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Generative AI for analysis and identification of Medicare improper payments by provider type and HCPC code

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ABSTRACT

The 2022 Medicare Fee-For-Service Improper Payments Report reveals an estimated $80.57 billion in improper payments, with a payment error rate of 15.62%. This paper uses generative AI to analyze and identify which provider types and HCPC codes are most strongly associated with these errors. The paper employs generative AI to produce two Python codes: one generates a time-series trend graph of Medicare improper payments from 2010 to 2022, and the other calculates the number of payment errors by provider type and HCPC code. These codes are designed for novice and non-programmers. Three datasets are used, such as Medicare Fee-for-Service Comprehensive Error Rate Testing dataset released on March 8, 2023, merged codes such as HCPC codes and PCT codes. The result suggests what systems should be improved to reduce Medicare improper payments. Generative AI is being introduced to help novice and non-programmers analyze Medicare improper payments with datasets, aiding researchers in conducting similar tasks in the future.

1. Introduction

The 2022 Medicare Fee-For-Service Improper Payments Report has recently been published in March 2023.[1,2] According to the report, an estimated $80.57 billion in improper payments were identified, with a payment error rate of 15.62%. The report details the most common services that were billed and paid in error, as well as the reasons for these errors, including issues with medical necessity, incorrect coding, and insufficient documentation.

This paper will examine and analyze what were wrong in Medicare payment systems by provider type and HCPC (Healthcare Common Procedure Coding) code respectively.

Improper payments are payments that don't meet program requirements. They mostly occur due to unintentional errors or insufficient documentation. They can include both overpayments and underpayments and don't necessarily represent expenditures that shouldn't have occurred. While fraud and abuse are improper payments, not all improper payments represent fraud. Improper payment estimates aren't fraud rate estimates. Most Medicare Fee-For-Service improper payments fall into two categories: insufficient or missing documentation, and documentation that doesn't sufficiently demonstrate medical necessity.

Medicaid was adopted in 1965, at a time when only 40% to 50% of poor children had any doctor visits in a year.[3] Some Medicare-reimbursed services are overused or improperly used, resulting in payments for unnecessary services.[4] In other words, reducing Medicare improper payments can lead to a reduction in Medicare expenditures. The aim of this paper is to identify the causes of improper payments by provider type and HCPC code, respectively.

Peng et al. addressed only Medicare problems on type-2 diabetes.[5] In their study, 12.6% of beneficiaries reported problems paying medical bills. Among those with and without problems, 59.5% and 12.8%, respectively, were dissatisfied with out-of-pocket costs. Beneficiaries who were dissatisfied with out-of-pocket costs were more likely to report problems paying medical bills. Younger beneficiaries, those with lower incomes, functional limitations, and multiple comorbidities were more likely to report problems.

Angeles et al. reviewed 76 articles and generalized the problems in Medicare.[6] A review of 76 articles identified seven major themes of problems in Australian healthcare: fragmentation and lack of integrated financing, access to services and medications for Aboriginal and Torres Strait Islander people, reform proposals for the Pharmaceutical Benefits Scheme, out-of-pocket costs, inequity, public subsidies for private health insurance, and other challenges for the universal system. However, specific problems were not addressed to improve Medicare expenditures.

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Tenpas et al. studied that billing issues are common in healthcare.[7] Undercoding leads to decreased reimbursement, but little data captures what is lost. Their study approximated how much Medicare reimbursement is lost annually to undercoding in Florida and discussed its hidden dangers, including hindering the ability of clinical pharmacists to build sustainable clinical services.

DiStefano et al. revealed that recent legislation establishing a $2000 out-of-pocket cap in Part D had the potential to lower out-of-pocket costs for more than 125,000 Part D beneficiaries who use ultra-expensive drugs and are ineligible for low-income subsidies, thus ameliorating increases in out-of-pocket spending when transitioning from commercial insurance to Part D.[8]

Namburi et al. summarized Medicare problems from economic perspectives.[9] The US is a leading power in medical technology, training, and research, but has high healthcare spending with poor outcomes compared to other high-income countries. From 1960 to 2017, US healthcare expenditure as a percentage of GDP increased from 5.0 to 17.9, with nearly 25% of spending wasted. The Health Maintenance Organization Act of 1973 spurred the growth of managed care, integrating financing and insurance to gain control and reduce costs. However, specific problems in Medicare were not addressed to reduce Medicare expenditures by eliminating payment errors.

While there are numerous articles[5–9] discussing problems in Medicare, none have specifically identified issues by provider type and HCPC code to reduce expenditures. This paper aims to use generative AI to identify payment errors by provider type and HCPC code. A new method is introduced, using generative AI to generate Python codes to achieve this goal. The proposed method has broad applicability to other problems in various industries.

Hassani et al. reported that ChatGPT is revolutionizing data science by automating workflows, analyzing unstructured data, and enhancing decision-making.[14] It can handle various language-related tasks but may struggle with untrained tasks. Despite concerns about bias and plagiarism, its benefits are deemed to outweigh the costs.[14]

Biswas addressed that ChatGPT, developed by OpenAI, is a versatile tool for computer programming.[15] It can perform tasks like code completion, error fixing, and answering technical queries. It aids in understanding complex concepts, improving support services, and enhancing efficiency and accuracy in programming.[15]

The proposed method involves preparing datasets and generating code using generative AI. Two Python codes are generated for novice and non-programmers to analyze datasets. The method enables readers to achieve their desired goal, with queries playing a key role in generating correct Python codes. A set of instructions is provided in the paper.

There are three free generative AI systems available at the following links.

ChatGPT-3.5 via any browser: https://chat.openai.com/
Bing.com via Edge browser with ChatGPT-4: https://bing.com/chat
Bard via any browser: https://bard.google.com

This paper uses Bing.com with ChatGPT-4. To ensure accuracy in statistical analysis, beginners should source their data from trustworthy origins, rather than relying on data generated by generative AI.[16] In other words, all the datasets utilized in this study were sourced exclusively from U.S. government websites.

2. Methods

This paper may be the first for novice and non-programmers to generate Python codes with generative AI to achieve goals such as visualizing trends in national Medicaid improper payment rates from 2010 to 2022 and generating a top-10 table on Medicare improper payments by provider type and HCPC code. Correct datasets, Python codes, and queries are key to generating accurate codes.

Rolling National Medicaid Improper Payment Rates can show the trends from 2010 to 2022.[10] From the web page,[10] medicare.csv was created as simple example.

The following query was fed to Bing.com with ChatGPT-4.

Query: use medicare.csv with 'Year' and 'Estimated Improper Payments (in billions)'. show the full code in python to show a graph. Use only values existing in 'Year' column name such as 2010 and 2022. Use the values in 'Estimated Improper Payments (in billions)' with the same rows of available values in 'Year' column name. The values are expressed with $ sign and amount of dollars such as $22.50.

In the query, identifying file name, column names can play a key role in generating correct code. The generated code, medicare.py is attached in APPENDIX.

The second query is to generate a top-10 table on Medicare improper payments by provider type and HCPC code. Three datasets are used: 2022 PartAPartB Public Data.csv,[11] DHS.csv[12] and code.csv.[13] 2023_DHS_Code_List_Addendum_12_01_2022.xlsx file was converted to DHS.csv and HCPC2023_JUL_ANWEB_v2.xlsx to code.csv respectively.

Query: Show the full code in Python to scan the number of 'Disagree' in 'Review Decision' column name and make unique categories with 'Provider Type' and 'HCPCS Procedure Code' column names with 2022 PartAPartB Public Data.csv file.

There are 'Disagree' and 'Agree' in 'Review Decision' column name. Sort the unique catetories with 'Disagree' with 'Provider Type' and 'HCPCS Procedure Code' column names. The code should calculate the number of 'Disagree' with the 'Provider Type' and 'HCPCS Procedure Code'. Show the sorted top ten of 'Disagree' in descending order with 'Provider Type' and no column number. Show the sorted top ten of 'Disagree" in descending order with 'HCPCS Procedure Code' and no column number. Merge code.csv and DHS.csv without duplication for replacing values of 'HCPCS Procedure Code'.

Use all data as string in code.csv and DHS.csv. Values of 'SHORT DESCRIPTION' column name in both code.csv and DHS.csv should be replaced with values of 'HCPCS Procedure Code'. 'HCPC' column name in code.csv and 'CPT'column name in DHS.csv are equivalent to 'HCPCS Procedure Code'.

The generated Python code is attached in APPENDIX.

3. Results

The generated codes successfully created Fig. 1 and Table 1. Fig. 1 shows trends of Medicare improper payments (billions) from 2010 to 2022. Table 1 shows a top-10 Medicare improper payments by Provider type and HCPC code. In queries, identifying column names plays a key role in generating correct codes. For novice and non-programmers, two codes were successfully generated with generative AI.

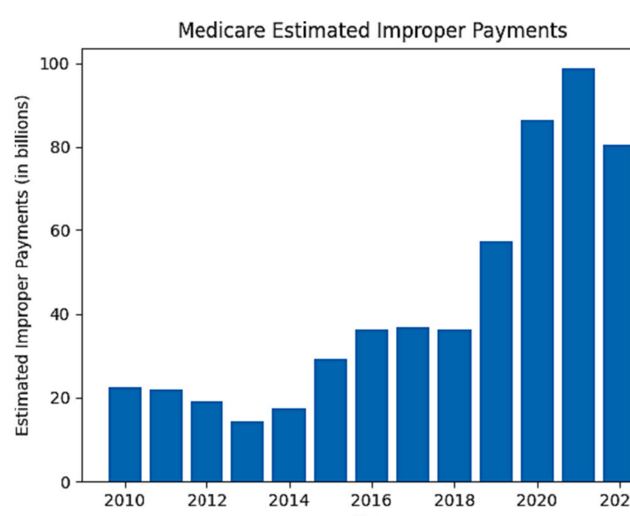

Fig. 1. Trends of Medicare improper payments (billions).

Table 1
2022 Medicare improper payments by Provider type and HCPC code.

Top 10 Provider Types with highest number of 'Disagree':

Provider type	Disagree count
OPPS, Laboratory (an FI), Ambulatory (Billing an FI)	2585
Medical supply company not included in 51, 52, or 53	2526
SNF	2407
Hospice	2224
HHA	2129
DRG Short Term	1646
Pharmacy	1392
Clinical Laboratory (Billing Independently)	1179
ESRD	842
Inpatient Rehab Unit	721

Top 10 HCPCS Procedure Codes with highest number of 'Disagree':

HCPCS procedure code	Disagree count
Hhs/hospice of rn ea. 15 min	978
Hhcp-svs of aide,ea. 15 min	755
Hhs/hospice of lpn ea. 15 min	405
Therapeutic exercises	311
Hospice or home hlth in home	305
Sbsq hosp ip/obs high 50	231
Therapeutic activities	215
1st hosp ip/obs high 75	193
Suspension sleeve lower ext.	184
Routine venipuncture	182

4. Discussion

Fig. 1 showed increasing trends of Medicare improper payments except 2022. Table 1 revealed top five providers such as OPPS, Laboratory (an FI), Ambulatory (Billing an FI), Medical supply company not included in 51, 52, or 53, SNF, Hospice, and HHA. Top five HCPC codes include Hhs/hospice of rn ea. 15 min, Hhcp-svs of aide,ea. 15 min, Hhs/hospice of lpn ea. 15 min, Therapeutic exercises, and Hospice or home hlth in home.

With the identified provider types and HCPC codes, Medicare expenditure can be reduced. It is important for readers to understand on how to use generative AI and to recognize current problems such as a reproducibility problem and incorrect code generation. The reproducibility problem implies that the same query may not generate the same code due to pseudorandom numbers. Users with generative AI must verify generated codes whether they are desired codes. In other words, verification skill is needed to use generative AI. The first query was simple, but the second one is sophisticated due to complex computations with three datasets. There was no free complete set of HCPC codes. This paper created a free complete set of HCPC codes as of July 5, 2023.

5. Conclusion

This study presents a novel approach using generative AI to create Python codes, particularly beneficial for beginners and non-programmers. The analysis of Medicare improper payments from 2010 to 2022 revealed increasing trends and identified key providers and HCPC codes. Addressing these could reduce Medicare expenditures without compromising services. However, users must understand the limitations of generative AI, including reproducibility issues and the need for code verification. Despite these challenges, the study demonstrates the potential of generative AI in creating expert systems or applications, marking a significant advancement in the field.

5.1. Implications

The findings of this study introduce a novel method using generative AI to generate Python codes, particularly beneficial for novice and non-programmers. The identification of provider types and HCPC codes associated with Medicare improper payments suggests potential areas of focus to reduce expenditures without service reduction. This paper also paves the way for the creation of expert systems or applications using generative AI with correct queries in the future.

5.2. Limitations

The study's findings are subject to certain limitations. The reproducibility problem with generative AI means the same query may not always generate the same code due to pseudorandom numbers. Users must verify the generated codes to ensure they are as desired, implying a need for verification skills. The complexity of computations with multiple datasets can also pose challenges. Additionally, while this paper created a free complete set of HCPC codes as of July 5, 2023, the availability and completeness of such codes can be a limiting factor.

CRediT authorship contribution statement

Yoshiyasu Takefuji: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The author has no conflict of interest.

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Appendix

APPENDIX: medicare.py: Trends of Medicare improper payments (billions).

```
import pandas as pd.
import matplotlib.pyplot as plt.
# Read the data from the CSV file.
data = pd.read_csv('medicare.csv').
# Filter the data to only include rows where the 'Year' column has a value between 2010 and 2022.
data = data[(data['Year'] ≥ 2010) & (data['Year'] ≤ 2022)].
# Convert the 'Estimated Improper Payments (in billions)' column to a numeric value by removing the '$' sign and converting to float.
data['Estimated Improper Payments (in billions)'] = data['Estimated Improper Payments (in billions)'].str.replace('$', '').astype(float).
# Create a bar chart using the filtered data.
plt.bar(data['Year'], data['Estimated Improper Payments (in billions)']).
# Add labels and title.
plt.xlabel('Year').
plt.ylabel('Estimated Improper Payments (in billions)').
plt.title('Medicare Estimated Improper Payments').
# Show the graph.
plt.savefig('medicare.png').
plt.show().
```

APPENDIX: inproper.py: Medicare improper payments by Provider type and HCPC code.

```
import pandas as pd.
# Load the data.
data = pd.read_csv('2022 PartAPartB Public Data.csv').
code = pd.read_csv('code.csv').
DHS = pd.read_csv('DHS.csv').
# Merge code.csv and DHS.csv without duplication for replacing values of 'HCPCS Procedure Code'.
merged = pd.concat([code, DHS]).drop_duplicates(subset = ['HCPC', 'CPT']).
# Use all data as string in code.csv and DHS.csv.
merged['HCPC'] = merged['HCPC'].astype(str).
merged['CPT'] = merged['CPT'].astype(str).
merged.to_csv('newcode.csv',index = False).
```

Replace values of 'SHORT DESCRIPTION' column name in both code.csv and DHS.csv with values of 'HCPCS Procedure Code'.

data['HCPCS Procedure Code'] = data['HCPCS Procedure Code']. replace(merged.set_index('HCPC')['SHORT DESCRIPTION']).replace (merged.set_index('CPT')['SHORT DESCRIPTION']).

Filter the data to only include rows where the 'Review Decision' is 'Disagree'.

disagree_data = data[data['Review Decision'] == 'Disagree'].

Group by 'Provider Type' and count the number of 'Disagree'.

provider_type_counts = disagree_data.groupby('Provider Type').size ().reset_index(name = 'Disagree Count').

Sort the counts in descending order and show the top 10.

top_10_provider_type = provider_type_counts.sort_values (by = 'Disagree Count', ascending = False).head(10).

Group by 'HCPCS Procedure Code' and count the number of 'Disagree'.

hcpcs_code_counts = disagree_data.groupby('HCPCS Procedure Code').size().reset_index(name = 'Disagree Count').

Sort the counts in descending order and show the top 10.

top_10_hcpcs_code = hcpcs_code_counts.sort_values(by = 'Disagree Count', ascending = False).head(10).

Display the results.

print("Top 10 Provider Types with highest number of 'Disagree':")

print(top_10_provider_type.to_string(index = False)).

print("\nTop 10 HCPCS Procedure Codes with highest number of 'Disagree':")

print(top_10_hcpcs_code.to_string(index = False)).

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