

# Comparing ChatGPT-4 to Physicians for Assigning Causes of Death from Verbal Autopsy: A Case Study of 6942 Deaths in Sierra Leone from 2019-2022

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## Abstract

**Background:** Verbal Autopsies (VAs) collect data on deaths and their causes outside of traditional hospital settings to provide more representative counts and

Causes of Death (CODs) for reducing premature mortality. Current computer models for COD assignment in VAs perform similar to physicians at the population level, but poorly at the individual level, due to a focus on structured questionnaire data and neglecting free text from the open narratives. Recently, a Generative Pre-trained Transformer (GPT) model called ChatGPT-4 has demonstrated human-level performance on professional and academic exams using free text input. ChatGPT-4 shows promise in mimicking physician behavior for assigning CODs, but to the best of our knowledge, has yet to be tested for assigning CODs using open narratives from VAs.

**Methods:** 6939 records collected from VA in Sierra Leone from 2019 to 2022 were used to compare four computer models, ChatGPT-3.5, ChatGPT-4, InterVA-5, and InSilicoVA, to physicians for assigning CODs at the population and individual level. Open narratives were used for Chat-3.5/ChatGPT-4 input, while structured questionnaires were used for InterVA-5/InSilicoVA input. All COD assignments were grouped into general COD categories consisting of 19, 10, and 7 categories for the adult, child, and neonatal age groups. Cause Specific Mortality Fraction (CSMF) accuracy and Partial Corrected Concordance (PCCC) were used to compare models to physicians at the population and individual level respectively. Comparisons in CSMF and PCCC to physicians among models were evaluated for all records and by COD, age group, and age ranges.

**Results:** x.

**Conclusion:** x.

**Keywords:** Cause of Death, Physician Coding, Verbal Autopsy, GPT

## 1 Background

In 2019, 41 million people die prematurely from noncommunicable diseases every year, accounting for 74% of all deaths globally [1]. Most of these deaths are preventable, but require adequate resource allocation, guided by evidence, to implement effective interventions and policies that target populations at risk [2]. Thus, reliable counts and diagnoses of deaths enable decision makers to identify populations at risk to save lives and reduce premature deaths worldwide [3–6]. However, most low-income countries do not have data on deaths or have registered less than half of the deaths in their country, with an even fewer 8% of these registered deaths having a Cause of Death (COD) recorded [7]. To fill this gap in death registrations, an alternative method known as Verbal Autopsy (VA) is used to collect data on deaths and determine their likely causes at scale [8–10], outside of traditional healthcare facilities where over half of deaths occur at home [11].

VA involves two major components: survey and COD assignment [12–14]. In the survey component, trained lay surveyors interview those familiar with the deceased (e.g. living spouse, children, family, friends) to gather information using standardized questionnaires and open narratives. In the COD assignment component, physicians evaluate information available from the questionnaires and open narratives to assign

probable CODs. Although VA surveys have been an effective alternative to collect mortality data at scale (e.g. less than \$3 USD per house in India [15, 16]), COD assignment has been criticized to be expensive and difficult to reproduce due to reliance on physician assignment [17–19]. As an alternative to physician assignment, computer models, such as InterVA [20] and InSilicoVA [17], have recently been studied to automatically assign CODs with performances close to physicians at the population level, but poor performances at the individual level [21–25]. These computer models often utilized data from the structured questionnaire, but often omit the free-text open narrative, which misses latent information, such as chronology or health-seeking behaviors, that may potentially help models perform better than using the questionnaire alone [26–28].

Recently, Large Language Models (LLM), leveraging massive datasets and deep learning approaches, have made advances in performing a variety of Natural Language Processing (NLP) tasks using free-text, such as question answering, code generation, and even medical diagnosis [29–32]. On November 30, 2022, a widely-available LLM called ChatGPT was released by OpenAI with capabilities of answering natural language text inquiries using training data up to September 2021. ChatGPT-3 was based on several Generative Pre-trained Transformer (GPT) models between 2018 to 2020, namely GPT-1 to GPT-3, which had notable differences in training data sizes of 5 gigabytes to 45 terabytes from web sources that resulted in 117 million to 175 billion parameter models [33]. On March 14, 2023, ChatGPT-4 was released with human-level performance on various professional and academic exams and benchmarks that outperformed ChatGPT-3 [34]. Given the limited usage of free-text open narratives in computer models for determining CODs, and recent advances in LLMs that leverage natural language text prompts, we conduct a case study with Sierra Leone deaths from VA in 2019 to 2022 to compare four models, ChatGPT-3.5, ChatGPT-4, InterVA-5, and InSilicoVA, to physicians for determining CODs.

## 2 Methods

This study uses 6939 physician agreed records of 11,920 records collected in 2019 to 2022 from the Healthy Sierra Leone (HEAL-SL) as described in Section 2.1. Section 2.2 describes the four models, ChatGPT-3.5, ChatGPT-4, InterVA-5, and InSilicoVA, for COD assignment, and their inputs and outputs, while section 2.3 details the performance evaluation of the four models relative to physicians overall, by ages, and by COD, using population and individual level metrics.

### 2.1 Physician Agreed Records

Initially, 11,920 records from the HEAL-SL study [35, 36] were collected from dual-coded EVA, where each record was randomly coded by two different physicians that assigned CODs as International Classification of Diseases Revision 10 (ICD-10) codes [37]. Physicians were able to assign CODs for 11,820 of the 11,920 records, where 100 of these records could not be assigned a COD due to missing or inadequate information (e.g. low quality narrative, data loss). To determine if two codes were in physician agreement per record, codes were compared for similarity using Central Medical Evaluation Agreement 10 (CMEA-10) codes, which groups a range of similar ICD-10 codes

together indicating codes in agreement [38] (see Additional File 1). When codes were not in agreement, a record enters the reconciliation phase, where the two physicians were provided reasoning and initial codes from each other to: (1) keep their initial code (2) assign the other physician’s code or (3) assign a new code. If codes were not in agreement after the reconciliation phase, a record enters the adjudication phase, where a third senior physician evaluates both physicians’ reasoning and codes before and after reconciliation, and assigns a final code based on their evaluation. The 11,820 physician coded records were further filtered for records where both physicians agreed on the assigned codes (records that were not reconciled or adjudicated), resulting in 6942 physician agreed records. Since computer models were compared to physicians in this study, there was more certainty that COD assignments agreed by both physicians were representative of physician assignment than when they disagreed [18, 39, 40].

## 2.2 Models for COD Assignment

Four computer models were used to assign COD for each of the 6942 physician agreed records: ChatGPT-3.5, ChatGPT-4, InterVA-5 , and InSilicoVA. Each model required pre-processing of the 6942 physician agreed records into input data, and standardization of output COD codes from models for performance evaluation as not all models produced comparable codes across outputs. Although each model can assign multiple CODs per record, only the first generated COD response from ChatGPT-3.5 and ChatGPT-4, and the most probable COD from InterVA-5 and InSilicoVA were used for evaluation. After conversion of all model and physician outputs to generalized Centre for Global Health Research 10 (CGHR-10) codes (see Additional File 2), 6939 records were comparable to evaluate performances of models for COD assignment relative to physicians.

### 2.2.1 Overview of ChatGPT-3.5/4, InterVA-5, and InSilicoVA

ChatGPT-3.5 [41] and ChatGPT-4 [34] are LLMs that utilize deep neural networks with transformer architectures [42] and reinforcement learning from human feedback [43–46] to follow instructions from prompts and provide human-level responses, with known differences in ChatGPT-4 possessing multimodal capabilities (e.g. image/voice input/output), more recent training data, and improved responses compared to ChatGPT-3 [33]. ChatGPT-3.5 and ChatGPT-4 were instructed with text prompts to assign CODs based on the open narrative. InterVA-5 and InSilicoVA are widely used and studied [13, 21, 22, 24, 25, 47, 48] standard statistical models for COD assignment in VAs under the openVA framework [49]. InterVA-5 applies Bayesian probabilistic modelling [50] using a set of standardized symptoms from reports and related conditional probabilities from medical experts to assign CODs based on the highest probability [20, 51]. InSilicoVA improves upon InterVA (e.g. comparable probabilities across individuals, measures of uncertainty, and inclusion of additional data sources) with a hierarchical Bayesian framework and Markov Chain Monte Carlo (MCMC) simulations [52–54] to incorporate multiple sources of uncertainty for assigning CODs based on the highest probability [17]. For assigning CODs, ChatGPT-3.5 and ChatGPT-4 require prompts containing conversation-like textual instructions as

input, while InterVA-5 and InSilicoVA require structured symptom and associated sociodemographic data as input.

### 2.2.2 Input Data and Model Parameters

For ChatGPT-3.5 and ChatGPT-4, text prompts were generated for each record as input to instruct the models to assign CODs based on the open narratives. Parameter `t_prob` was set to 0.3. Prompts were generated with a template involving `<narrative>` from the free-text open narratives, and associated `<age>`, (age) `<unit>`, `<sex>` from the standardized questionnaire:

```
Determine the underlying cause of death and provide a ICD-10 code  
for the following narrative based on a verbal autopsy of a death in  
Sierra Leone, Age <age> <unit>, <sex>: <narrative>
```

For InterVA-5 and InSilicoVA, the standardized questionnaire data from the HEAL-SL EVA were first converted into 2016 World Health Organization (WHO) VA questionnaire revision 1.5.1 Open Data Kit (ODK) format [55], followed by further conversion into OpenVA format [49] using the `pyCrossVA` Python package [56], and used as input for InterVA-5 and InSilicoVA. The `Nsim` (number of iterations to run) parameter for InSilicoVA was set to 10,000, while the `HIV` (level of prevalence of human immunodeficiency virus) and `Malaria` (level of prevalence of Malaria) parameters were both set to '`h`' (high).

The 6942 physician agreed records were all converted into instructional text prompts for ChatGPT-3.5 and ChatGPT-4. Only 6897 of the 6942 physician agreed records were converted into OpenVA formatted records for InterVA-5 and InSilicoVA, where 45 records caused conversion errors and were skipped or removed.

### 2.2.3 Output Data with CGHR-10 Codes

Of the 6942 physician agreed records, ChatGPT-3.5 and ChatGPT-4 were able to assign CODs for 6932 and 6912 records respectively, while InterVA-5 and InSilicoVA both assigned CODs for 6833 records. All 6833 records with WHO VA 2016 v1.5 codes [57] from InterVA-5 and InSilicoVA output were converted into ICD-10 codes. After all model outputs contained ICD-10 codes, they were further converted to CGHR-10 codes that generalized ICD-10 codes into 19, 10, and 7 categories for the adult (12 years or older), child (28 days to 11 years), and neonatal (under 28 days) age groups (see Additional file 2). The 6932 and 6912 records with ICD-10 codes from ChatGPT-3.5 and ChatGPT-4 output were converted into CGHR-10 codes, resulting in 6894 and 6857 records, where 38 and 55 records did not have matching CGHR-10 codes respectively. The 6833 records with ICD-10 codes from InterVA-5 and InSilicoVA output were also converted into CGHR-10 codes, resulting in 6805 and 6729 records, where 28 and 104 records did not have matching CGHR-10 codes respectively. The 6942 physician agreed records with COD assignments in ICD-10 were also converted to CGHR-10 codes, which resulted in 6939 physician agreed records for comparison across physician and model assignments (three records in ICD-10 were not captured by the CGHR-10 ranges).

## 2.3 Comparing Models to Physician COD Assignment

The performance of four models, ChatGPT-3.5, ChatGPT-4, InterVA-5, and InSilicoVA, were evaluated with metrics on the population and individual level by comparing their CGHR-10 COD outputs to 6939 physician agreed records. Cause Specific Mortality Fraction (CSMF) accuracy was used to evaluate models on the population level, while Partial Chance Corrected Concordance (PCCC) was used to evaluate models on the individual level [58]. Records that were assigned a COD by physicians, but not by a model were considered to be an incorrect COD assignment by the model. CSMF accuracy and PCCC were calculated for each model by three age groups, and further into age ranges and cause of death for each age group.

### 2.3.1 Cause Specific Mortality Fraction (CSMF) Accuracy

CSMF accuracy measures the performance of models at the population level, comparing distributions of CODs between the physicians and the models [58]. To calculate CSMF accuracy, we first calculate  $CSMF_j$  as is the fraction of physician or model records for cause  $j$ , given by dividing the number of records for cause  $j$  with the total number of records as seen in Equation 1. Then, the  $CSMFMaximumError$ , representing the worst possible model, is calculated using Equation 2. Finally, the CSMF accuracy is given by Equation 3, where  $k$  is the number of causes,  $j$  is a cause,  $CSMF_j^{true}$  is the true physician CSMF for cause  $j$ , and  $CSMF_j^{pred}$  is the prediction model CSMF for cause  $j$ . CSMF accuracy ranges from 0 to 1, where 1 means that the model completely matched the physician COD distribution and 0 means that it did not match the distribution at all.

$$CSMF_j = \text{Records}_j / \text{Records} \quad (1)$$

$$CSMFMaximumError = 2(1 - \text{Min}(CSMF_j^{true})) \quad (2)$$

$$CSMFAccuracy = 1 - \frac{\sum_{j=1}^k |CSMF_j^{true} - CSMF_j^{pred}|}{CSMFMaximumError} \quad (3)$$

### 2.3.2 Partial Chance Corrected Concordance (PCCC)

PCCC measures the performance of models at the individual level, comparing COD assignments between the physicians and models on a record by record basis, correcting for COD assignments made purely by chance [58]. PCCC is given by Equation 5, where  $k$  is the number of top COD assignments from the model to consider,  $N$  is number of causes, and  $C$  is fraction of records where the physician COD assignment is one of the top COD assignments from the model. For this study, we set  $k$  to 1, making  $C$  equivalent to the fraction of true positives  $TP$  or records where the physician COD assignment is equal to the model COD assignment as shown in Equation 4. Higher PCCC values closer to 1 indicate that model COD assignments are similar to physician COD assignments, while values closer to 0 indicate that model COD assignments are not similar to physicians.

$$C = \frac{TP}{Records} \quad (4)$$

$$PCCC(k) = \frac{C - \frac{k}{N}}{1 - \frac{k}{N}} \quad (5)$$

### 2.3.3 Metrics Overall and by Age and Cause of Death

The CSMF accuracy and PCCC metrics were calculated and compared for each model overall and by age group, followed by age ranges and cause of death for each age group as model performance can vary across ages and specific causes [47, 48, 59]. Metrics were calculated overall for three age groups: adult (12 years or older), child (28 days to 11 years), and neonatal (under 28 days). For each of the adult and child age groups, metrics were calculated for five-year age ranges for records with ages at death of one-year or older and five-month age ranges for 28 days or older. For the neonatal age group, the age ranges of 0-6 days and 7-27 days were used. Metrics were also calculated by CODs defined by CGHR-10 codes, which include 19, 10, and 7 CODs for adult, child, and neonatal records respectively.

## 3 Results

x.

## 4 Discussion

Discussions should be brief and focused. In some disciplines use of Discussion or ‘Conclusion’ is interchangeable. It is not mandatory to use both. Some journals prefer a section ‘Results and Discussion’ followed by a section ‘Conclusion’. Please refer to Journal-level guidance for any specific requirements.

## 5 Conclusion

Conclusions may be used to restate your hypothesis or research question, restate your major findings, explain the relevance and the added value of your work, highlight any limitations of your study, describe future directions for research and recommendations.

In some disciplines use of Discussion or ‘Conclusion’ is interchangeable. It is not mandatory to use both. Please refer to Journal-level guidance for any specific requirements.

**Supplementary information.** Additional files were used to supplement this paper:

- Additional file 1: Central Medical Evaluation Agreement 10 (CMEA-10) codes. ICD-10 code ranges considered in physician agreement. (.csv)
- Additional file 2: Centre for Global Health Research 10 (CGHR-10) codes. Codes grouping ICD-10 code ranges into generalized categories. (.csv)

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## Declarations

### Availability of data and materials

The datasets supporting the conclusions of this article are included within the article (and its additional files).

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