

Computer Assisted Verbal Autopsy: Comparing
Large Language Models to Physicians for
Assigning Causes to 6939 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 representative Causes of Death (CODs). Current computer models for COD assignment in VAs perform similar to physicians at the population level, but poorly at the individual level, due to focuses on questionnaire data and neglecting free text from narratives. Recently, a

047 large language model called ChatGPT-4 demonstrated human-level performance
048 on professional and academic exams. ChatGPT-4 shows promise in assigning
049 CODs similar to physicians, but has yet been examined for assigning CODs using
050 VA narratives.

051 **Methods:** 6939 VA records in Sierra Leone from 2019 to 2022 were used to
052 compare four computer models, GPT-3.5, GPT-4, InterVA-5, and InSilicoVA, to
053 physician COD assignment at population and individual levels. Narratives were
054 used for GPT-3.5/4, while questionnaires were used for InterVA-5/InSilicoVA.
055 COD assignments were grouped into general COD categories consisting of 19, 10,
056 and 7 categories for adult, child, and neonatal age groups. Cause Specific Mor-
057 tality Fraction (CSMF) accuracy and Partial Corrected Concordance (PCCC)
058 were used to compare models to physicians at population and individual levels
059 respectively. CSMF and PCCC were evaluated overall and by COD, age group,
060 and age.

061 **Results:** GPT-4 had the best performance overall (0.61 PCCC), followed by
062 GPT-3.5 (0.56 PCCC), and InSilicoVA/InterVA-5 (0.44 PCCC). GPT-4 had
063 the best performance for adult and neonatal records (0.64 and 0.58 PCCC),
064 with GPT-3.5 for child records (0.54 PCCC). All models' performances trended
065 upwards from 1 month to 14 years (\sim 0.1-0.75 PCCC) and downwards from 15-69
066 years (\sim 0.7-0.35) of age. GPT-4, GPT-3.5, and InSilicoVA had the highest per-
067 formances for 17, 9, and 4 of all 30 CODs respectively. At the population level,
068 all models had CSMF accuracies between 0.74-0.79.

069 **Conclusion:** All models performed similarly at the population level, while GPT-
070 3.5/4 and InSilicoVA performed better for some CODs at the individual level.
071 GPT models made improvements over InSilicoVA and InterVA-5. Our research
072 lays the foundation for future work in computer assisted VA, where physicians
073 utilize alternative COD assignments from computer models to help reduce ill-
074 defined codes and physician disagreement.

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

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078 1 Background

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081 In 2019, 41 million people died prematurely from noncommunicable diseases every
082 year, accounting for 74% of all deaths globally [1]. Most of these deaths are preventable,
083 but require adequate resource allocation, guided by evidence, to implement effective
084 interventions and policies that target populations at risk [2]. Thus, reliable counts and
085 diagnoses of deaths enable decision makers to identify populations at risk to save lives
086 and reduce premature deaths worldwide [3–6]. However, many low-income countries
087 do not have data on deaths or have registered less than half of the deaths in their
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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].	093 094 095 096 097 098 099 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138
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. This component has been criticized to be difficult to reproduce due to reliance on physician assignment [15–19]. As an alternative to physician assignment, computer models, such as InterVA [20] and InSilicoVA [17], have 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 utilize 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].	124 125 126 127 128 129 130 131 132 133 134 135 136 137 138
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]. In 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	124 125 126 127 128 129 130 131 132 133 134 135 136 137 138

139 GPT-3, which had notable differences in training data sizes of 5 gigabytes to 45 ter-
140 abytes from web sources that resulted in 117 million to 175 billion parameter models
141 [33]. In March 2023, ChatGPT-4 was released with human-level performance on vari-
142 ous professional and academic exams and benchmarks that outperformed ChatGPT-3
143 [34]. Given the limited usage of free-text open narratives in computer models for
144 determining CODs, and recent advances in LLMs that leverage natural language text
145 prompts, we conducted a study with Sierra Leone deaths from VA in 2019 to 2022 to
146 compare four models, GPT-3.5, GPT-4, InterVA-5, and InSilicoVA, to physicians for
147 determining CODs.
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150 2 Methods

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152 This study details the methods used to compare the COD assignment from four mod-
153 els, GPT-3.5, GPT-4, InterVA-5, and InSilicoVA, to physicians as seen in Figure 1.
154 The initial VA data was filtered for physician agreed records as described in Section
155 2.1. Section 2.2 describes the input and output of the four models for COD assignment,
156 while section 2.3 details the performance evaluation of the models relative to physi-
157 cians using population and individual level metrics. See Appendix A for additional
158 details on the methods used in this study.

159 2.1 Verbal Autopsy (VA) Data

160 Initially, 11,920 records from the HEAL-SL study [35, 36] were collected from dual-
161 coded EVA, where each record was randomly coded by two different physicians that
162 assigned CODs as International Classification of Diseases Revision 10 (ICD-10) codes
163 [37]. For each record, two codes were assigned by two different randomly selected
164 physicians, where codes were evaluated for agreement using Central Medical Evalu-
165 ation Agreement 10 (CMEA-10) codes. CMEA-10 groups a range of similar ICD-10
166 codes together, where if they are in agreement if they are within the same group [38]
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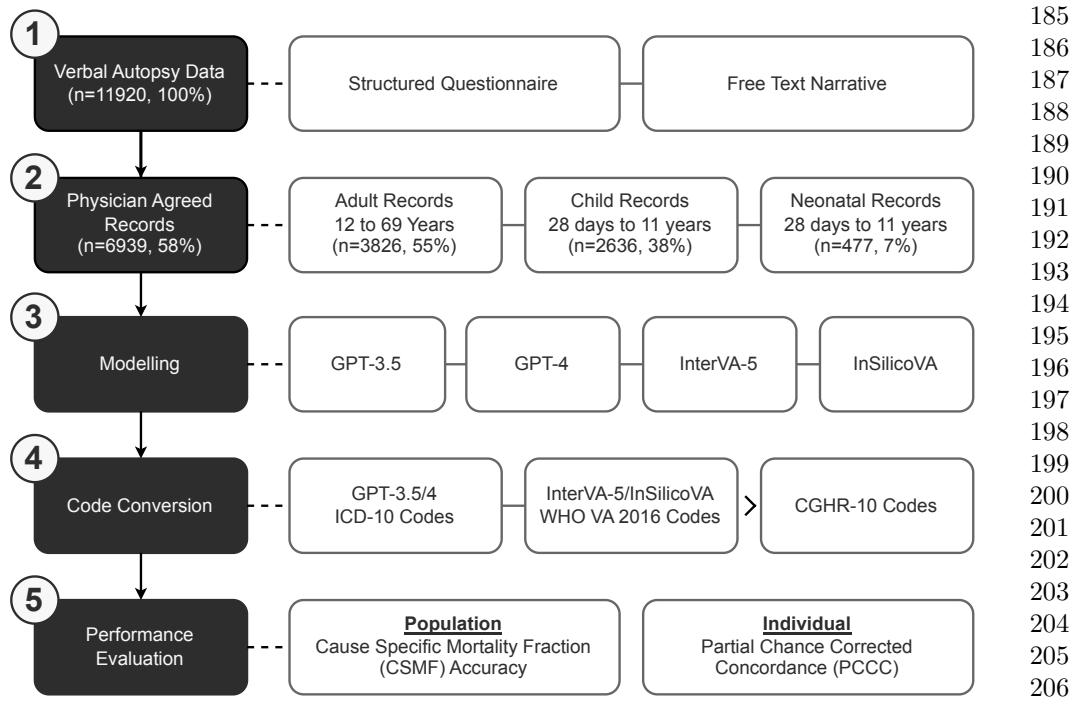


Fig. 1 Study methods.

(see Additional File 2). 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.

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]. Thus, we used 6942 physician agreed records of the 11,920 total records. For better comparison, we standardized all codes to CGHR-10 codes (see Additional File 1) that generalized ICD-10 codes into

231 19, 10, and 7 categories for the adult (12 to 69 years), child (28 days to 11 years), and
232 neonatal (under 28 days) age groups. After conversion, a final total of 6939 physician
233 agreed records (3826 adult, 2636 child, and 477 neonatal) were used for modelling and
234 performance evaluation. See Appendix A.1 for further details on data preprocessing
235 and Tables A1 and A2 for COD and age range distributions of the physician agreed
236 records.

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242 2.2 Modelling

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244 Four computer models were used to assign COD for each of the 6939 physician agreed
245 records: GPT-3.5, GPT-4, InterVA-5, and InSilicoVA. InterVA-5 and InSilicoVA are
246 widely used and studied standard statistical models [13, 21, 22, 24, 25, 41, 42] for COD
247 assignment in VAs under the openVA framework [43]. InterVA-5 applies Bayesian prob-
248 abilistic modelling [44] using a set of standardized symptoms from reports and related
249 conditional probabilities from medical experts to assign CODs based on the highest
250 probability [20, 45]. InSilicoVA improves upon InterVA (e.g. comparable probabilities
251 across individuals, measures of uncertainty, and inclusion of additional data sources)
252 with a hierarchical Bayesian framework and Markov Chain Monte Carlo (MCMC)
253 simulations [46–48] to incorporate multiple sources of uncertainty for assigning CODs
254 based on the highest probability [17]. GPT-3.5 [49] and GPT-4 [34] are LLMs that
255 utilize deep neural networks with transformer architectures [50] and reinforcement
256 learning from human feedback [51–54] to follow instructions from prompts and pro-
257 vide human-level responses, with known differences in GPT-4 possessing multimodal
258 capabilites (e.g. image/voice input/output), more recent training data, and improved
259 responses compared to ChatGPT-3 [33].

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261 For GPT-3.5 and GPT-4, the following user prompt was used to instruct each
262 model to produce COD assignments as ICD-10 codes, where <age> and <sex> from
263 the questionnaire, and <narrative> from the narratives, were replaced with values
264 from the data:

Determine the underlying cause of death and provide the most probable ICD–10 code for a verbal autopsy narrative of a <age> years old <sex> death in Sierra Leone: <narrative>	277 278 279 280 281 282 283 284 285 286 287 288 289 290 291 292 293 294 295 296 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322
For InterVA-5 and InSilicoVA, the standardized questionnaire data from EVA were converted into OpenVA format [43], before being used as input for each model to produce COD assignments as WHO VA 2016 codes [55]. All model outputs were converted to CGHR-10 codes to evaluate performances of models for COD assignment relative to physicians. See Appendix A.2 for additional details regarding input parameters, output data, and code conversions for each model.	
2.3 Performance Evaluation	293 294 295 296 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322
The performance of the four models were evaluated with metrics at the population and individual level by comparing their CGHR-10 COD outputs for 6939 records. Cause Specific Mortality Fraction (CSMF) accuracy was used to evaluate models on the population level (see Appendix A.3.1), while Partial Chance Corrected Concordance (PCCC) was used to evaluate models on the individual level (see Appendix A.3.2) [56]. Both CSMF accuracy and PCCC metrics are between 0 and 1 with 0 indicating low performance and 1 indicating perfect performance at the population and individual level respectively. As model performance can vary across ages and specific causes [41, 42, 57], the CSMF accuracy and PCCC metrics were compared for each model overall, by age group (adult, child, neonatal), by CGHR-10 COD codes, and across ages. For each of the adult and child age groups, metrics were calculated for five-year ages for records with ages at death of one-year or older and five-month ages for 28 days or older. For the neonatal age group, the ages of 0-6 days and 7-27 days were used. See Appendix A.3 for more details on performance metrics and evaluation strategy for comparing each model.	

323 **3 Results**

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325 This section details the performance results of GPT-3.5, GPT-4, InterVA-5, and InSil-
326 icoVA models for assigning CGHR-10 CODs after applying the methods in Section 2.
327 GPT-4 performed the best overall at 0.61 PCCC followed by GPT-3.5 at 0.56 PCCC.
328 GPT-4 also had the highest PCCC for most ages and CODs across the adult (12 to
329 69 years), child (28 days to 11 years), and neonatal (under 28 days) age groups with
330 GPT-3.5, InterVA-5, and InSilicoVA having higher PCCC values for a few ages and
331 CODs. Overall performance results are seen in Section 3.1, and performance by adult,
332 child, and neonatal records are seen in Sections 3.2, 3.3, and 3.4 respectively.
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334 **3.1 Overall Performance**

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336 Of all 6939 records, GPT-4 (0.61 PCCC) had the highest individual performance
337 followed by GPT-3.5 (0.56 PCCC), InSilicoVA (0.44 PCCC), and InterVA-5 (0.44
338 PCCC) (Figure 2). GPT-3.5 and GPT-4 had improvements ranging from 0.14-0.18
339 PCCC over InSilicoVA and InterVA-5, while GPT-4 slightly improved over GPT-3.5
340 by 0.05 PCCC. Population level performances were similar for all models (0.74-0.79
341 CSMF). Figure 3 shows the PCCC performance across three age groups (adult, child,
342 and neonate). GPT-4 had the best individual performance for adult and neonatal
343 records (0.64 and 0.58 PCCC), while GPT-3.5 had the best performance for child
344 records (0.54 PCCC) with GPT-4 performing slightly worse (0.51 PCCC). InSilicoVA
345 and InterVA-5 performed the worse for adult and child records (≤ 0.5 PCCC), while
346 GPT-3.5 performed the worse for neonatal records (0.42 PCCC). Across ages, all
347 models followed a similar pattern in individual performance (Figure 4). PCCC trended
348 upwards for 1 month to 14 years ($\sim 0.1-0.75$), and downwards for ages 15 to 69 years
349 ($\sim 0.7-0.35$). The highest and lowest performances were observed for ages 10-29 years
350 (\sim) and 1-11 months respectively. Performances varied more across models for ages 0
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days to 5 years, while less variation was seen between GPT-3.5 and GPT-4, as well as InSilicoVA and InterVA-5, from 5 to 69 years.

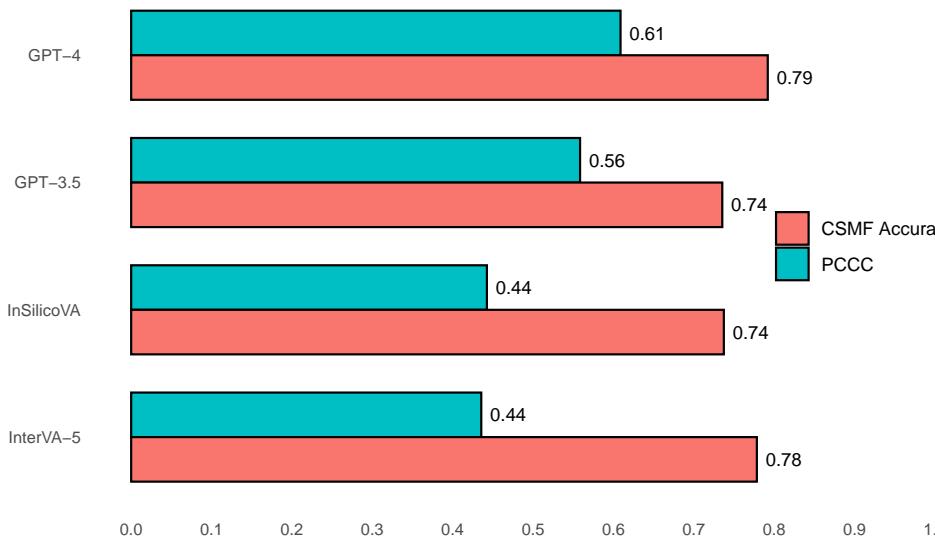


Fig. 2 Overall model performance.

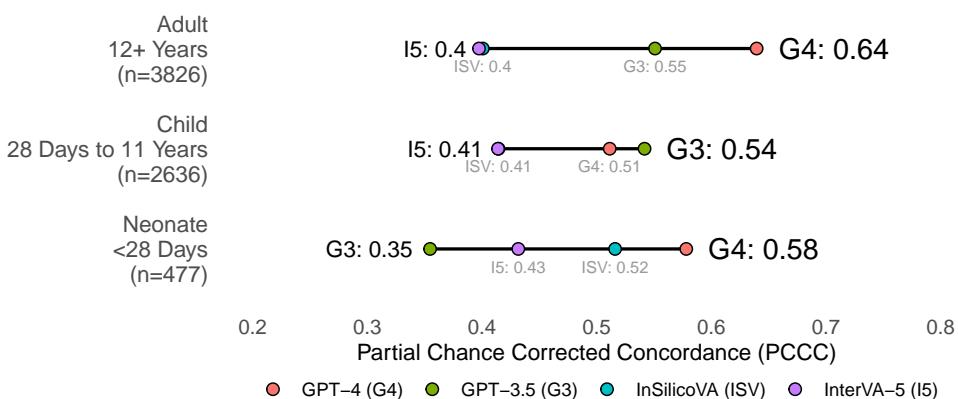


Fig. 3 Model performance by age group.

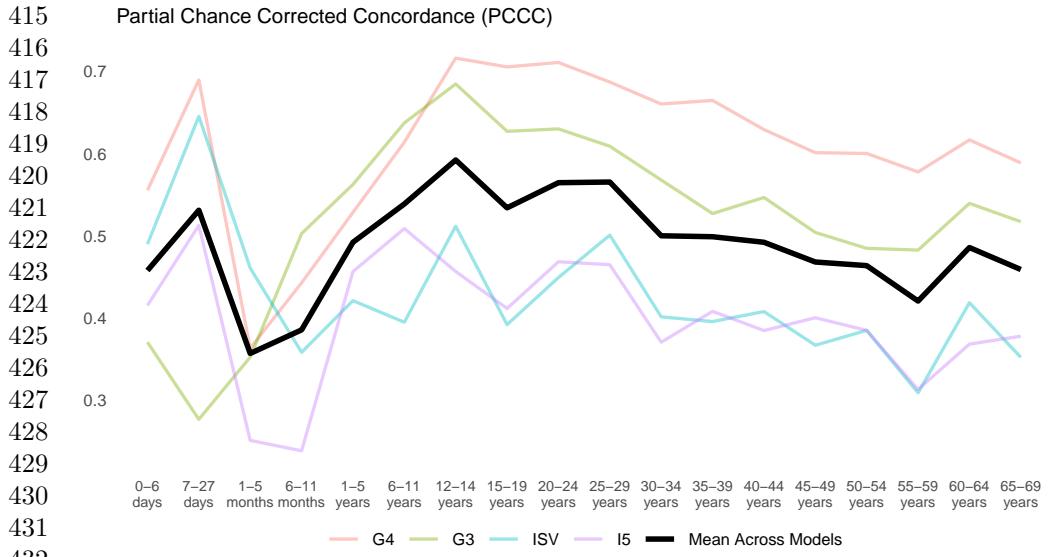


Fig. 4 Model performance by age range.

3.2 Performance for 3826 Adult Records (12 to 69 years)

Figure 5 shows model performance by PCCC across 17 adult CODs excluding suicide due to low sample size ($n=3$, <1%). GPT-4 had the highest individual performance for 10 of 17 CODs (0.35 to 0.99 PCCC), GPT-3.5 for 5 CODs (0.43-0.94 PCCC), and InSilicoVA for 2 CODs (0.71 and 0.84 PCCC). InterVA-5 had the lowest performance for 8 of 17 CODs (0-0.79 PCCC), InSilicoVA for 6 CODs (0.01-0.41 PCCC), and GPT-3.5 for 2 CODs (0.38 and 0.53 PCCC). GPT-3.5/4 models improved over InSilicoVA/InterVA-5 the most for chronic respiratory diseases (0.74-0.94 PCCC difference), and the least for Malaria (0.09-0.17 PCCC difference). All models had >0.7 PCCC for maternal conditions (0.79-0.99 PCCC), while <0.5 PCCC for unspecified infections, malaria, and ill-defined CODs. GPT-4 had performance improvements >0.2 PCCC compared to all other models for cancers (+0.25-0.36 PCCC), stroke (+0.27-0.45 PCCC), and diarrhoeal diseases (+0.37-0.51 PCCC), while GPT-3.5 had similar improvements for liver and alcohol related diseases (+0.27-0.52 PCCC).

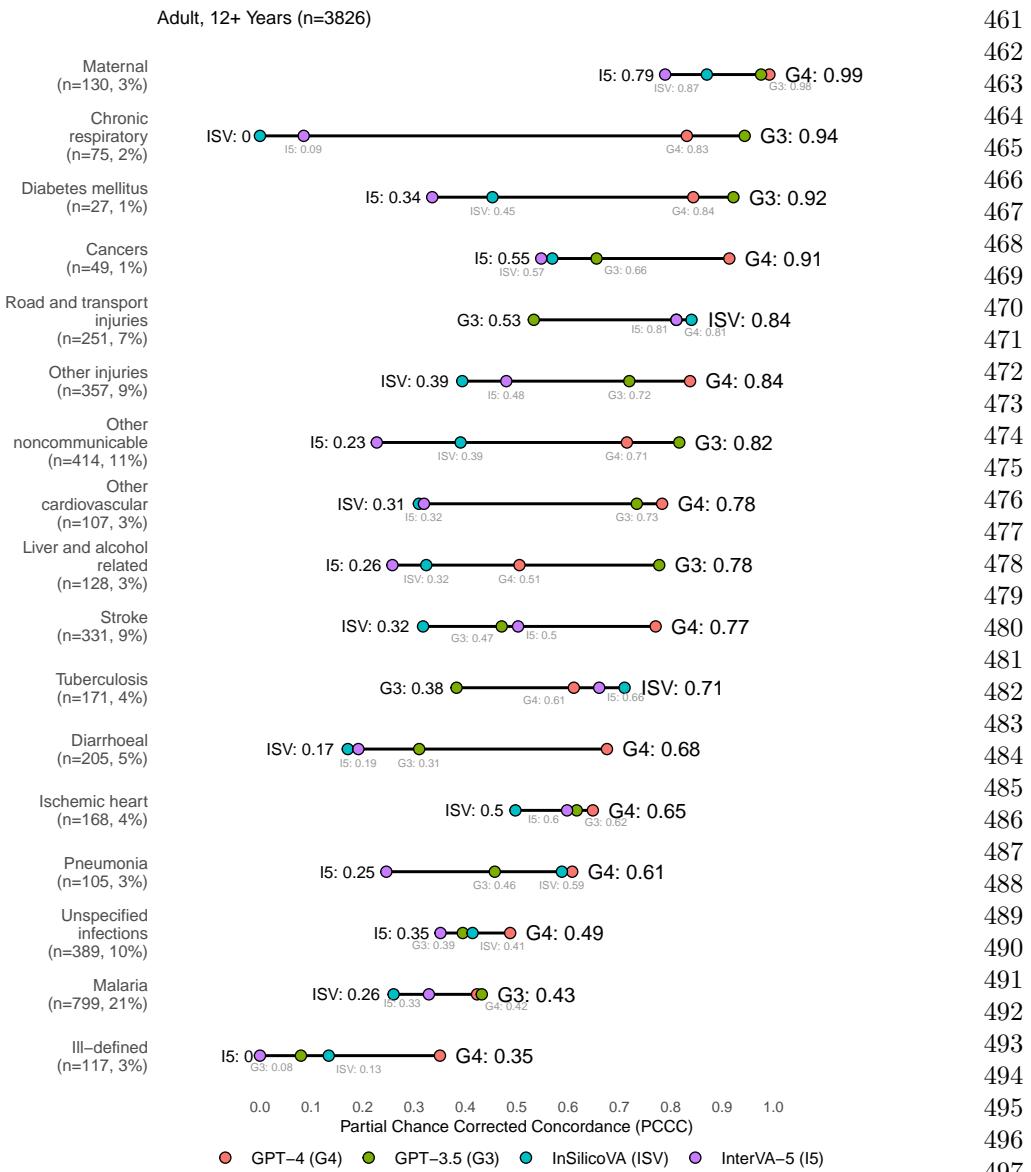


Fig. 5 Model performance for adult records by COD.

3.3 Performance for 2636 Child Records (28 Days to 11 Years)

Figure 6 presents individual performances for each of the models by 8 child CODs, excluding congenital anomalies due to low sample size ($n=1$, <1%). GPT-4 had the

507 highest individual performance for 4 of 8 CODs (0.65-0.94 PCCC), GPT-3.5 for 3
 508 CODs (0.44-0.88 PCCC), and InSilicoVA for 1 COD (0.78 PCCC). InterVA-5 had
 509 the lowest performance for 4 of 8 CODs (0.09-0.79 PCCC), InSilicoVA for 3 CODs
 510 (0-0.35 PCCC), and GPT-3.5 for 1 COD (0.58 PCCC). All models had >0.7 PCCC
 511 for injuries (0.79-0.94 PCCC), and <0.6 PCCC for malaria (0.35-0.54 PCCC) and
 512 other infections (0.29-0.44 PCCC). GPT-4 had improvements >0.3 PCCC compared
 513 to other models for ill-defined CODs (+0.38-0.65 PCCC), and larger improvements
 514 over other models for injuries (+0.11-0.15 compared to +0.01-0.04 PCCC).
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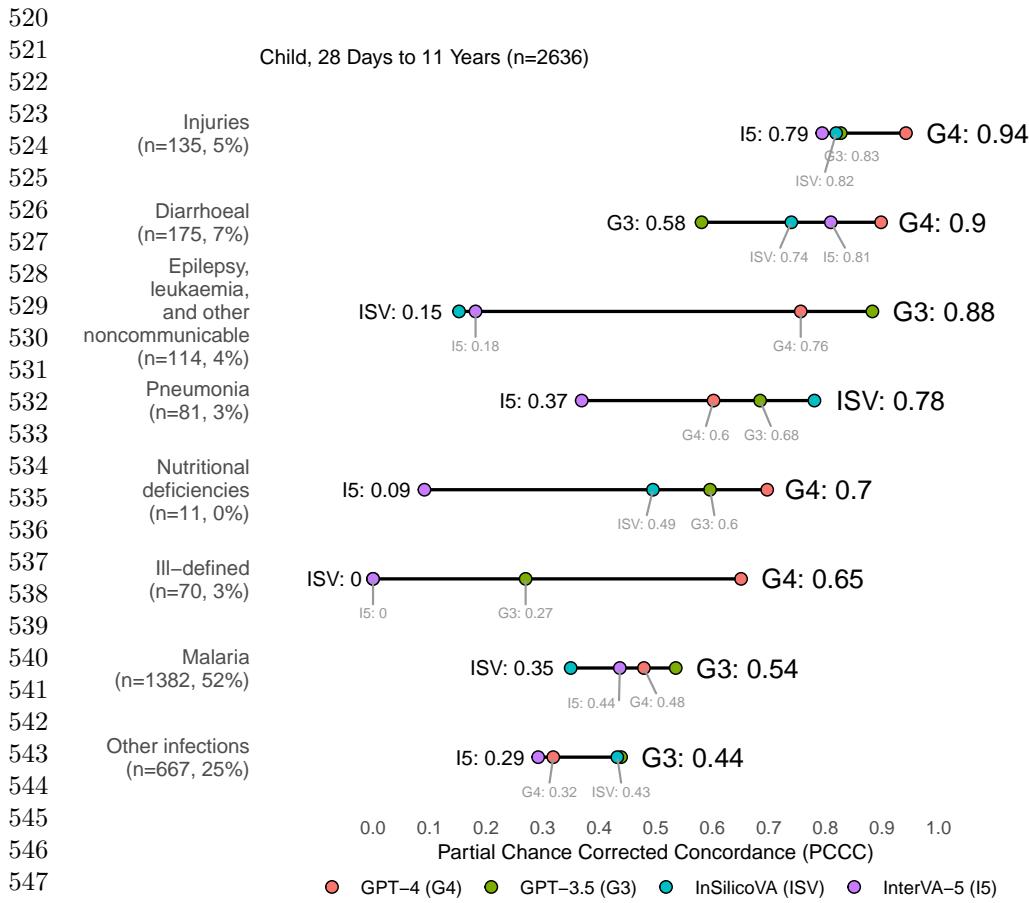


Fig. 6 Model performance for child records by COD.

3.4 Performance for 477 Neonatal Records (Under 28 Days)

Model performance across 5 neonatal CODs, excluding congenital anomalies (n=2, <1%) and other (n=5, 1%) due to small sample sizes is shown in Figure 7. GPT-4 had the highest individual performance for 3 of 5 CODs (0.39-0.71 PCCC), GPT-3.5 for 1 COD (0.57 PCCC), and InSilicoVA for 1 COD (0.86 PCCC). GPT-3.5 had the lowest performance for 3 of 5 CODs (0-0.13 PCCC) and InterVA-5 for 2 CODs (0.01 and 0.48 PCCC). All models had similar performance for stillbirth deaths (0.48-0.57 PCCC), while only GPT-4 had a PCCC >0 PCCC. InSilicoVA had improvements over all other models for neonatal infection deaths (+0.18-0.73 PCCC).

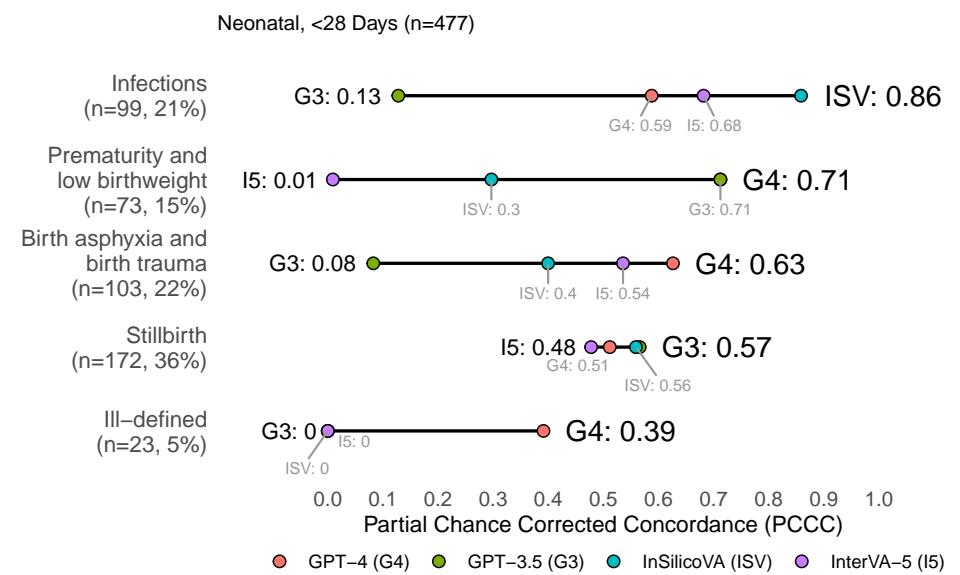


Fig. 7 Model performance for neonatal records by COD.

4 Discussion

This section discusses and summarizes the results from Section 3. Advantages and disadvantages of using GPT-3.5, GPT-4, InterVA-5, and InSilicoVA models for assigning

599 CODs are discussed in Sections 4.1 and 4.2. Limitations of the study are mentioned
600 in Section 4.3, while opportunities and future work are detailed in Section 4.4.
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603 4.1 Advantages

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605 This section identifies the advantages of models for assigning CODs. Section 4.1.1
606 details the application of models for particular CODs and ages. Section 4.1.3 details
607 the resource efficiency of computer models for assisting in physician COD assign-
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609 ment. Section 4.1.4 notes the strength of using natural language text in GPT models
610 compared to structured questionnaire data for physician COD assignment.
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613 4.1.1 Cause-specific Models

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615 At the population level, overall performances for all models were similar to physicians
616 (0.74-0.79 CSMF), indicating potential for adequately estimating COD distributions
617 for large populations. Although all models did not perform well for all records at
618 the individual level (0.44-0.61 PCCC), several models performed well for certain
619 CODs (0-0.99 PCCC). For most CODs, GPT-3.5/GPT-4 performed better than
620 InSilicoVA/InterVA-5 (top PCCC for 15 of 17, 7 of 8, and 4 of 5 adult, child, and
621 neonatal CODs respectively), while InSilicoVA performed better for particular CODs
622 (road and transport injuries, tuberculosis, pneumonia, and neonatal infections with
623 0.84, 0.71, 0.78, and 0.86 PCCC respectively). For CODs with high performance (e.g.
624 GPT-3.5/4 with 0.91-0.99 PCCC for maternal conditions, chronic respiratory disease,
625 diabetes melitus, and cancers, InSilicoVA with 0.84 and 0.86 PCCC for road and
626 transport injuries, and neonatal infections), the results suggest that GPT-3.5/4 and
627 InSilicoVA may assign CODs that are very similar to physicians. Thus, it may be ben-
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629 efitcial to evaluate performance at the COD level, and apply a combination of models
630 that perform well in comparison to physicians for each COD. For example, different
631 models perform well for various leading CODs as seen in Table 1 [58, 59].
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Table 1 Leading causes globally in 2021 and most relevant models.

Leading Causes of Death (~53% of 68M deaths) ¹	Deaths (% of 68M) ²	Best Model(s)	PCCC	
Ischaemic heart disease	9M (13%)	GPT-4	0.65 (n=168)	645
Stroke	7M (10%)	GPT-4	0.77 (n=331)	646
Cancers	4.3M (4%)	GPT-4	0.91 (n=49)	647
Lower respiratory infections	2.4M (3%)	GPT-3.5/4	0.78 (n=180) ³	648
Diabetes mellitus	1.6M (2%)	GPT-3.5	0.92 (n=27)	649
Tuberculosis	1.4M (2%)	InSilicoVA	0.71 (n=171)	650
Hypertensive heart disease	1.4M (2%)	GPT-4	0.78 (n=107) ⁴	651
Cirrhosis of the liver	1.3M (2%)	GPT-3.5	0.78 (n=128) ⁵	652
Diarrhoeal diseases	1.2M (2%)	GPT-4	0.68 (n=205)	653
Road injury	1,183 (2%)	InSilicoVA	0.84 (n=357)	654
Preterm birth complications	0.9M (1%)	GPT-4	0.71 (n=73)	655
Falls	0.7M (1%)	GPT-4	0.89 (n=492) ⁶	656
				657
				658

¹COVID-19, kidney disease, alzheimer disease, other dementias, and self-harm were excluded as a relevant CGHR-10 code was not present. Trachea, bronchus, lung, colon, rectum, stomach, and breast cancers were generalized into cancers.

²Percentage of ~68 Million (M) deaths globally. Numbers are rounded.

³Mean of chronic and acute respiratory infections.

⁴Derived from other cardiovascular diseases.

⁵Derived from liver and alcohol related diseases.

⁶Mean of adult and child injuries.

4.1.2 Age-specific Performance Patterns

Across ages, all models followed a similar upward trend from 6 months to 14 years of age, and a downward trend from 15-69 years with GPT models having higher performance than InSilicoVA/InterVA-5 models, while more mixed trends were observed from 0 days to 5 months (recall Figure 4). For adult ages, performance generally decreased as age increased, which suggested that models had difficult assigning CODs for older than younger adults with some improvements after the age of 59. For child and neonatal ages, the performance improved drastically as the age increased after 5 months, suggesting less difficulty in COD assignment when children and neonates are more developed. As the models did not perform particularly well (≥ 0.8 PCCC) for any specific five-year age range, it is not recommended to apply specific models that target cases by age. However, the patterns of increases and decreases of performance in

691 relation to age provide valuable insight for comparison to expected physician diagno-
692 sis patterns in well-studied medical literature and knowledge. For example, it may be
693 expected that physicians are more uncertain in diagnosing diseases that are prevalent
694 in neonatal patients [60, 61], which are present in our findings from Figure 4.
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698 **4.1.3 Scalability and Availability**

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701 The models in this study can assist physicians in assigning CODs in a variety of ways
702 due to low costs and speed of COD assignment. Similar to differential diagnoses, GPT
703 and InSilicoVA models offer alternative COD assignments for physicians to consider
704 [39], which can potentially help lower the number of records with ill-defined causes or
705 reduce disagreement between physicians. At the time of this study, running GPT-3.5
706 cost ~\$1.6 USD (\$0.5 per one million tokens), GPT-4 cost ~\$115 USD (\$30 per one
707 million tokens), and InSilicoVA was cost free on 6939 records [62]. These costs were
708 lower than physicians (e.g. less than \$3 USD per house in India [15, 16]), while it is
709 possible to code over 10,000 records in under a day. When physicians are unavailable,
710 GPT and InSilicoVA models can be a cost-efficient alternative to code large amounts
711 of records for population estimates of CODs. However, it is recommended to apply
712 these models only for certain CODs where models perform well, such as in Table 1. In
713 addition, these models can also help divert physician resources to cases that are more
714 difficult to code or require more attention. For example, physicians can validate cases
715 where models performed well (e.g. maternal conditions at 0.79-0.99 PCCC), while
716 spending more time on cases where models performed poorly (e.g. acute respiratory
717 infections at 0.25-0.61 PCCC).
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720 **4.1.4 Natural Language Input and Output**

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722 Training data was not required to assign CODs for all models, which allowed appli-
723 cation without domain expertise or supplying training datasets. The main advantage
724 to GPT-3.5/4 was the use of natural language text as input and output. Compared
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735 to GPT-3.5/4 was the use of natural language text as input and output. Compared
736 to GPT-3.5/4 was the use of natural language text as input and output.

to InterVA-5 and InSilicoVA, GPT models were able to assign COD codes in ICD-10 standard, as physicians do, and potentially assign CODs in more broad categories depending on the prompts. In comparison, InterVA-5 and InSilicoVA relied on structured input and output data from WHO VA 2016 questionnaires, and assigned CODs in WHO VA 2016 codes only. This required that these codes and forms be maintained with conversions between different form (e.g. WHO VA 2012 to WHO VA 2016) and code standards (e.g. WHO VA 2016 to ICD-10), which reduces interoperability and comparability with other incompatible models. GPT models did not require strict formats for training and testing data, which can capture latent and more ambiguous patterns (e.g. health-seeking behaviours and social issues) outside the scope of WHO VA codes and forms [26, 28]. For example, GPT-3.5/4 had higher performance (+0.35-0.65 PCCC) than InterVA-5 and InSilicoVA for ambiguous ill-defined records across age groups. GPT models also performed better (+0.11-0.61 PCCC) on CODs with a rarer occurrence, such as nutritional deficiencies (n=11) and diabetes mellitus (n=27). Rarer CODs may be more difficult to capture by questionnaire due to lack of sample data, but it may possibly have richer contextual information from articles, web sources, or books that offer knowledge for GPT models to leverage.

4.2 Disadvantages

This section discusses the disadvantages of GPT models for COD assignment. Section 4.2.1 identifies issues in reproducing GPT outputs for repeated runs on the same records and lack of up-to-date information, while Section 4.2.2 discusses the resource intensive infrastructure required by GPT and its relation to data privacy.

4.2.1 Reproducibility and Timeliness

Recall that the GPT models in this study had the temperature parameter set to 0 for more reproducible and reliable results. A short experiment in Appendix B revealed that GPT-3.5 assigns the same COD for the same record only more than 60% of the

783 time, based on repeated runs on a sample of 100 records. This suggests that GPT
784 models do not always reliably assign identical CODs for the same case on multiple runs,
785 which may pose issues in reproducibility and reliability. For example, GPT models
786 may achieve correct COD assignments solely due to random chance, but are difficult to
787 test with large numbers (e.g. 10,000) of reruns due to costs (e.g. costs increased 10 fold
788 per record when rerun 10 times). In comparison, InterVA-5 and InSilicoVA are open
789 source and free, allowing a large number of reruns without incurring additional fees.
790 In addition, InterVA-5 and InSilicoVA assign CODs and provide probabilities for each
791 alternative COD, which offers more reproducible and reliable COD assignments despite
792 lower performance overall. Lastly, a major disadvantage in all models was that they
793 were trained on historical data up to particular points in time, which may not utilize
800 the most up-to-date data available (e.g. latest online articles, social media, or books
801 for GPT models). Emergent diseases (e.g. COVID-19) and changes in distributions
802 (e.g. outbreaks) may not be caught by these models depending on how often they are
803 updated.
804

805 **4.2.2 Infrastructure and Data Privacy**

806 GPT-3.5 and GPT-4 models required large computing infrastructure to train and run,
807 which was not possible to run on local computers, or setup due to costs and ownership
808 of the models. This poses issues with data privacy as sensitive data (e.g. identifying
809 information) need to be sent to company servers, which can be collected by companies
810 (e.g. OpenAI) and misused [63]. For example, in our study, GPT models use prompts,
811 which contain the narrative data, to assign CODs, and the data in these prompts
812 may be unknowingly collected and misused by companies (e.g. companies) or their
813 users (e.g. malicious prompts) to identify participants or leak sensitive sensitive data
814 [64, 65]. In contrast, InterVA-5 and InSilicoVA can be run on local computers, which
815 allows data to stay with the owner to protect data privacy, without reliance on external
816 services.

4.3 Limitations	829
	830
This section identifies limitations in this research in the context of GPT models.	831
Section 4.3.1 identifies the omission of ICD-10 performance evaluations. Section 4.3.2	832
mentions the need for parameter tuning and evaluation of consistency and multiple	833
COD assignments.	834
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4.3.1 ICD-10 Evaluation and Low Sample Sizes	839
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For the scope of this study, all models were evaluated for their performance in broad	841
CGHR-10 COD categories as opposed to more specific ICD-10 codes. However, in	842
practical cases, physicians assign more specific ICD-10 codes rather than broader COD	843
categories. InterVA-5 and InSilicoVA assigned broader WHO VA codes, and were	844
unable to assign ICD-10 codes, as the number of cases for specific ICD-10 codes are	845
often low and inadequate for training statistical models. In relation, some broader	846
CGHR-10 CODs were even removed for performance evaluation as <10 cases were	847
captured (e.g. congenital anomalies, suicide). Although GPT models were able to	848
assign ICD-10 codes, lower performance may be expected as even physicians do not	849
agree completely on ICD-10 codes, noted that broader categories (CMEA-10 codes in	850
Additional file 2) were used to assign equivalency or agreement.	851
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4.3.2 Model Tuning, Consistency, and Multiple Outputs	860
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GPT-3.5 and GPT-4 models used default parameters with the exception of setting	862
the temperature to 0 for more consistent results. However, the temperature and other	863
model settings may be adjusted to possibly improve performance for GPT models	864
[66]. This was not examined as sensitivity analyses on model parameters are costly	865
across multiple reruns, noted in Section 4.2.1, which is required when testing various	866
parameter settings. In addition, GPT models may possibly produce inconsistent results	867
even with the temperature set to 0. Thus, it is important to also test the reliability	868
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875 and consistency of GPT outputs to avoid coincidental results due to randomness [67–
876 69]. InterVA-5 and InSilicoVA were able to provide multiple COD assignments with
877 probabilities for each COD. GPT models can be prompted to produce more than one
878 COD assignment, but was not explored in this study as we only evaluated the most
880 probable COD. This may be useful to evaluate the performance of multiple alternative
881 COD assignments, which may provide additional diagnoses that have a higher chance
882 of being similar to physician assignment, and better reflect causes leading to death
883 [19].

888

889 **4.4 Opportunities**

890 This section discusses research opportunities to improve GPT models for assigning
891 CODs. Section 4.4.1 discusses the potential to improve GPT models with prompt
892 engineering and exploration of misclassified records, while Section 4.4.2 describes the
893 application of GPT models for improving household surveys for better data quality.
894 Section 4.4.3 identifies an opportunity to integrate GPT, InterVA-5, and InSilicoVA
895 models into VA systems for improving physician COD assignment.

896

897 **4.4.1 Prompt Engineering and Custom Models**

898 Prompt engineering, the design of prompts to guide GPT models for better results [70],
899 presents an important research opportunity that may improve performance of GPT
900 models for COD assignment. An example exploration was conducted in Appendix C on
901 misclassified GPT-4 records for neonatal infections, which found potential issues with
902 the categorization of CGHR-10 codes, order of information in narratives, and guide-
903 lines of COD assignments. An analysis of misclassified records with domain experts
904 (e.g. physicians, specialists) may yield insights on adjusting prompts to assign more
905 correct CODs, or apply more relevant broad COD categories for evaluation. In addi-
906 tion, subsequent prompts, data, and examples can be used to include correctional
907 instructions and refine results, while additional information from the questionnaire and
908

physician VA manuals can provide contextual information (e.g. retrieval augmented generation [71]) for further performance improvements [72]. Sensitivity analyses may be conducted to assess the effects on performance and consistency of results from modified prompts on a COD basis. GPT models may also be customized to specific domains or contexts, where objectives, behaviours, extra data, privacy, and evaluation tests can be adjusted to produce custom models that perform better in targeted domains or circumstances (e.g. custom models for particular CODs) [73].

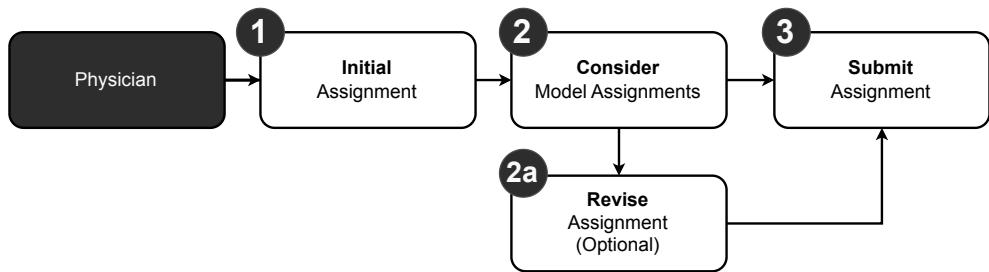
4.4.2 Guided and Monitored Household Surveys

Recall that VAs involve surveyors that visit households to gather information about the deceased from their family, next-of-kin, friend, or community. Although standard questionnaires are used during this visit, there is significant information, containing latent patterns, from the narrative that is not always captured by the questionnaire [26, 28]. These narratives often require a human connection between the surveyor and household members, where surveyor characteristics vary in social ability, cultural understanding, emotional capacity, and medical knowledge that affect the quality and bias of narratives [19, 74]. GPT models may help guide surveyors during VA interviews to probe households for better narrative information by generating and suggesting better questions, or providing questions that may have been missed by the surveyors. In addition, as models can assign CODs on-demand, there is potential for models to provide immediate COD estimates during the data collection process to monitor data quality on-demand (e.g. comparing estimated to expected COD distributions for known areas as quality checks).

4.4.3 Computer Assisted Verbal Autopsy

Our study lays the foundation for the integration of GPT, InterVA-5, and InSilicoVA models into VA systems to assist physicians in COD assignment. In dual-coded VA systems (described in Section 2.1), two physicians are randomly assigned to each record

967 and require second inspections of each other's assignment (reconciliation) and evalua-
 968 tion by a third more senior physician if their assignments do not agree. As mentioned
 969 in Section 4.1.3, suggestion of alternative assignments from GPT and InSilicoVA mod-
 970 els potentially reduces the disagreement between physicians, and ill-defined records,
 971 while allowing physicians to focus on more difficult records. Thus, model suggestions
 972 can be integrated into VA systems by presenting COD suggestions to physicians after
 973 their initial COD assignment, which allows them to consider alternative assignments
 974 and possibly revise their assignments based on the suggestions. At step 2 in Figure 8,
 975 GPT, InterVA-5, and InSilicoVA models can suggest COD assignments to consider,
 976 providing the option in step 2b to revise or proceed with their initial assignment.
 977 Our future work will be a first step in computer assisted verbal autopsy, assessing the
 978 effects of these model suggestions on improve VA data quality (e.g. increase in agreed
 979 records, reduction of ill-defined deaths). In preparation, we have integrated GPT-
 980 4, InterVA-5, and InSilicoVA model suggestions into our on-going HEAL-SL study
 981 after survey round 2 [35] with goals of increasing physician agreement and reducing
 982 ill-defined COD assignments.
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 995 **Fig. 8** Model suggestions integrated in the physician assignment process.
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5 Conclusion	1013
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This study evaluates the performance of GPT-3.5, GPT-4, InterVA-5, and InSilicoVA models compared to physicians for assigning CODs for 6939 VA records in Sierra Leone (2019-2022). At the population level, all models were similar (0.74-0.79 CSMF accuracy). At the individual level, GPT-4 had the best performance (0.61 PCCC), followed by GPT-3.5 (0.58 PCCC), and InSilicoVA/InterVA-5 (0.44 PCCC). Across CODs, GPT-4 had performed best for 10 of 17 adult, 4 of 8 child, and 3 of 5 neonatal CODs, with GPT-3.5 for 5 adult, 3 child, and one neonatal CODs, and InSilicoVA for 2 adult, one child, and one neonatal CODs. Model performance increased (~0.1-0.75 PCCC) as children and neonates developed (0 days to 14 years), and decreased (~0.7-0.35) as adults aged (15 to 69 years). Thus, GPT and InSilicoVA models were comparable to physicians for several CODs, but not across ages. As performance varied across CODs and ages, it is advantageous to combine several models to target CODs that each model performs well for, and to compare age-related performance patterns in relation to physicians. In addition, all models were able to scale to a large number of records and were available on-demand in comparison to physicians, enabling COD estimation and alternative diagnoses in low resource or physician scarce scenarios. As GPT models operate on natural language, they are able to adapt to more loosely defined data structures (e.g. assign in different COD coding standards, provide reasoning, and use contextual information when samples are low), making them behave more similarly to physician assignment. However, GPT models do not provide reliable CODs on repeated assignment, and were limited to past training data, with large computing infrastructure requirements, leading to reproducibility issues in COD assignments, difficulty adapting to new or changing CODs, and data privacy issues. Limitations of this study included difficulty comparing ICD-10 codes directly due to incompatible COD outputs from each model and low sample sizes, difficulty in conducting sensitivity analyses for GPT models due to costs, and omitting evaluation of	1015 1016 1017 1018 1019 1020 1021 1022 1023 1024 1025 1026 1027 1028 1029 1030 1031 1032 1033 1034 1035 1036 1037 1038 1039 1040 1041 1042 1043 1044 1045 1046 1047 1048 1049 1050 1051 1052 1053 1054 1055 1056 1057 1058

1059 multiple COD assignments due to study scope. We identified research opportunities
1060 in refining GPT models using prompt engineering and custom models for improving
1061 performance, guided household surveys to improve narrative quality, and future work
1062 1063 in computer assisted VA, where GPT and other models will be used to assist physician
1064 1065 COD assignment by offering multiple alternative assignments, with goals of increasing
1066 1067 agreement on COD assignment and reducing ill-defined deaths. GPT-4, InterVA-5,
1068 1069 and InSilicoVA has been integrated into future survey rounds of the HEAl-SL study
1070 1071 from 2022 onwards, offering alternative COD assignments to assist physicians with
1072 1073 second opinions. Future work in evaluating the effectiveness of computer assisted VA
1074 1075 to reduce disagreements among physicians and ill-defined deaths will help support the
1076 advancement of more accurate and efficient VA systems across the world.
1077

1078 **Supplementary information.** Additional files were used to supplement this paper:
1079

- 1080 • Additional file 1: Centre for Global Health Research 10 (CGHR-10) codes. Codes
1081 grouping ICD-10 code ranges into generalized categories. (.csv)
1082
1083 • Additional file 2: Central Medical Evaluation Agreement 10 (CMEA-10) codes. ICD-
1084 10 code ranges considered in physician agreement. (.csv)
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1086

1087 **Acknowledgments.** TBD.
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1090 **Declarations**

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1092

1093 **Funding**

1094
1095 TBD.
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1097

1098 **Competing interests**

1099
1100 Not applicable.
1101
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Ethics approval	1105
Not applicable.	1106
	1107
	1108
	1109
Consent for publication	1110
Not applicable.	1111
	1112
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Availability of data and materials	1115
The datasets supporting the conclusions of this article are included within the article (and its additional files), at https://openmortality.org (available upon request) and at https://github.com/cghr-toronto/heasl-gpt-paper . Verbal Autopsy (VA) and narra- tive data by age group and survey rounds 1 and 2 available at https://openmortality.org/dataset/heal-sl . Cause of death code mappings to convert between ICD-10, WVA-2016, and CGHR-10 codes available at https://openmortality.org/dataset/icd . Model evaluation result files at https://github.com/cghr-toronto/heasl-gpt-paper/tree/main/data .	1116
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Code availability	1132
All code for this paper is available at https://github.com/cghr-toronto/heasl-gpt-paper .	1133
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Authors' contributions	1139
PJ and PB are the study Principal Investigators. ATA and RK implemented the data collection procedures. RW, and TKSN processed, documented, and prepared the data. RW, ASL, and RK ran the models. RW wrote the paper and conducted the analysis. AB and RCM provided medical domain guidance and feedback. All authors reviewed the results and contributed to the report. All authors read and approved the final manuscript.	1140
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1151 **Appendix A Details on Methods**

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1153 This section provides additional details on the methods described in Section 2. An
1154 overview of the methods used in this study is seen in Figure A1 as a five-step process.
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1156 Section A.1 provides details on the preprocessed data used for modelling. Section A.2
1157 describes the data and parameter inputs and outputs for each model, while Section
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1159 1160 A.3 details the evaluation of model outputs at the individual and population level
1161 across different CODs, age groups, and ages.

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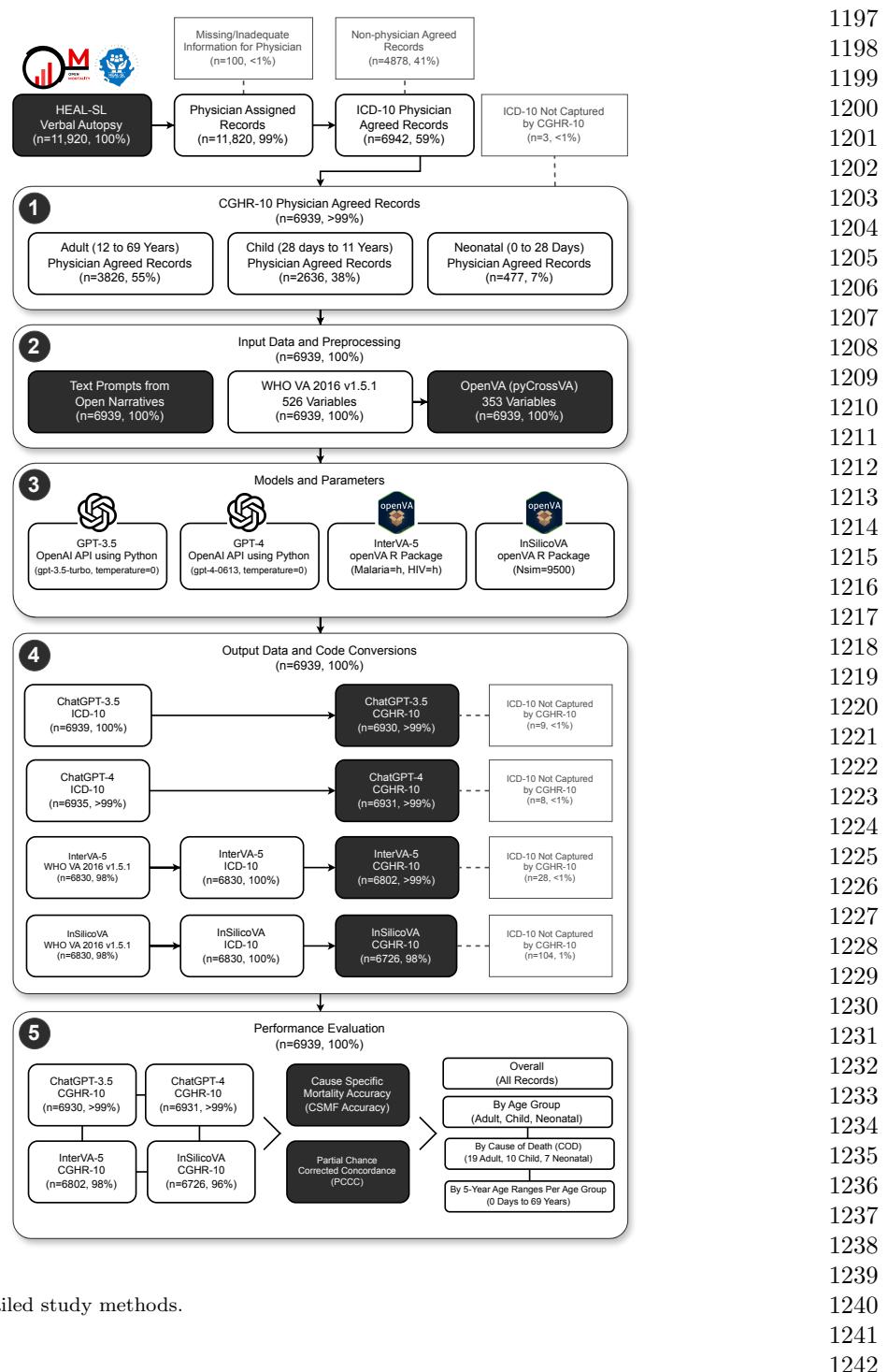


Fig. A1 Detailed study methods.

1243 **A.1 CGHR-10 Physician Agreed Records**

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1245 Initially, 11,920 records were collected from dual-coded EVA in the HEAL-SL study.
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1247 Physicians were able to assign CODs for 11,820 of the 11,920 records, where 100 of
1248 these records could not be assigned a COD due to missing or inadequate information
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1250 (e.g. low quality narrative, data loss). The 11,820 physician coded records were further
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1252 filtered for records where both physicians agreed on the assigned codes (records that
1253 were not reconciled or adjudicated) resulting in 6942 physician agreed records (based
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1255 on comparisons using CMEA-10 codes, see Additional File 2). The 6942 records were
1256
1257 converted into CGHR-10 codes (see Additional File 1) that generalized ICD-10 codes
1258 into 19, 10, and 7 categories for the adult (12 to 69 years), child (28 days to 11
1259 years), and neonatal (under 28 days) age groups. After conversion, a final total of
1260
1261 6939 physician agreed records (3826 adult, 2636 child, and 477 neonatal) were used
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1263 for modelling and performance evaluation, where three records were removed as their
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1265 ICD-10 codes did not have a matching CGHR-10 code.

1266

1267 The 6939 physician agreed records were collected using VA from the HEAL-SL
1268 study between 2019-2022, where records were collected using nation wide samples
1269 across Sierra Leone provinces seen in Figure A2. More populous areas (e.g. southern
1270
1271 and north east provinces with ~197,000 and ~135,000 population respectively) had
1272 more sampling areas versus less populous areas (e.g. north west and eastern provinces
1273 with ~50,000 and ~69,000 people respectively). The distribution of the study data are
1274
1275 shown by CGHR-10 causes of death in Table A1. All age groups had relatively evenly
1276 distributed female and male records (44-55% of 6939 records each). Across CODs,
1277
1278 there were noticeably more female records for cancers (65%), and maternal condi-
1279 tions (100%), while more male records for chronic respiratory diseases (61%), other
1280
1281 noncommunicable diseases (61%), other injuries (77%), road and transport injuries
1282 (71%), and tuberculosis (68%). Most records were coded by physicians as malaria for
1283 adults (20%) and children (52%), and stillbirth (36%) and neonatal infections (21%)
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for neonates. Suicide, congenital anomalies, nutritional deficiencies, and other had low sample sizes for each age group (<1% of total records for each age group). Table A2 shows the distribution of the study data by age. Across ages, there were more male records for 50-59 years (60-62%), while all other records had between 49-59% female and male records. Most records were in the 65-69 years age range for adults (15%), 1-5 years for children (62%), and 0-6 days for neonates (83%).

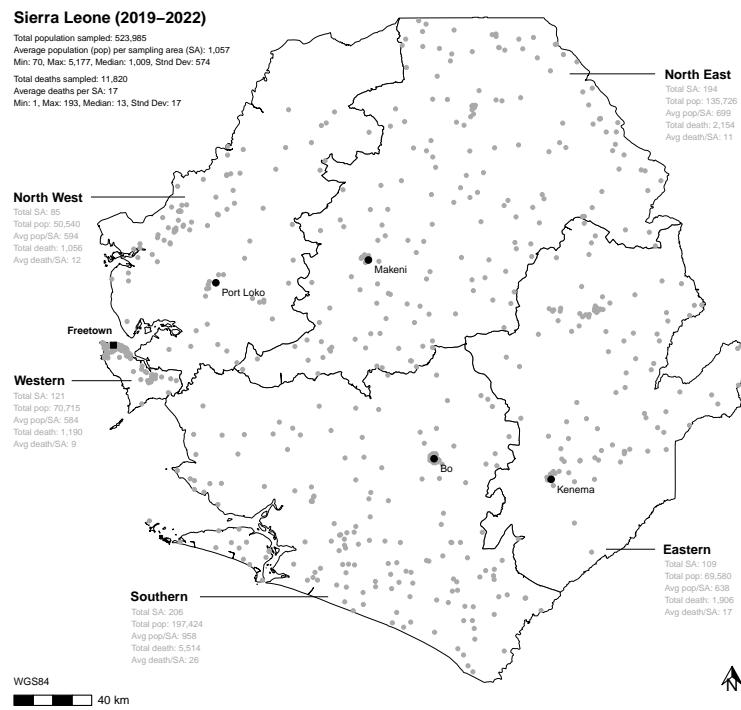


Fig. A2 Study data sampling areas.

A.2 Modelling Details

Each model (GPT-3.5, GPT-4, InSilicoVA, and InterVA-5) required pre-processing of the 6939 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

1335

1336 **Table A1** Study data by cause of death.

1337	Age Group	CGHR-10 Cause of Death (COD)	Female	Male	Total
1338		Acute Respiratory Infections	48 (45.7%)	57 (54.3%)	105 (2.7%)
1339		Cancers	32 (65.3%)	17 (34.7%)	49 (1.3%)
1340		Chronic Respiratory Diseases	29 (38.7%)	46 (61.3%)	75 (2%)
1341		Diabetes Mellitus	14 (51.9%)	13 (48.1%)	27 (0.7%)
1342		Diarrhoeal Diseases	102 (49.8%)	103 (50.2%)	205 (5.4%)
1343		Ill-Defined	56 (47.9%)	61 (52.1%)	117 (3.1%)
1344	Adult, 18 CODs (n=3826, 55.1%)	Ischemic Heart Disease	89 (53%)	79 (47%)	168 (4.4%)
1345	Adult Female (n=1681, 43.9%)	Liver And Alcohol Related Diseases	58 (45.3%)	70 (54.7%)	128 (3.3%)
1346	Adult Male (n=2145, 56.1%)	Malaria	372 (46.6%)	427 (53.4%)	799 (20.9%)
1347		Maternal Conditions	130 (100%)	N/A	130 (3.4%)
1348		Other Cardiovascular Diseases	59 (55.1%)	48 (44.9%)	107 (2.8%)
1349		Other Noncommunicable Diseases	160 (38.6%)	254 (61.4%)	414 (10.8%)
1350		Other Injuries	83 (23.2%)	274 (76.8%)	357 (9.3%)
1351		Road And Transport Injuries	73 (29.1%)	178 (70.9%)	251 (6.6%)
1352		Stroke	147 (44.4%)	184 (55.6%)	331 (8.7%)
1353		Suicide	N/A	3 (100%)	3 (0.1%)
1354		Tuberculosis	54 (31.6%)	117 (68.4%)	171 (4.5%)
1355	Child, 9 CODs (n=2636, 38%)	Unspecified Infections	175 (45%)	214 (55%)	389 (10.2%)
1356		Congenital Anomalies	1 (100%)	N/A	1 (0%)
1357	Child Female (n=1290, 48.9%)	Diarrhoeal Diseases	79 (45.1%)	96 (54.9%)	175 (6.6%)
1358	Child Male (n=1346, 51.1%)	Epilepsy, Leukaemia, And Other Noncommunicable Diseases	61 (53.5%)	53 (46.5%)	114 (4.3%)
1359		Ill-Defined	34 (48.6%)	36 (51.4%)	70 (2.7%)
1360		Injuries	51 (37.8%)	84 (62.2%)	135 (5.1%)
1361		Malaria	680 (49.2%)	702 (50.8%)	1382 (52.4%)
1362	Neonate, 7 CODs (n=477, 6.9%)	Nutritional Deficiencies	7 (63.6%)	4 (36.4%)	11 (0.4%)
1363		Other Infections	338 (50.7%)	329 (49.3%)	667 (25.3%)
1364	Neonate Female (n=227, 47.6%)	Pneumonia	39 (48.1%)	42 (51.9%)	81 (3.1%)
1365	Neonate Male (n=250, 52.4%)	Birth Asphyxia And Birth Trauma	38 (36.9%)	65 (63.1%)	103 (21.6%)
1366		Congenital Anomalies	2 (100%)	N/A	2 (0.4%)
1367		Ill-Defined	11 (47.8%)	12 (52.2%)	23 (4.8%)
1368		Neonatal Infections	49 (49.5%)	50 (50.5%)	99 (20.8%)
1369		Other	2 (40%)	3 (60%)	5 (1%)
1370		Prematurity And Low Birthweight	39 (53.4%)	34 (46.6%)	73 (15.3%)
1371		Stillbirth	86 (50%)	86 (50%)	172 (36.1%)

1372

1373 generated COD response from GPT-3.5 and GPT-4, and the most probable COD
 1374 from InterVA-5 and InSilicoVA were used for evaluation. Section [A.2.1](#) describes the
 1375 input data and parameters for each model, while Section [A.2.3](#) details the outputs
 1376 from running each model.

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Table A2 Study data by age range.

Age Group	Age Range	Female	Male	Total
Adult (n=3826, 55.1%)	12-14 Years	51 (37.8%)	84 (62.2%)	135 (3.5%)
Adult Female (n=1681, 43.9%)	15-19 Years	115 (42.8%)	154 (57.2%)	269 (7%)
Adult Male (n=2145, 56.1%)	20-24 Years	146 (53.1%)	129 (46.9%)	275 (7.2%)
	25-29 Years	159 (45.2%)	193 (54.8%)	352 (9.2%)
	30-34 Years	174 (50.9%)	168 (49.1%)	342 (8.9%)
	35-39 Years	153 (45.4%)	184 (54.6%)	337 (8.8%)
	40-44 Years	134 (42%)	185 (58%)	319 (8.3%)
	45-49 Years	148 (47%)	167 (53%)	315 (8.2%)
	50-54 Years	134 (39.6%)	204 (60.4%)	338 (8.8%)
	55-59 Years	96 (37.6%)	159 (62.4%)	255 (6.7%)
	60-64 Years	128 (40.8%)	186 (59.2%)	314 (8.2%)
	65-69 Years	243 (42.3%)	332 (57.7%)	575 (15%)
Child (n=2636, 38%)	1-5 Months	146 (47.4%)	162 (52.6%)	308 (11.7%)
Child Female (n=1290, 48.9%)	6-11 Months	160 (50.8%)	155 (49.2%)	315 (11.9%)
Child Male (n=1346, 51.1%)	1-5 Years	822 (50.3%)	811 (49.7%)	1633 (61.9%)
	6-11 Years	162 (42.6%)	218 (57.4%)	380 (14.4%)
Neonate (n=477, 6.9%)	0-6 Days	184 (46.6%)	211 (53.4%)	395 (82.8%)
Neonate Female (n=227, 47.6%)	7-27 Days	43 (52.4%)	39 (47.6%)	82 (17.2%)
Neonate Male (n=250, 52.4%)				

A.2.1 Input Data and Preprocessing

For GPT-3.5 and GPT-4, 6939 text prompts were generated for each physician agreed record as input to instruct the models to assign CODs based on the open narratives. Two types of text prompts were used: user prompts and system prompts. System prompts contained textual instructions to assign the role of a physician ICD-10 coder with expertise in Sierra Leone. The following system prompt was used for each record:

```
You are a physician with expertise in determining underlying causes
of death in Sierra Leone by assigning the most probable ICD-10
code for each death using verbal autopsy narratives. Return only
the ICD-10 code without description. E.g. A00. If there are
multiple ICD-10 codes, show one code per line.
```

User prompts contained textual instructions to perform coding of VA records based on the age, sex, and narrative of the deceased. The following template was used to

1427 generate user prompts for each record, where <age> and <sex> from the questionnaire,
1428
1429 and <narrative> from the narratives, were replaced with values from the data:
1430
1431 Determine the underlying cause of death and provide the most
1432 probable ICD–10 code for a verbal autopsy narrative of a <age>
1433
1434 years old <sex> death in Sierra Leone: <narrative>
1435
1436 For InterVA-5 and InSilicoVA, the standardized questionnaire data from the HEAL-SL
1437 EVA were first converted into 2016 World Health Organization (WHO) VA question-
1438 naire revision 1.5.1 Open Data Kit (ODK) format [75, 76] consisting of 526 variables
1439
1440
1441 [77], followed by further conversion into OpenVA format [43] consisting of 353 vari-
1442 ables [78] using the pyCrossVA version 0.97 Python package [79]. The 6939 records
1443
1444 were all converted into OpenVA formatted records for InterVA-5 and InSilicoVA.
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1447 **A.2.2 Models and Parameters**

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1449 The GPT-3.5 and GPT-4 Application Programming Interface (API) was accessed
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1451 using Python version 3.11.4 and used to assign CODs for each record. GPT-3.5 used
1452 the gpt-3.5-turbo model, while GPT-4 used the gpt-4-0613 model. The parameter
1453 temperature for GPT-3.5 and GPT-4, representing the sampling temperature ranging
1454
1455 from 0 to 2 (default of 1), was set to 0 to produce more deterministic outputs [66].
1456
1457 Higher values closer to 2 may produce less deterministic outputs, while lower values
1458
1459 closer to 0 produce more deterministic outputs.

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1461 The openVA R package was used to run InterVA-5 and InSilicoVA models to assign
1462 CODs for each record in R version 4.3.1. The openVA package version 1.1.1 used
1463 dependent packages InterVA5 version 1.1.3 and InSilicoVA version 1.4.0. The Nsim
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1465 (number of iterations to run) parameter [80] for InSilicoVA was set to 9500, while
1466
1467 the HIV (level of prevalence of human immunodeficiency virus) and Malaria (level
1468
1469 of prevalence of Malaria) parameters [81] for InterVA-5 were both set to 'h' (high)
1470
1471 reflecting HIV and Malaria disease assumptions in Sierra Leone [82, 83]. Note that the
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default value of `Nsim=10000` for InSilicoVA ran until 9500 iterations before it stopped due to errors, thus `Nsim=9500` was used and ran successfully for all iterations.

A.2.3 Output Data and Code Conversion

Of the 6939 input records, GPT-3.5, GPT-4, InterVA-5, and InSilicoVA were able to assign CODs for 6939 (100%), 6935 (>99%), 6830 (98%), 6830 (98%) records respectively. All 6830 (100%) InterVA-5 and InSilicoVA records with WHO VA 2016 v1.5 output codes [55] were converted into ICD-10 codes respectively. After all model outputs were converted to ICD-10 codes, they were further converted to CGHR-10 codes. The 6939 GPT-3.5 and 6935 GPT-4 output records with ICD-10 codes were converted into 6930 (>99%) and 6931 (>99) records with CGHR-10 codes, where <1% (9 and 8) records did not have matching CGHR-10 codes respectively. The 6830 InterVA-5 and InSilicoVA records with ICD-10 codes were converted into 6802 (>99%) and 6726 (98%) records with CGHR-10 codes respectively, where 28 (<1%) and 104 (1%) of records could not be converted into CGHR-10 codes.

A.3 Performance Evaluation Details

The performance of GPT-3.5, GPT-4, InSilicoVA, and InterVA-5 models were evaluated with metrics at the population and individual level by comparing their CGHR-10 COD outputs for 6939 records to physician COD assignments. Section A.3.1 describes CSMF accuracy in detail for evaluating models on the population level, Section A.3.2 describes PCCC for evaluating models on the individual level. 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 overall and by three age groups (adult, child, and neonatal), then further into age and COD for each age group.

1519 **A.3.1 Cause Specific Mortality Fraction (CSMF) Accuracy**

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1521 CSMF accuracy measures the performance of models at the population level, compar-
1522 ing distributions of CODs between the physicians and the models [56]. To calculate
1523 CSMF accuracy, we first calculate $CSMF_j$ as is the fraction of physician or model
1524 records for cause j , given by dividing the number of records for cause j with the total
1525 number of records as seen in Equation A1. Then, the $CSMFMaximumError$, repre-
1526 senting the worst possible model, is calculated using Equation A2. Finally, the CSMF
1527 accuracy is given by Equation A3, where k is the number of causes, j is a cause,
1528 $CSMF_j^{true}$ is the true physician CSMF for cause j , and $CSMF_j^{pred}$ is the prediction
1529 model CSMF for cause j . CSMF accuracy ranges from 0 to 1, where 1 means that the
1530 model completely matched the physician COD distribution and 0 means that it did
1531 not match the distribution at all.

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$$CSMF_j = Records_j / Records \quad (A1)$$

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$$CSMFMaximumError = 2(1 - \text{Min}(CSMF_j^{true})) \quad (A2)$$

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A.3.2 Partial Chance Corrected Concordance (PCCC)

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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 [56]. PCCC is given by Equation A5, 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 A4. 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.

$$C = \frac{TP}{Records} \quad (\text{A4})$$

$$PCCC(k) = \frac{C - \frac{k}{N}}{1 - \frac{k}{N}} \quad (\text{A5})$$

Appendix B Experiment on Repeated Runs of GPT-3.5

A short experiment was conducted to test the consistency of GPT-3.5 outputs repeated on the same record. 100 records, sampled randomly with approximately equal proportions across age groups, CODs, and survey rounds 1 and 2, were used to test repeated runs of GPT-3.5. Each record from the 100 records was rerun 10 times through GPT-3.5, resulting in ten COD outputs per record. The ICD-10 codes were then converted to CGHR-10 codes and tested for consistency, where completely inconsistent results had different ICD-10 or CGHR-10 codes for each of the 10 reruns (1 times+), and completely consistent results had the same ICD-10 or CGHR-10 code for all 10 reruns (10 times), on the same record.

The results are shown in Table B3. For all 100 records, GPT-3.5 assigns the same ICD-10 and CGHR-10 code for the same record 5 times or more out of 10. For 66 and 79 records, GPT-3.5 assigns the same ICD-10 and CGHR-10 code respectively for each record. This number increases to 94 (from 66) and 96 (from 79) when reducing the number of times out of 10 that GPT-3.5 assigns the same ICD-10 and CGHR-10 code respectively. Thus, GPT-3.5 does not always produce the same outputs when repeated on the same record (10 times out of 10), even when the temperature is set

1611 to 0, but does so for more than half the records. For most records (more than 90%),
1612 GPT-3.5 will produce the same outputs for the same record 7 times or more out of 10.
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1615 **Table B3** Records with same GPT-3.5 outputs based on 10 repeated
1616 reruns of 100 records

	Times with Same GPT-3.5 Outputs	ICD-10 Records	CGHR-10 Records
1619	1 times+ (inconsistent)	100	100
1620	2 times+	100	100
1621	3 times+	100	100
1622	4 times+	100	100
1623	5 times+	100	100
1624	6 times+	94	96
1625	7 times+	92	94
1626	8 times+	86	91
1626	9 times+	79	86
1626	10 times (consistent)	66	79

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1631 **Appendix C Exploration of Neonatal Infections**

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1633 An exploration of neonatal infections (n=99, 21% of 477 records) was done to under-
1634 stand the low performance of GPT models (0.23 PCCC) for neonatal infections, and
1635 high performance of InSilicoVA (0.87 PCCC). In Table C4, about half the records
1636 were assigned correctly, and a majority (n=33, 33%) of the other records were mis-
1637 classified as other, while prematurity and low birthweight, birth asphyxia & birth
1638 trauma, and ill-defined make up the rest. On closer inspection of the 49 records with
1639 misclassified assignments, the ICD-10 code R50 was assigned in 20 records. R50 falls
1640 under unspecified infections in the adult CGHR-10 category, but in the other cate-
1641 gory for neonates. B50 was assigned in 4 records, falling under malaria, but a similar
1642 B54 falls under neonatal infections. P81 was assigned in 3 records, referring to fever
1643 of unknown origin, which falls under other, and P07 was assigned in 7 records, falling
1644 under prematurity and low birthweight.

1645

1646 In most misclassified records, there is mention of infections, but the misclassifica-
1647 tions occur due to the finer details of the ICD-10 code classifications, the categorization
1648

decisions of the CGHR-10 codes, and missing information from the questionnaire. For R50 misclassifications, GPT may have confused descriptions across adult and neonatal age groups. Using the same definition of R50, but in the context of neonates, may result in codes closer to neonatal infections (e.g. B54). For B50 misclassifications, the similar B54 was categorized in CGHR-10 as neonatal infections, but B50 was categorized as other. P81 refers to fever of unknown origin, which may be difficult to differentiate between infection and other causes without information from the questionnaire. P07 refers to prematurity and low birthweight, where GPT initially assigned P07 as the age of the neonate was mentioned first, but later mentions infections as an alternative following the order of information in the narratives. Thus, it may be possible to improve the performance GPT models using better prompts based on the context of VA manuals and CGHR-10 codes, and by also including questionnaire information in the prompts.

Table C4 GPT-4 CGHR-10 COD assignment for physician coded neonatal infections records.

GPT-4 Assigned Cause of Death (CGHR-10)	Records
Neonatal infections	50 (51%)
Other	33 (33%)
Prematurity and low birthweight	9 (9%)
Birth asphyxia & birth trauma	5 (6%)
Ill-defined	2 (2%)
Total	99 (100%)

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