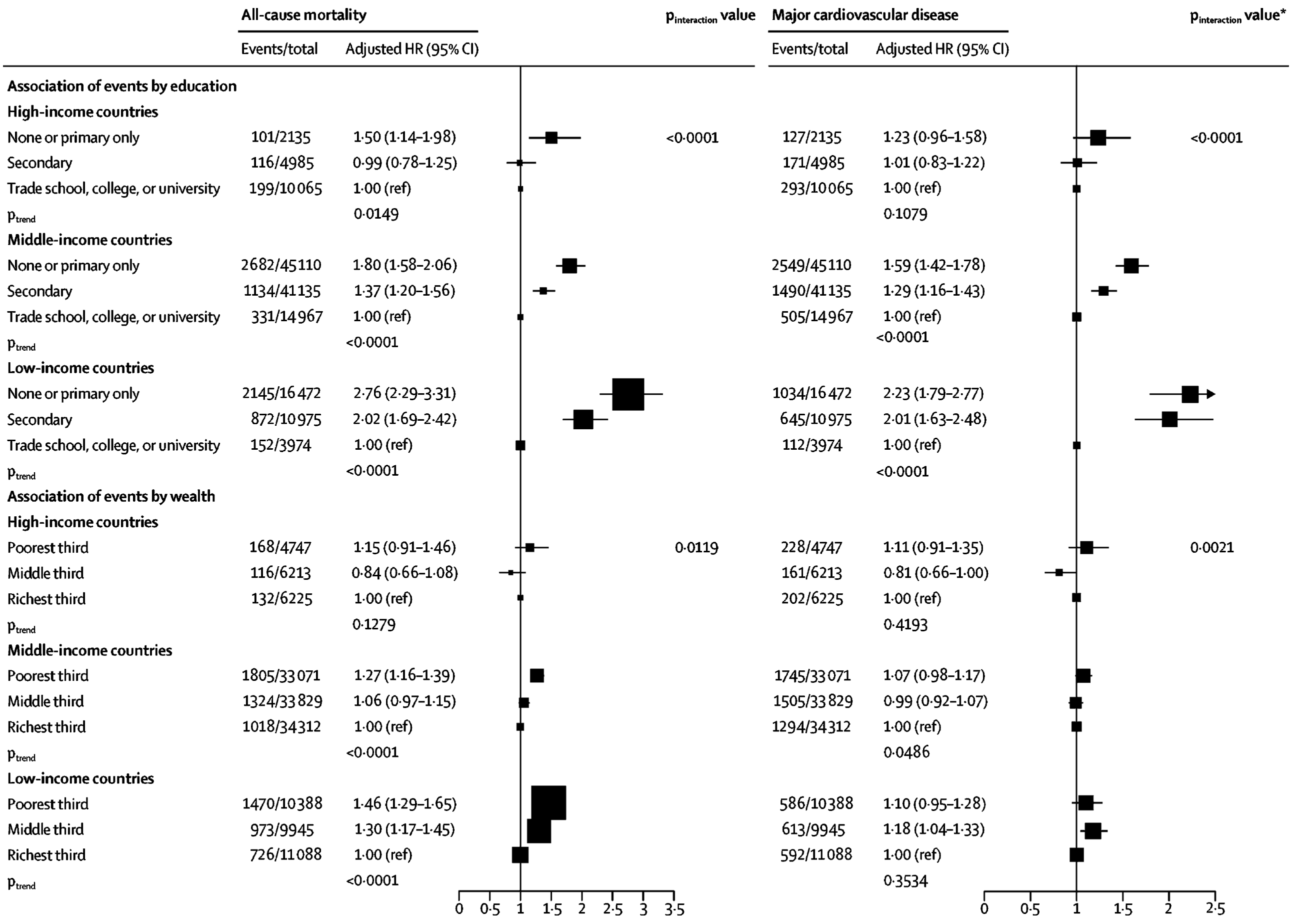

Figure 1. HRs (95% CI) for all-cause mortality and major cardiovascular disease by country income and level of education (Rosengren et al., 2019), https://www.thelancet.com/journals/langlo/article/PIIS2214-109X(19)30045-2/fulltext.

access to necessary health services Nguyen, Gilstrap, Chernew, McWilliams, Landon, & Landrum (2019). The importance of coding ethically underscores this point. It is not an easy thing to address those disparities (Kocher, 2021). however, it should be done because healthcare is not meant for the select few. The results from using machine learning models showed that risk scores depended upon beneficiary characteristics. Predictability implies that risk adjustment has firm evidence and database (Krumholz et al., 2019). It also questions the impact of non-clinical variables on a risk score. The trust of donors, medical staff, and insurers necessitates transparency by coding (McGuire, Schillo, & Van Kleef, 2020). With a view to improving transparency, machine learning models could also be helpful in signposting parts within the application of coding techniques that require revision.

As showed in below **Figure 2** (Socioeconomic status and risk of cardiovascular disease in 20 low-income, middle-income, and high-income countries: the Prospective Urban Rural Epidemiologic (PURE) study by Prof Annika Rosengren, MD Andrew Smyth, MD Sumathy Rangarajan, MSc Chinthanie Ramasundarahettige, MSc Shrikant I Bangdiwala, PhD Prof Khalid F AlHabib, MD et al. (Rosengren et al., 2019). Education, rather than wealth, was the factor most strongly associated with the study primary outcomes, with low education being

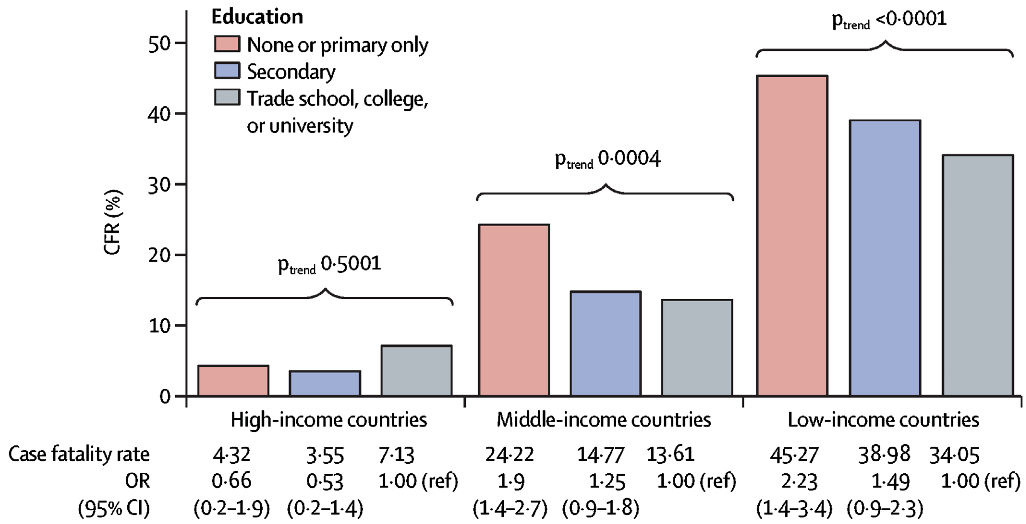

Figure 2. 28-day CFR after a first cardiovascular event and OR by country income and level of education among participants without previous cardiovascular disease (Rosengren et al., 2019), https://www.thelancet.com/journals/langlo/article/PIIS2214-109X(19)30045-2/fulltext.

associated with an increased risk of major cardiovascular disease and higher case fatality, despite lower proportions of cardiovascular risk factors in low-income countries than in high-income countries. Improved education and access to effective health care might mitigate some of the substantial excess burden of cardiovascular disease and mortality in low-income countries and narrow global health inequalities.

Future research and policy considerations

The findings of this study hold several policy implications. Fr instance, continual monitoring and adjusting their practice to make them fair, accurate, and transparent. An ongoing analysis of the changing environment of health care and the effect that it has on coding practices. Working together with various stakeholders like policymakers, healthcare providers, and data scientists, whose task is to make sure that risk adjustment remains appropriate in line with evolving healthcare dynamics.

6. Conclusion

Medicare risk adjustment coding remains a critical element in the current U.S. healthcare structure that impacts the viability of health insurance firms and quality of services delivered to recipients. Our research provides critical insights into the effectiveness, fairness, and transparency of the current risk adjustment methodologies, highlighting several key conclusions. As such, our study reinforces the critical significance of proper risk adjustment coding within the context of the American healthcare system. Accurate risk scores represent the key element which provides healthcare providers with reasonable compensation and beneficiaries of different disorders or illnesses with required care. However, risk adjustment does not stop at being just a financial matter; it is the basis of healthcare equality and quality. Health status greatly impacts risk-adjusted coding. Beneficiaries' risk scores vary depending on chronic diseases, severe illnesses, and complicated medical needs. Fair and equitable risk adjustment requires recognizing the whole breadth of patient health. Temporal analysis showed that risk-adjustment coding practice was not stable over the defined time period. With regards to healthcare, the medical directives change over time, thus necessitating for coding practices to be modified as well. The health system's ability to change enables risk adjustment to maintain flexibility as medicine advances, making this an asset of adaptation. Our results pinpoint critical variation in risk adjustment coding, especially concerning socioeconomic dimensions and ethnicity. Such beneficiaries may be drawn from low socio-economic classes and might be assigned with a low-risk score thereby barring them from receiving necessary health care services. Ethnicity in risk score illustrates the necessity of equal treatment of all codes. It requires dealing with these inequalities if one wants to construct an even healthcare service provision system.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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