MINISTRY OF ECONOMY
DEPARTMENT OF STATISTICS MALAYSIA

Healthcare Insurance Fraud Detection using Benford's Law

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OVERVIEW

1. INTRODUCTION
2. METHODOLOGY
3. RESULT
4. DISCUSSION
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INTRODUCTION

INTRODUCTION – Losses due to Fraud

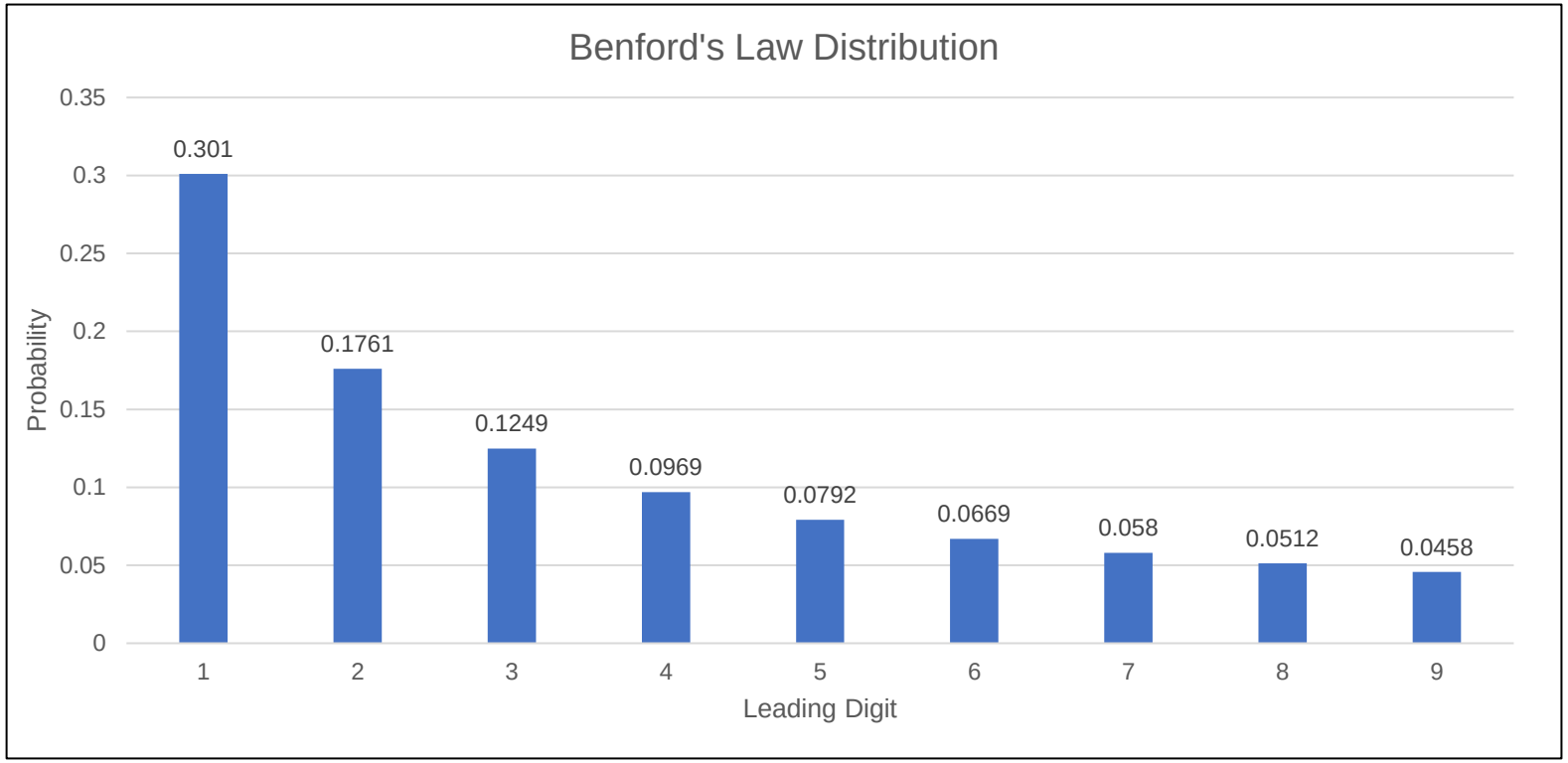
- An alarming annual loss of USD 308.6 billion due to insurance fraud (Kilroy, 2024)
- Conservative pricing – transfers financial burden to policyholders – higher premiums (Chen et al., 2020)
- Automated fraud detection technologies – machine learning models (Nabrawi & Alanazi, 2023) – sophisticated and computationally expensive

INTRODUCTION – Benford's Law

- A straightforward statistical tool
- Applied successfully in forensic accounting (Druica et al., 2018) and electoral fraud detection (Gueron & Pellegrini, 2022)
- Applies exclusively to naturally occurring numbers (insurance claim amounts, stock prices, etc)
- Not applicable to manipulated or pre-assigned numbers (phone numbers, aggregate claim amounts after the policy limit is applied)

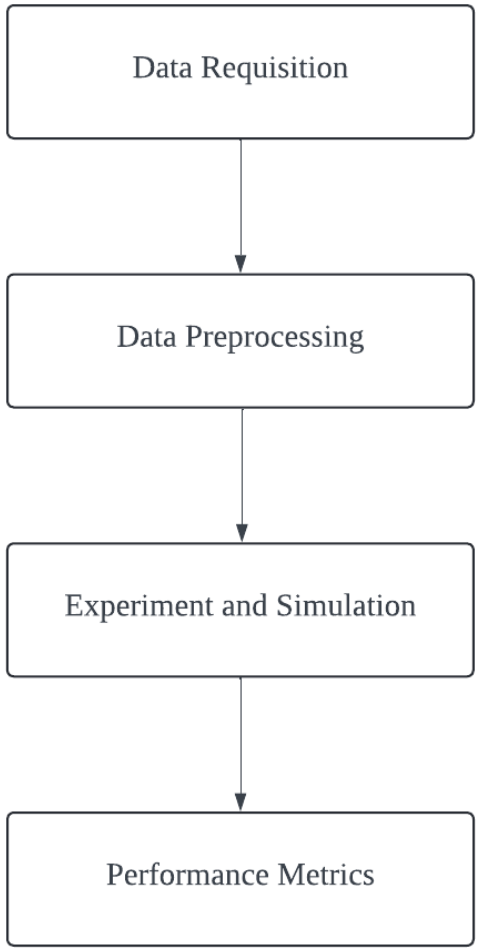
INTRODUCTION – Benford's Law – Formula and Distribution

$$P(d) = \log_{10}\left(1 + \frac{1}{d}\right), \text{ where } d = \{1, 2, \ldots, 9\}.$$



METHODOLOGY

METHODOLOGY - Flowchart



1. Data Requisition

- Synthetic dataset obtained from Kaggle
- A dataset with 63,968 observations focusing on annual reimbursement amounts for Medicare
- Research focus on IPAnnualReimbursementAmt, IPGrossClaim, OPAnnualReimbursementAmt, and OPGrossClaim

2. Data Preprocessing

- Utilised both Microsoft Excel and R-programming
- The first digit of the respective inpatient and outpatient reimbursement amount and gross claim were extracted

3. Experiment and Simulation

- The distribution of each category is fitted to Benford's Law distribution.
- Combo charts were generated for data visualization.

METHODOLOGY - Flowchart

4) Performance Metrics

$$Z = \frac{|AP - EP| - \frac{1}{2N}}{\sqrt{\frac{EP(1-EP)}{N}}}$$

- **Z-test** is used to measure how many standard deviations the observed distribution of each respective digit are from Benford's Law distribution.

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$

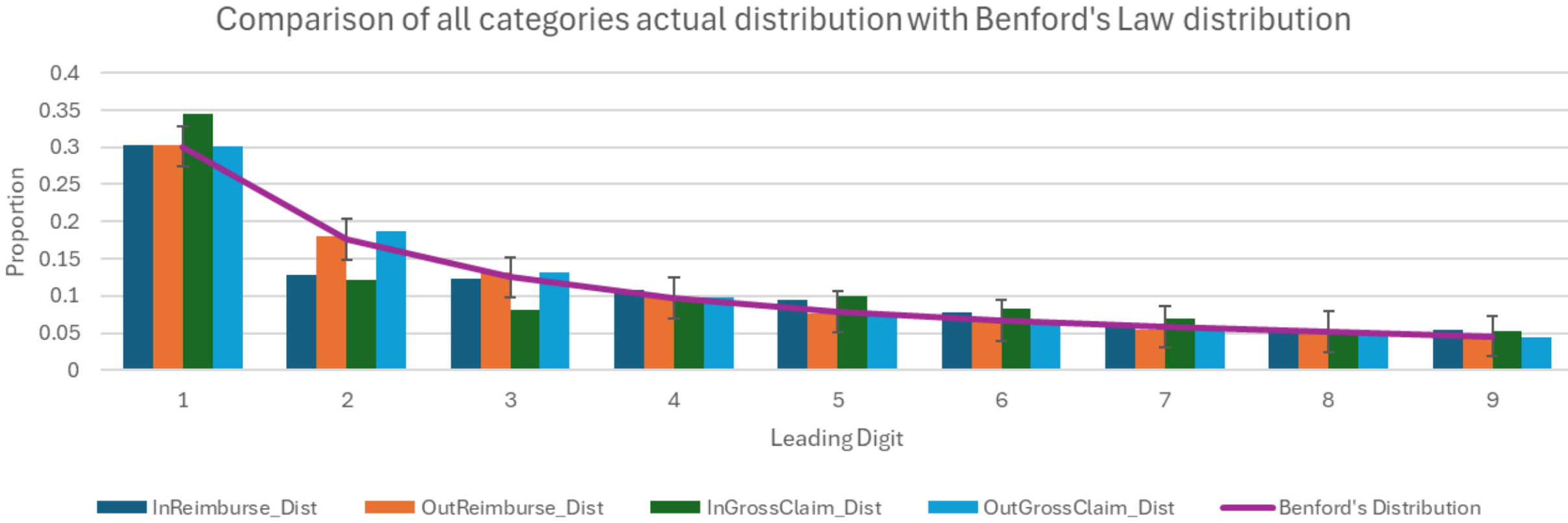
- **Chi-squared goodness-of-fit test** compares the overall conformity of the observed distribution to the expected distribution, is affected by the number of observations.

$$MAD = \frac{\sum_{i=1}^{k} |AP - EP|}{k}$$

- **Mean Absolute Deviation (MAD)** compares the overall conformity of the observed distribution to Benford's Law distribution, not affected by the number of observations

RESULT

RESULT – Comparison of All Categories



RESULT – Inpatient Categories

Digit	Benford's law	Inpatient Reimbursement	z-stat	Inpatient Gross Claim	z-stat
1	0.3010	0.3024	0.4212	0.3455	13.7297*
2	0.1761	0.1280	17.7637*	0.1214	20.3182*
3	0.1249	0.1232	0.7501	0.0803	19.0966*
4	0.0969	0.1073	4.9091*	0.0980	0.5256
5	0.0792	0.0948	8.1215*	0.0990	10.3752*
6	0.0669	0.0771	5.7159*	0.0823	8.6848*
7	0.0580	0.0577	0.1366	0.0686	6.4413*
8	0.0512	0.0559	3.0317*	0.0517	0.3400
9	0.0458	0.0536	5.2667*	0.0531	4.9286*
χ^2 p-value		1.494e-83	χ^2 p-value	6.662e-216	* $Z > 1.96$
MAD		0.0111	MAD	0.0221	
Interpretation		Acceptable conformity	Interpretation	Non-conformity	

RESULT – Outpatient Categories

Digit	Benford's law	Outpatient Reimbursement	z-stat	Outpatient Gross Claim	z-stat
1	0.3010	0.3029	0.9958	0.3011	0.0496
2	0.1761	0.1796	2.3193*	0.1870	7.1578*
3	0.1249	0.1317	5.1056*	0.1322	5.5429*
4	0.0969	0.0978	0.7309	0.0984	1.2497
5	0.0792	0.0754	3.4714*	0.0749	3.9737*
6	0.0669	0.0653	1.6151	0.0619	5.0904*
7	0.0580	0.0542	4.0552*	0.0533	5.0172*
8	0.0512	0.0487	2.7934*	0.0475	4.1746*
9	0.0458	0.0444	1.6193	0.0437	2.4504*
χ^2 p-value		1.442e-11	χ^2 p-value	1.287e-29	* $Z > 1.96$
MAD		0.00288	MAD	0.00439	
Interpretation		Close conformity	Interpretation	Close conformity	

DISCUSSION

DISCUSSION – Contradictory Results

- Inpatient gross claim – raw loss data
- Inpatient reimbursement amount – revised amount after deductible
- Intuitively speaking, the raw data would conform to Benford's law
- Contradicting results

DISCUSSION – Excess Power Problem

- **Large sample size – *p*-values obtained are small, while the test statistics have large values**

- **Excess power problem encountered by the chi-squared test (Kossovsky, 2021).**

- **Other statistical tests, such as the MAD, should be used to complement the chi-squared test to provide additional insights**

CONCLUSION

CONCLUSION – Concluding Remarks

- **Inpatient reimbursement amount conforms to Benford's Law more than inpatient gross claim (raw data), which contradicts Benford's Law.**

- **Excess power problem faced by chi-square test and z-test**

CONCLUSION – Limitations

- Lack of accessibility of real-world insurance datasets due to privacy matters.
- Deviations from Benford's Law do not necessarily imply fraudulent cases as Benford's Law only serves as a preliminary statistical tool.
- More advanced tests and algorithms should be employed for further investigation.

CONCLUSION –Future Works

- Using simulated datasets (Campo & Antonio, 2023) that are realistic and representative of actual insurance datasets.
- Complementing the results from Benford's Law with more advanced machine learning models to accurately identify fraudulent cases
- To examine insurance datasets that include co-payments

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Thank you