Performance of InSilicoVA for assigning causes of death to verbal autopsies: multisite validation study using clinical diagnostic gold standards

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# Abstract

### Background

Recently, a new algorithm for automatic computer coding of verbal autopsy data named InsilicoVA was published. The authors present their algorithm as a statistical method and assess performance using a single set of model predictors and age group.

### Methods

We perform a standard procedure for analyzing the predictive accuracy of verbal autopsy classification methods using the same data and the publicly available implementation of the algorithm released by the authors. We extend the original analysis to include children and neonates, instead of only adults, and test accuracy using different sets of predictors, including the set used in the original paper and the set that matches the released software.

### Results

The population-level performance (i.e. predictive accuracy) of the algorithm varied from 2.2% to 37.0% when trained on data preprocessed similarly to the original study. When trained on data that matched the software default format performance ranged from -13.8% to 12.3%. When using the default training data provided performance ranged from -119.7% to -53.4%. Overall InSilicoVA predictive accuracy was found to be 11.1 to 20.9 percentage points lower than an alternative algorithm.

### Conclusions

The default format and training data provided by the software lead to results that are at best suboptimal, with poor cause of death predictive performance. This method is likely to generate erroneous prediction and, even if properly configured, is not as accurate as alternative automated diagnostic methods.

# Keywords

verbal autopsy, cause of death diagnosis, validation

# Background

Reliable population-level causes-of-death estimates are critically important for designing effective public health policies. [1] Verbal autopsy is a key component of enhancing health information systems in many countries that do not have reliable civil registration and vital statistics systems. [2,3] Verbal autopsy consists of a structured interview with family members of the deceased with the purpose of gathering enough information to infer the likely cause of death. [4] In some countries where up to 80-90% percent of deaths occur without medical attendance, verbal autopsy provides the only usable information for generating population-level cause of death estimates with reasonable and representative coverage. [5] Computer algorithms that can reliably assign a cause of death greatly increase the feasibility of integrating VA routinely into CRVS systems. Computer coding of verbal autopsy (CCVA) allows systems to be scalable, consistent, and sustainable. [6]

Numerous algorithms for predicting the cause of death from verbal autopsies have been developed over the last decade. [7–11] We previously developed a framework for validating the predictive accuracy of different diagnostic methods that allows for direct comparison of methods using the same standard set of criteria. [12] It provides a way of determining how well an algorithm will perform in different populations when the true distribution of causes of death is not known. This is crucial for generalizing results to new study populations and accurately capturing unknown changes in cause of death composition in the same population across time. We have used this procedure to determine the accuracy of a wide range of previously developed methods. [13]

Recently a new algorithm for CCVA called *InSilicoVA* was developed and published. [14] This method builds off previous research on the InterVA algorithm, and advances the approach by introducing an algorithm that quantifies uncertainty in the individual-level predictions and uses this information to better predict the cause distribution at the population-level. This aligns well with the current global interest in using VA to estimate the distribution of causes of death for populations through routine application in vital registration systems. The authors use a range of metrics to determine the performance of their algorithm, including applying our assessment framework. However, the authors only validated the results for adult deaths and not child or neonatal deaths. Moreover, given the potential of such methods for transforming knowledge about cause of death patterns in populations for which little is currently known about the leading causes of death, we believe that an independent validation of their results is warranted, before the method can be recommended for routine application.

In this study, we assess the diagnostic accuracy of the InSilicoVA algorithm for all ages using the same validation environment as used in the original InSilicoVA paper, namely the Population Health Metric Research Consortium (PHMRC) gold standard database. We applied the validation procedure developed by Murray et al [12] and assessed performance at the individual-level, using chance-corrected concordance (CCC), and at the population-level, using chance-corrected cause-specific mortality fraction (CCCSMF) accuracy.

# Methods

## Algorithm

InSilicoVA [14] is a Bayesian framework that improves upon InterVA [10] by using information about symptoms that are, and are not endorsed, to estimate probabilities for each cause of death in a way that is comparable across observations, and by estimating the individual-level and population-level predictions simultaneously. The model is estimated using Markov-Chain Monte-Carlo (MCMC) simulations. To produce usable results, the algorithm must run a sufficient number of samples to ensure convergence. The authors have released their algorithm as an R package, with computationally intensive MCMC calculation implemented in Java through the rJava package. The algorithm utilizes a matrix of conditional probabilities between each cause and each symptom. These propensities, which the authors call the *probbase*, capture the user's initial estimate of the relative likelihood of a symptom being endorsed for a given cause of death. These estimates can be derived from data or from expert judgement. The R package allows the user to input their own probbase file and also provides a default probbase based on the InterVA project. Open-source code (licensed under the GNU Public License version 3) for the R implementation of InSilicoVA is freely available online.

## Data

We used the publicly available Population Health Metrics Research Consortium (PHMRC) gold standard database [15,16] to validate the InSilicoVA algorithm. This dataset contains verbal autopsies matched to cause of death diagnoses from medical records, with variable confidence. Cases in the dataset were initially identified from deaths in hospitals where strict, pre-determined diagnostic criteria were satisfied. This ensured that the true cause of death was known with greater certainty than is often the case for deaths recorded in vital registration systems where diagnostic misclassification is typically estimated to range between 30 and 60 percent. [17,18] After identifying cases, blinded verbal autopsies were collected using a modified version of the WHO verbal autopsy instrument. This resulted in a validation database of 12,530 records for which the true cause of death was known with reasonable certainty, and for which a full verbal autopsy interview had been conducted.

Verbal autopsies were collected from six sites in four different countries: Andhra Pradesh, India; Bohol, Philippines; Dar es Salaam, Tanzania; Mexico City, Mexico; Pemba Island, Tanzania; and Uttar Pradesh, India between 2007 and 2010. The database includes deaths from 7,841 adults, 2,064 children, 1,620 neonates and 1,005 stillbirths. Following practice from previous research, we used the most aggregated cause list with 34 adult causes, 21 child causes and 6 neonate causes (including stillbirth) to assess accuracy of cause of death predictions. These cause of death lists are shown in Annex 1.

## Validation Framework

In this study we follow the recommendations of Murray et al. for validating verbal autopsy diagnostic methods. [12] For this procedure, the validation dataset is divided into 500 train-test sets. For each set, any given record appears in either the train set or the test set, but not both. The test set is then resampled to an uninformative Dirichlet distribution. This ensures that the cause composition of the train and test sets are completely uncorrelated and the algorithm is tested on datasets with a wide variety of cause distributions. To assess performance at the individual level, we use the median chance-corrected concordance (CCC) across causes. [12] To assess performance at the population level we use chance-corrected cause-specific mortality fraction accuracy (CCCSMF). [19] Chance-corrected concordance for a single cause is calculated as:

where is the number of true positives for cause , is the number of true negatives and is the number of causes. Values range between -1.0 and 1.0 where 1.0 indicates perfect ability to detect (i.e. diagnose) a cause, 0.0 indicates random guessing, and negative 1.0 indicates no ability to detect a cause. To create an overall metric of individual-level prediction accuracy, we use the mean of the cause-specific CCCs. Cause-specific mortality fraction (CSMF) accuracy is calculated as:

where is the true fractions for cause and is the predicted fraction for cause . This statistic can be corrected for chance (see Flaxman et al. [19]); we calculate chance-corrected CMSF Accuracy as:

Similarly to CCC, perfect CCCSMF Accuracy is attained at value 1.0, and values near 0.0 indicate that the diagnostic procedure being applied is essentially equivalent to random guessing.

## InSilicoVA Validation

The InSilicoVA R package allows for a range of customizations to the inputs used to predict the cause of death. We validate the algorithm using three different configurations of inputs to assess its usability and performance. These configurations are: 1) using the built-in default training data, 2) training the algorithm with inputs that resemble the defaults, and 3) training the algorithm with inputs that do not resemble the defaults. Following the practice established in Murray et al., we also conduct the analysis without predictors derived from questions related to previous contact with the health care system. This produces estimates of diagnoistic accuracy which could be more appropriate for generalizing to community deaths where decedents had no medical contact. [16] For each of the three configurations we test all three age groups both with and without health care experience questions.

The default configuration assumes the input data matches the InterVA4 format with 245 symptoms. It uses the conditional probabilities from InterVA to predict one of 60 causes. With the default configuration, no ancillary training data is required. To validate the default configuration, we mapped the PHMRC database to the InterVA format, and then we used InSilicoVA to predict the cause of death. We then mapped the predicted causes to the PHMRC gold standard list. We compared these mapped predictions to the known underlying cause as listed in the PHMRC database to calculate performance. Since the algorithm was not trained empirically with this configuration, we used the entire validation dataset to test the predictive performance. However, it is still essential to test the algorithm on datasets with different cause compositions, so we repeated this process on 500 test datasets, each with a cause composition drawn from an uninformative Dirichlet distribution and samples drawn from the complete dataset with replacement according to this cause composition. The predicted causes included 36 adult causes of death 20 child causes, and 7 neonate causes. Of the 245 symptom predictors used by InSilicoVA, the PHMRC dataset contained data for 124 adult symptoms, 69 child symptoms and 62 symptoms for neonates.

Next, we assessed how InSilicoVA performed with training data that matched its expected inputs. For this assessment, we mapped the PHRMC database to the InterVA symptoms and the 'gold standard' causes were mapped to the predicted causes. For each of the 500 test-train splits, we used the train split to calculate the empirical probability of an InterVA symptom being endorsed, conditional on the mapped cause. This conditional probabilities matrix was used as the input probbase for the algorithm. The test split was resampled to a Dirichlet cause distribution and the algorithm predicted a cause from the default set of causes.

Finally, we assessed how the algorithm performed with training data of a different format than the standard inputs. For this assessment, the PHMRC database was mapped to the set of symptoms used by the Tariff 2.0 algorithm. [7] Data were mapped to 171 adult symptoms, 86 child symptoms, and 110 neonate symptoms. For each of the 500 test-train splits, we used the train split to calculate the empirical probability of a Tariff 2.0 symptom being endorsed conditional on the original PHMRC gold standard cause. We then used this empirical probabilty matrix in the InSilicoVA algorithm to predict causes of death. As before, we predicted for data in the test split after it had been resampled to a Dirichlet cause distribution. Of the three assessments, this configuration should be the most favorable towards InSilicoVA since it avoids any possible discrepancies between definitions of the PHMRC causes and the default causes, and provides more symptom predictors for the algorithm to use.

The InSilicoVA R package provides 10 hyperparameters which allow users to tune the estimation procedure. Except where specifically mentioned, we used the default value provided by the InSilicoVA packages. The validity of the results depends on the Monte Carlo experiment successfully converging to a stable result. We repeated each experiment using three times the default number of simulations and assessed the number of splits that converged and any differences in the results. Convergence was assessed using the Heidelberger and Welch test included with the R package. We used the extract.prob function provided by the InSilicoVA package in all training exercises.

# Results

Tables 1 and 2 show the algorithmic performance of InSilicoVA at the individual-level and population-level, respectively, using the default probbase, training the algorithm on data with the same causes and symptoms as the default probbase, and training the algorithm on data with different causes and symptoms. At both the individual-level and the population-level, the configuration using the causes published with the dataset and the Tariff 2.0 symptoms performed best across all age groups regardless of whether health care experience (HCE) variables were included. These variables are intended to reflect the impact of the extent of contact with health services prior to death in terms of additional information that might improve diagnostic accuracy.

At the individual-level, InSilicoVA performed best for predicting the cause of death for child deaths. Without HCE variables, the median CCC for child VAs was 30.1% (UI 30.0%, 30.2%) using the default probbase, 35.2% (UI 34.7%, 35.7%) when training the algorithm on the default cause list and symptoms, and 38.4% (UI 37.7%, 39.0%) when using the causes and symptoms which best matched the data. For adults and neonates, InSilicoVA performed substantially worse with the default probbase than with the Tariff 2.0 causes and symptoms. The CCC for adults was 10.6% (UI 10.5%, 10.6%) using the defaults and 28.0% (UI 27.7%, 28.3%) using Tariff 2.0 causes and symptoms. The CCC for neonates was 1.8% (UI 1.7%, 1.9%) using the defaults and 36.6% (UI 35.9%, 37.2%) using the Tariff 2.0 causes and symptoms. For adults, training the algorithm using the default causes and symptoms yielded diagnostic accuracy very similar to that resulting from using Tariff 2.0 causes and symptoms, 26.5% (UI 26.2%, 26.8%) compared to 28.0% (UI 27.7%, 28.3%). For neonates, training using default symptoms and causes produced lower CCC, 27.7% (UI 27.1%, 28.2%) compared to 36.6% (UI 35.9%, 37.2%) when training using the Tariff 2.0 symptoms.

At the population-level, InSilicoVA performed best in predicting the CSMF for neonates when provided with training data. The algorithm performed substantially worse than chance for all age groups using the default probbase, despite predicting better than chance at the individual-level for adults and children. The median CCCSMF was -114.2% (UI -115.2%, -112.2%) for adults, -54.9% (UI -57.6%, -50.9%) for children and -113.6% (UI -116.1%, -110.7%) for neonates. The median CCCSMF is higher for all age groups when using the Tariff 2.0 causes and symptoms. The CCCSMF was 2.2% (UI 1.0%, 3.7%) for adults, 19.4% (UI 17.5%, 21.6%) for children and 34.1% (UI 31.8%, 37.5%) neonates. For the child and neonate age groups, the uncertainty interval appears centered around a positive value.

At both the individual-level and the population-level, Tariff 2.0 outperforms InSilicoVA in all age groups. At the individual-level without HCE variables, the median CCC across splits was 9.8 percentage points higher for adults, 6.2 percentage points higher for children and 5.7 percentage points higher for neonates using Tariff 2.0 to diagnose the VAs, compared to InSilicoVA. At the population-level, the median CCCSMF for Tariff 2.0 was 20.9 percentage points higher for adults, 11.1 percentage points higher for children and 15.1 percentage points higher for neonates. Figure 1 shows the individual-level and population-level performance of InSilicoVA using different configuration compared to Tariff 2.0.

Further, when using training data, the model did not always converge for every test-train split. Across the three modules and different mappings of training data, 20.6% to 98.4% of the 500 test-train splits the model did not converge when using the default number of Monte Carlo simulations. We increased the number of simulations performed during the fitting process to three times the default to see of the model would eventually converge. Even with these extra samples, up to 34.0% splits still failed to converge for some configurations.

###### Figure 1: Comparison of InSilicoVA and Tariff 2.0 at the individual and population levels.

Note:

*Individual-level accuracy is assessed using chance-correct concordance. Population-level accuracy is assessed using chance-corrected cause-specific mortality fraction (CSMF) accuracy. Values of zero in either dimension are equivalent to random guessing and range up to 100% for perfect accuracy. InSilico is tested using the default expert-derived probbase, a probbase empirically trained using InterVA symptoms, and a probbase empircally trained using Tariff 2.0 symptoms. Published accuracies of Tariff 2.0 are shown for comparison.*

##### Table 1: Median chance-corrected concordance (%) for InsilicoVA

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | InsilicoVA  (Default Probbase) | | InsilicoVA  (InterVA training) | | InSilicoVA  (Tariff 2.0 training) | | Tariff 2.0 | |
|  |  | Median | 95% UI | Median | 95% UI | Median | 95% UI | Median | 95% UI |
| Adult | No HCE | 10.6 | (10.5, 10.6) | 26.5 | (26.2, 26.8) | 28.0 | (27.7, 28.3) | 37.8 | (37.6, 37.9) |
|  | HCE | 12.6 | (12.5, 12.7) | 30.2 | (30.0, 30.3) | 33.6 | (33.5, 34.0) | 50.5 | (50.2, 50.7) |
| Child | No HCE | 30.1 | (30.0, 30.2) | 35.2 | (34.7, 35.7) | 38.4 | (37.7, 39.0) | 44.6 | (44.2, 45.0) |
|  | HCE | 30.2 | (30.0, 30.3) | 35.4 | (35.0, 35.9) | 38.1 | (37.6, 38.5) | 52.5 | (52.1, 53.0) |
| Neonate | No HCE | 1.8 | (1.7, 1.9) | 27.7 | (27.1, 28.2) | 36.6 | (35.9, 37.2) | 42.3 | (41.9, 42.6) |
|  | HCE | 0.6 | (0.5, 0.6) | 28.4 | (27.8, 28.9) | 37.0 | (36.4, 37.4) | 45.1 | (44.6, 45.4) |

Table 1 shows the median value and uncertainty interval across 500 test-train splits using different probbase matrices for prediction, by age group, with and without health care experience questions included. InSilicoVA was run without training using the default probbase, with an empirical probbase derived from training data mapped to the InterVA format, and with an empirical probbase derived from training data mapped to the Tariff 2.0 format. Previously published Tariff 2.0 results are shown for comparison.

##### Table 2: Median chance-corrected cause-specific mortality fraction accuracy for InsilicoVA.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | InsilicoVA  (Default Probbase) | | InsilicoVA  (InterVA training) | | InSilicoVA  (Tariff 2.0 training) | | Tariff 2.0 | |
|  |  | Median | 95% UI | Median | 95% UI | Median | 95% UI | Median | 95% UI |
| Adult | No HCE | -114.2 | (-115.2, -112.2) | -6.8 | (-8.5, -5.8) | 2.2 | (1.0, 3.7) | 23.1 | (21.6, 24.3) |
|  | HCE | -94.2 | (-95.5, -92.7) | -1.5 | (-3.1, -0.1) | 14.0 | (13.0, 15.1) | 37.6 | (36.5, 38.9) |
| Child | No HCE | -54.9 | (-57.6, -50.9) | -13.0 | (-15.0, -11.1) | 19.4 | (17.5, 21.6) | 30.5 | (28.4, 32.4) |
|  | HCE | -53.4 | (-56.5, -51.5) | -13.8 | (-16.5, -11.3) | 20.9 | (18.9, 23.4) | 41.1 | (39.2, 42.0) |
| Neonate | No HCE | -113.6 | (-116.1, -110.7) | 4.8 | (0.3, 9.2) | 34.1 | (31.8, 37.5) | 49.2 | (47.4, 52.2) |
|  | HCE | -119.7 | (-123.5, -115.0) | 12.3 | (7.8, 16.0) | 37.0 | (33.3, 40.1) | 53.1 | (50.9, 55.1) |

Table 2 shows the median value and uncertainty interval across 500 test-train splits using different probbase matrices for prediction, by age group, with and without health care experience questions included. InSilicoVA was run without training using the default probbase, with an empirical probbase derived from training data mapped to the InterVA format, and with an empirical probbase derived from training data mapped to the Tariff 2.0 format. Previously published Tariff 2.0 results are shown for comparison.

# Discussion

As expected, InsilicoVA performed best when using the causes and symptoms that closely matched the data. The differences between using the causes and symptoms from the data versus mapping to the InterVA causes and symptoms was greatest for neonates. The differences in population-level accuracy were generally larger than at the individual level. Even when using the ideal configuration InSilicoVA always had lower diagnostic accuracy than the Tariff 2.0 method. The difference was greatest for adults where, without health care variables, the predictive accuracy of InSilicoVA was 9.8 percentage points lower at the individual level, and 20.9 percentage points lower at the population level. This poorer performance, particularly for adult deaths, has significant implications for estimating cause of death patterns in countries where, in all cases, the vast majority of deaths occur among the in the adult population. [20]

We have reviewed InSilicoVA for two complimentary purposes. First, we assessed the performance of the InSilicoVA method as a diagnostic algorithm for verbal autopsy. Second, InSilicoVA is a new piece of software that potentially could be applied routinely into vital statistics systems for deaths without physcian certification. Knowing that this is a potential use for this software, it is obviously important that the method can be easily applied, and with confidence about diagnostic accuracy, in settings with little technical and statistical support. The need for continuous vetting of model input parameters and verification of model convergence is likely to be problematic in many countries, and likely to result in low-quality cause of death statistics in countries where there are insufficient resources to procure these services.

Compared with Tariff 2.0, we found that InSilicoVA performs significantly worse in correctly predicting causes of death. In particular, InSilicoVA appears to be no better than chance in predicting causes of death at the population-level for adults without the health care experience questions. We were not able to identify any configuration of input parameters, for any age group, that outperformed published estimates from the Tariff 2.0 algorithm. InSilicoVA shows the most promising results for child and neonates, despite having noticeably fewer symptom predictors for these age groups, but even for these age groups still has noticeably lower diagnostic accuracy than Tariff 2.0.

To predict with this algorithm, users must decide what conditional probabilities matrix to use. The InSilicoVA authors propose that, in practice, ranked conditional probabilities be derived from expert panels that rank the propensities of seeing a symptom given a particular cause of death. [14] They show that the predictive accuracy of the method is heavily dependent on the quality of this input. However, deriving these probabilities may not be straightforward. The required value is the probability of a *respondent saying* the decedent had a given symptom. This is subtly but importantly different from the probability of the *decedent having* the symptom. The value needed for this algorithm requires that a decedent had a symptom, the decedent communicates this symptom to someone or someone notices it, the interviewer finds this person who knew about the symptom, and the respondent remembers the symptom months later when the VA interview is being conducted. The respondent may not notice or may forget key symptoms. An example of this is 'pallor', which is a key clinical indicator of anemia. In the Tariff 2.0 analysis, 30% of the causes have a small, but statistically significant positive tariff for pallor and no cause has even a moderate tariff. This indicates the symptom is reported at a low background level with no significant cause-specific pattern. Yet the InterVA conditional probabilities put a high emphasis on pallor which seems to result in over-estimating the fraction of anemia deaths in our sample. Another key symptom, as highlighted in a recent critical review of the PHMRC database [21], finds that in 1% of deaths from maternal causes, respondents did not know the decedent was pregnant. Also, non-specific symptoms may be mentioned even if they were not the key clinical symptoms. Breathing difficulty, as that review points out, has a very high background rate of endorsement and is mentioned in many cases with non-respiratory causes of death. Another example is fever, which many would assume would be associated with malaria, but is also endorsed in a non-specific way. When medical professionals create these ranked conditional probabilities, they may implicitly estimate the probability of identifying a symptom themselves in their expert, clinical evaluation. This value could mislead the algorithm and result in inaccurate predictions. It is necessary that experts who select these conditional probabilities balance both the presentation of symptoms due to a disease and the ability of non-experts to reliably identify, remember, and report on these symptoms.

We report here, for the first time, the predictive performance of InSilicoVA using the default conditional probabilities (from InterVA). Given resource constraints in the settings where VA is likely to be used, and the logistical difficulties of collecting location-specific probbase information from medical professionals familiar with the area, it is quite probable that the InSilicoVA defaults will be used in practice. We found that the default configuration and conditional probabilities consistently perform worse than chance at all ages at the population-level. The authors claim that InSilicoVA is applicable in a wider range of setting because it does not need to rely on "gold standard" data. [14] However, we have demonstrated that using expert-derived training as opposed to empirically derived training data results in unacceptably poor performance.

The results from this study match a previous validation of the InterVA algorithm which found that, once corrected for chance, population-level accuracy of predictions using an expert-derived probbase are worse than random guessing. [22] The InterVA probbase used by InSilico has undergone extensive field testing and review by numerous investigators in multiple countries. [23] Given this, we believe it is extremely unlikely for expert-derived probbases to produce estimates that rival empirically derived training such as that used by Tariff 2.0. Additionally, expert-derived training has the unfortunate effect of often appearing plausible since it reconfirms the intuition of the experts training and evaluating the method, which can be, and often is, incorrect. The net result is a situation in which information diagnostic information being provided by InSilicoVA is likely to be worse than acting on no information whatsoever.

In this study we used test data with a cause distribution uncorrelated with the training data. This resulted in scenarios in which the training data and test data were sufficiently different that the model could not successfully converge. The R package displays a warning about non-convergence and says the results may be unreliable, but still yields outputs. This raise two operational considerations with the use of InSilicoVA. First, it is possible to create a conditional probabilities matrix in which the model does not successfully produce reliable results. Second, the R package produces results even in this circumstance. It is possible that InSilicoVA users may unintentionally overlook the warning that Markov Chain Monte Carlo process has not converged, leading to adoption of results which are known to be statistical inaccurate.

Installing Java and properly configuring R and Java to work together requires considerable technical expertise and is not standardized across different computer systems. Although InSilicoVA is freely available, it may require expert technical consultation to be usable.

# Conclusions

Verbal autopsy as a diagnostic method is now being actively considered by countries for routine widespread use in surveillance and vital statistics systems [24]. It is important to keep improving the science behind estimation and validation of different cause of death prediction strategies so that policy makers can be provided the highest quality estimates based on the best possible measurement methods. It is also important that methods be independently investigated and evaluated for usability for governments in low and middle-income countries seeking to reduce ignorance about who dies of what.

The InSilicoVA algorithm provides some key advances in CCVA. Unlike previous algorithm, it provides a method for calculating the uncertainty in each prediction. However, implementing the algorithm effectively requires both an increased level of technical expertise to utilize R and Java and conceptual expertise to tune model hyperparameters and interpret convergence from a hierarchical Bayesian model. Additionally, our results indicate that the default setting for conditional probabilities that come with the R package is suboptimal. This means that users should be very cautious about applying this new method.

Moreover, in the validation environment we have defined using the PHMRC database, InSilicoVA was found to be significantly less accurate than Tariff2.0 in predicting both causes of death for individuals (by about 10%) and the cause of death distribution in a population (about 20% less accurate), with the differences being more marked for adult and child death deaths than for neonates. Since the vast majority of deaths in low and middle income countries now occur among children and adults, rather than neonates, the significantly higher performance of Tariff2.0 in predicting causes of death, along with its ease of application, should make it the method of choice for countries seeking to maximize the accuracy and cost-effectiveness of automated verbal autopsy in their national CRVS systems.

# Declarations

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## Contributors

ADF, CJLM, IR and ADL designed the analysis. ADF and JJ conducted the analysis and led writing the first draft of the manuscript. All authors reviewed the interpretation of results and contributed to writing the final version of the manuscript.

## Ethics approval and consent to participate

Not applicable. This study uses a publicly-released database.

## Avaliability of data and materials

The dataset analyzed in this study is available in the Global Health Data Exchange (GHDx) repository, http://ghdx.healthdata.org/record/population-health-metrics-research-consortium-gold-standard-verbal-autopsy-data-2005-2011 .

## Competing interests

The authors declare that they have no competing interests.

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