

# <sup>1</sup> EAVA: An R package for Expert Algorithm Verbal Autopsy (EAVA) cause of death assignment

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<sup>9</sup> EAVA (Expert Algorithm Verbal Autopsy) is an R package for determining cause of death (COD)  
<sup>10</sup> using verbal autopsy (VA) interview questionnaire data, a predominant tool to determine cause  
<sup>11</sup> of death in under-resourced settings ([Nichols et al., 2018](#)). The EAVA R package translates the  
<sup>12</sup> methodology created and validated by Kalter and colleagues ([Kalter et al., 2016](#)) to diagnose  
<sup>13</sup> a cause of death from VA records of neonates and children (1 to 59 months of age). EAVA  
<sup>14</sup> inputs data from the 2016 version of the WHO Verbal Autopsy (VA) questionnaire and outputs  
<sup>15</sup> a cause of death (COD) for each VA record based on a deterministic hierarchy of causes. The  
<sup>16</sup> assignment approach utilizes the decedent's age to decide which of two separate hierarchies  
<sup>17</sup> will determine a cause of death.

## <sup>18</sup> Statement of need

<sup>19</sup> Most deaths occur outside of a medical setting and as a result, the causes of these deaths  
<sup>20</sup> are not captured. Verbal autopsies conducted in the community, usually at the homes of  
<sup>21</sup> children who died, are used to understand the most common causes of death in settings where  
<sup>22</sup> civil registration systems need to be strengthened ([WHO, 2016](#)). Physicians assess signs and  
<sup>23</sup> symptoms, which were reported to be present at the time of death by a decedent's caregiver  
<sup>24</sup> during the Verbal Autopsy, and assign a cause of death deemed most likely. To account for  
<sup>25</sup> bias, physician-coded verbal autopsy (PCVA) requires that verbal autopsy questionnaire data  
<sup>26</sup> are read by multiple physicians. PCVA is time-intensive for physicians in resource-limited  
<sup>27</sup> settings and repeatability can be low in childhood deaths ([Chandramohan et al., 1998](#)).

<sup>28</sup> Over the last decade, there has been increased adoption of algorithmic cause-ascertainment from  
<sup>29</sup> VA. These algorithms, termed as Computer-Coded Verbal Autopsy (CCVA), are considerably  
<sup>30</sup> less time- and resource-intensive than PCVA, facilitating scalability of obtaining COD for large  
<sup>31</sup> (national- or sub-national-level) VA databases. There now exists a suite of CCVA algorithms  
<sup>32</sup> for COD ascertainment from VA data – EAVA, InterVA4, InterVA5, InSilicoVA, Tariff, and  
<sup>33</sup> Naïve Bayes Classifier ([Li et al., 2022](#)). Each algorithm differs in implementation details and  
<sup>34</sup> underlying methodology. However, except EAVA, most of these are primarily data-driven,  
<sup>35</sup> estimating some form of a conditional probability symptom-given-cause matrix. These estimates  
<sup>36</sup> are primarily derived from the Population Health Metrics Research Consortium (PHMRC)  
<sup>37</sup> study, conducted in 2011, which contains both VA records and validated 'gold-standard' causes  
<sup>38</sup> ([Murray et al., 2011](#)). Reliance on PHMRC limits generalizability in newer VA studies. It has  
<sup>39</sup> been shown that most CCVA algorithms misclassify the cause for a substantial proportion of  
<sup>40</sup> deaths ([Datta et al., 2021; Fiksel et al., 2022](#)).

41 EAVA addresses some of the drawbacks of physician coding and is not reliant on PHMRC  
42 data. It automates and replicates the decision trees of human physician coders as it assesses  
43 signs and symptoms of common causes of death, arriving at a single diagnosis using ICD-10  
44 classifications in the hierarchy. If diagnostic criteria are not met for any cause, the neonate  
45 or 1-to-59-month-old child is assigned a COD of “unspecified” (Appendices 1 and 2). EAVA  
46 has been shown to yield comparable accuracy to the other CCVA algorithms (Fiksel et al.,  
47 2023; Gilbert et al., 2023). The COD outputs from EAVA can also be used in the VA  
48 calibration algorithm which combines COD ascertainment from multiple CCVA algorithms  
49 and adjusts for their biases to produce a calibrated estimate of population-level cause-specific  
50 mortality fractions (Datta et al., 2021; Fiksel et al., 2022; Pramanik et al., 2023). Inclusion  
51 of CCVA algorithms with different cause-ascertainment logic ensures robustness of results for  
52 VA calibration. Hence, due to the fundamentally different decision-making nature of EAVA  
53 compared to other CCVA algorithms, it is now a central component of the VA calibration  
54 algorithm and has been used in VA-calibration to produce bias-corrected estimates of CSMF  
55 for child (1-59 months) and neonatal deaths in Mozambique (Fiksel et al., 2023; Gilbert et al.,  
56 2023; Macicame et al., 2023)

57 The EAVA R package takes EAVA analytical scripts originally compiled in SAS and R and  
58 makes the methodology publicly available in CRAN, which expands the potential for research  
59 use, ongoing development, and future integration into VA pipelines and toolkits.

## 60 State of the field

61 Many of the aforementioned CCVA algorithms (EAVA, InterVA4, InterVA5, InSilicoVA, Tariff,  
62 and Naïve Bayes Classifier) are implemented in the openVA R package (Zehang et al., 2024).  
63 The CrossVA package converts 2016 WHO VA questionnaire data to a standard input format  
64 for use in openVA (Thomas et al., 2021). There is also standalone software for some CCVA  
65 algorithms, for example, the InterVA algorithm (Byass, 2020) and the SmartVA algorithm  
66 (Flaxman, 2025). There has been no publicly available version of EAVA prior to this R package.

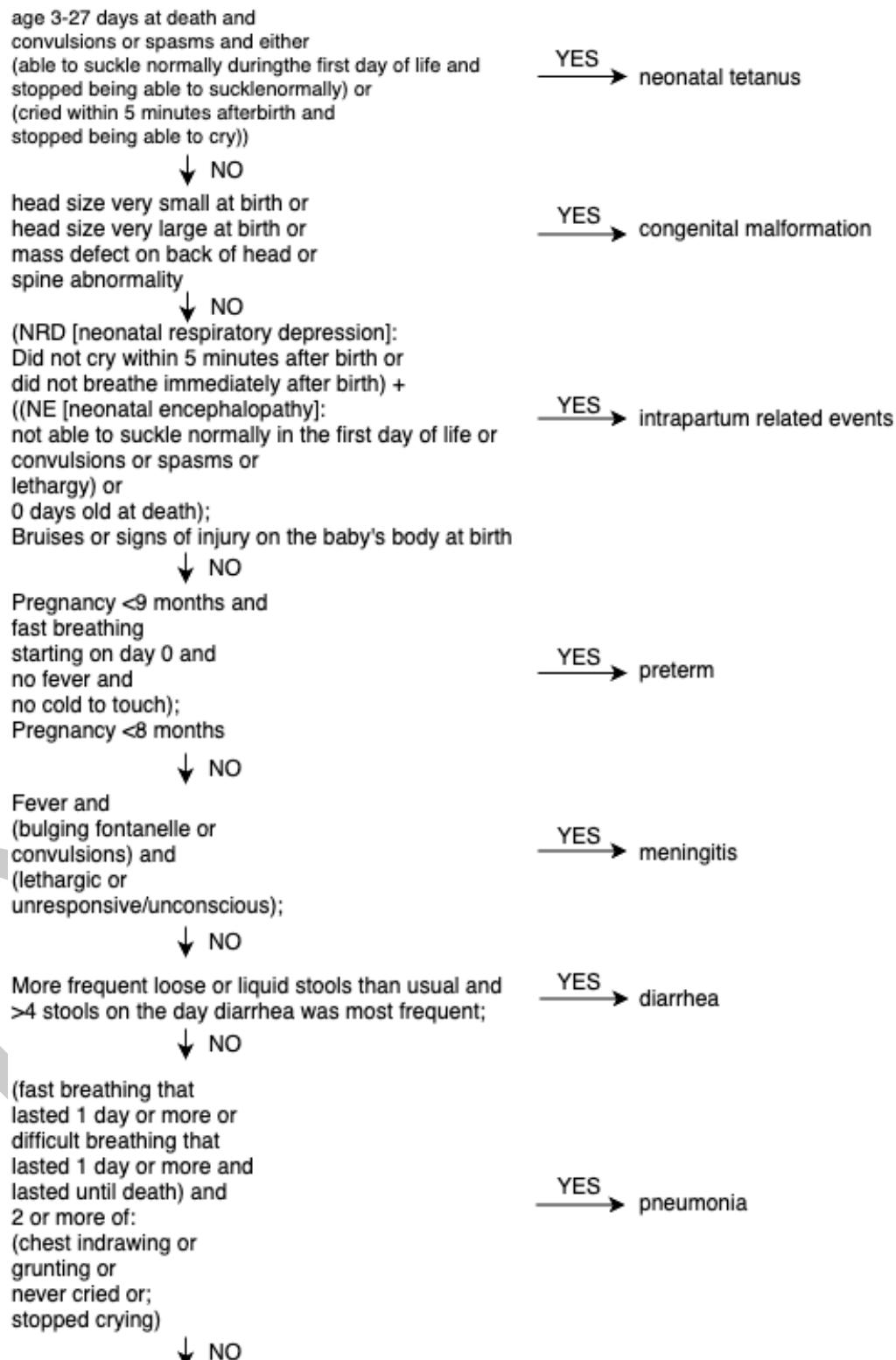
## 67 The EAVA package

68 The EAVA R package comprises two functions (Wilson et al., 2025). The first function is  
69 odk2EAVA which builds on the CrossVA package to convert interview responses from the 2016  
70 WHO Verbal Autopsy questionnaire into standardized inputs for use in codEAVA. The second  
71 function, codEAVA, evaluates whether reported symptoms meet diagnostic criteria of common  
72 causes of death and assigns a main cause based on a hierarchy of causes. The algorithm utilizes  
73 age-group specific ascertainment logic due to significant differences between the common causes  
74 of death of neonates 0-27 days (Appendix 1) and children aged 1-to-59-months (Appendix 2).

## 75 Acknowledgements

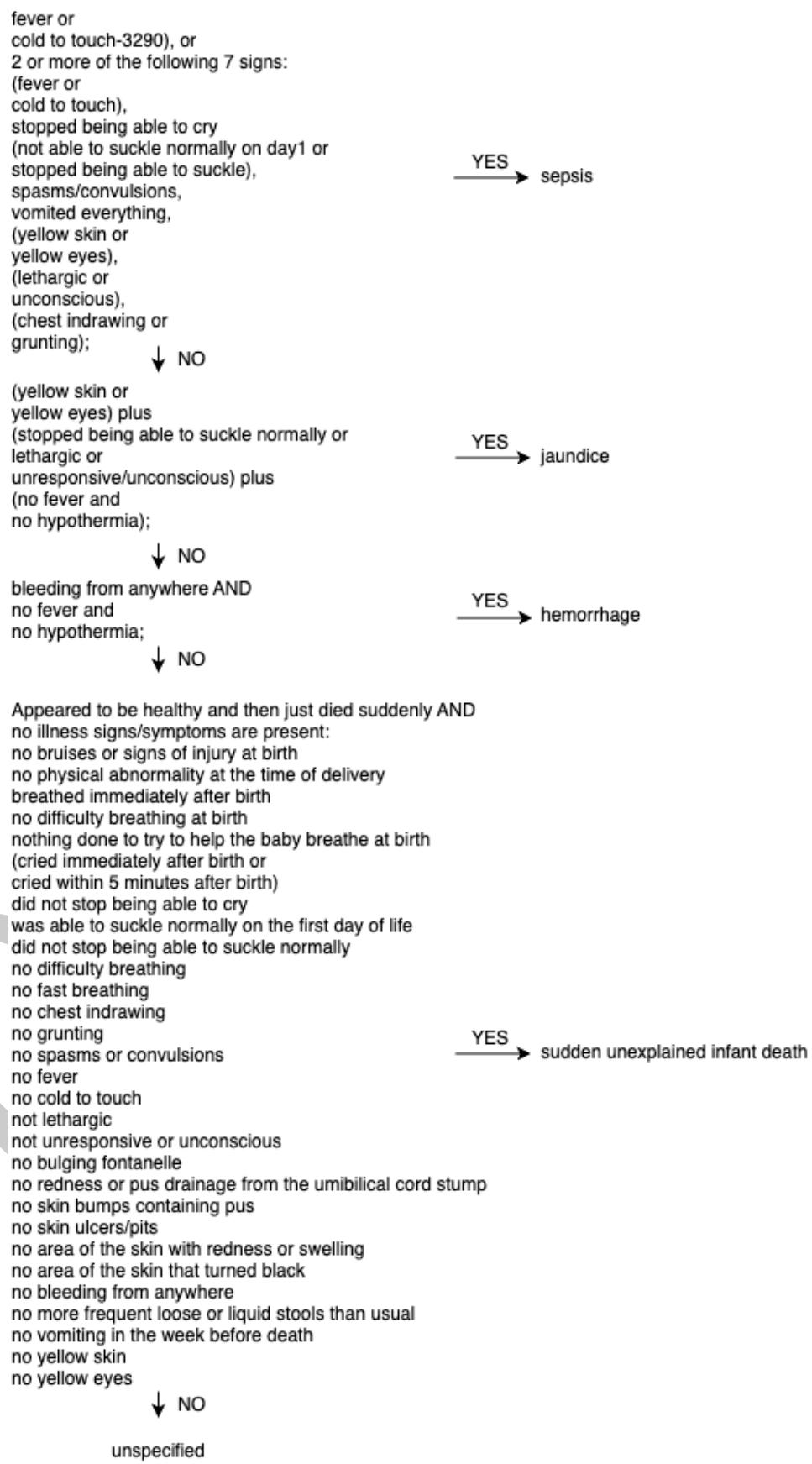
76 This work was supported by The Gates Foundation Grant INV-03484. We would like to thank  
77 the families who participated in VA interviews for the Countrywide Mortality Surveillance for  
78 Action project.

<sup>79</sup> **Appendix 1: deterministic hierarchical algorithm to reach a single  
cause of death in neonates**

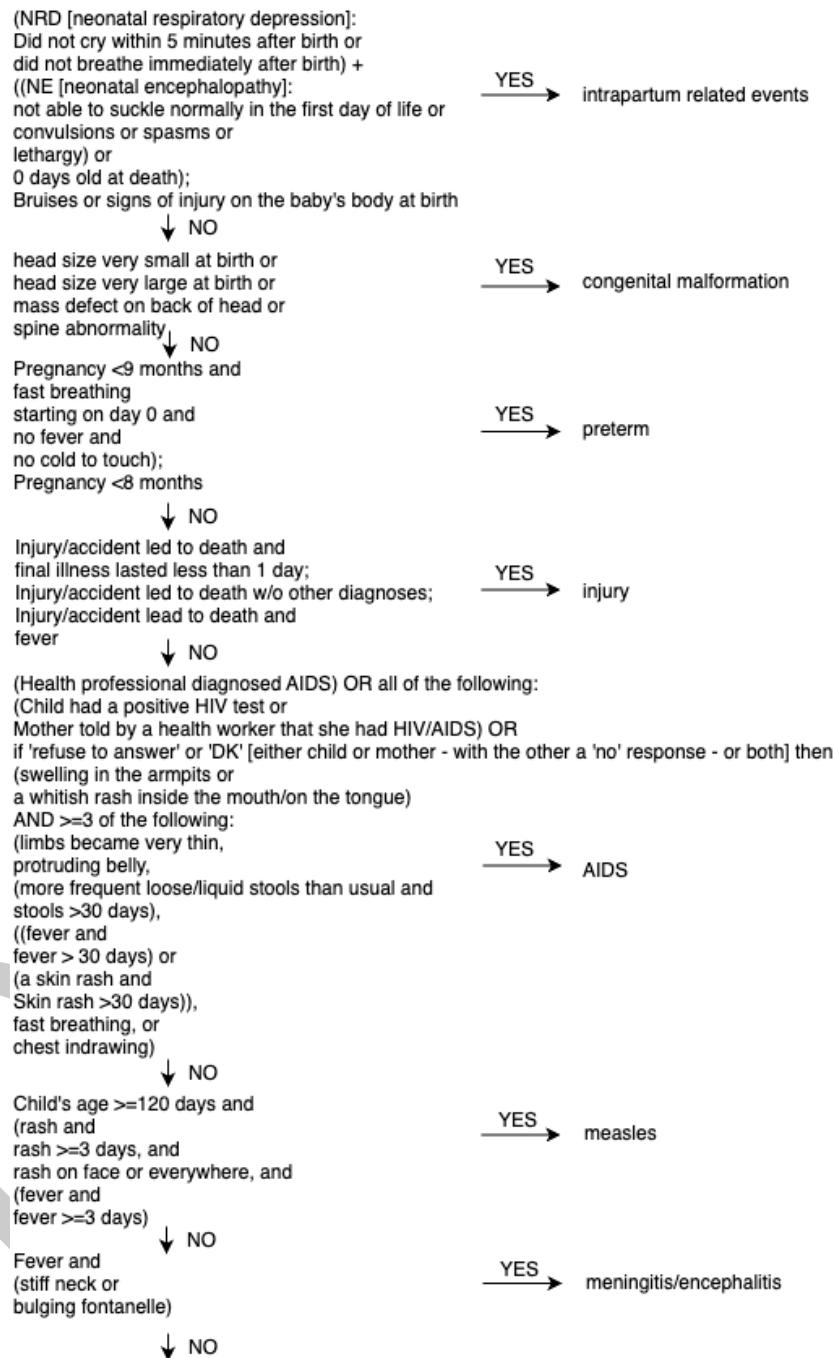


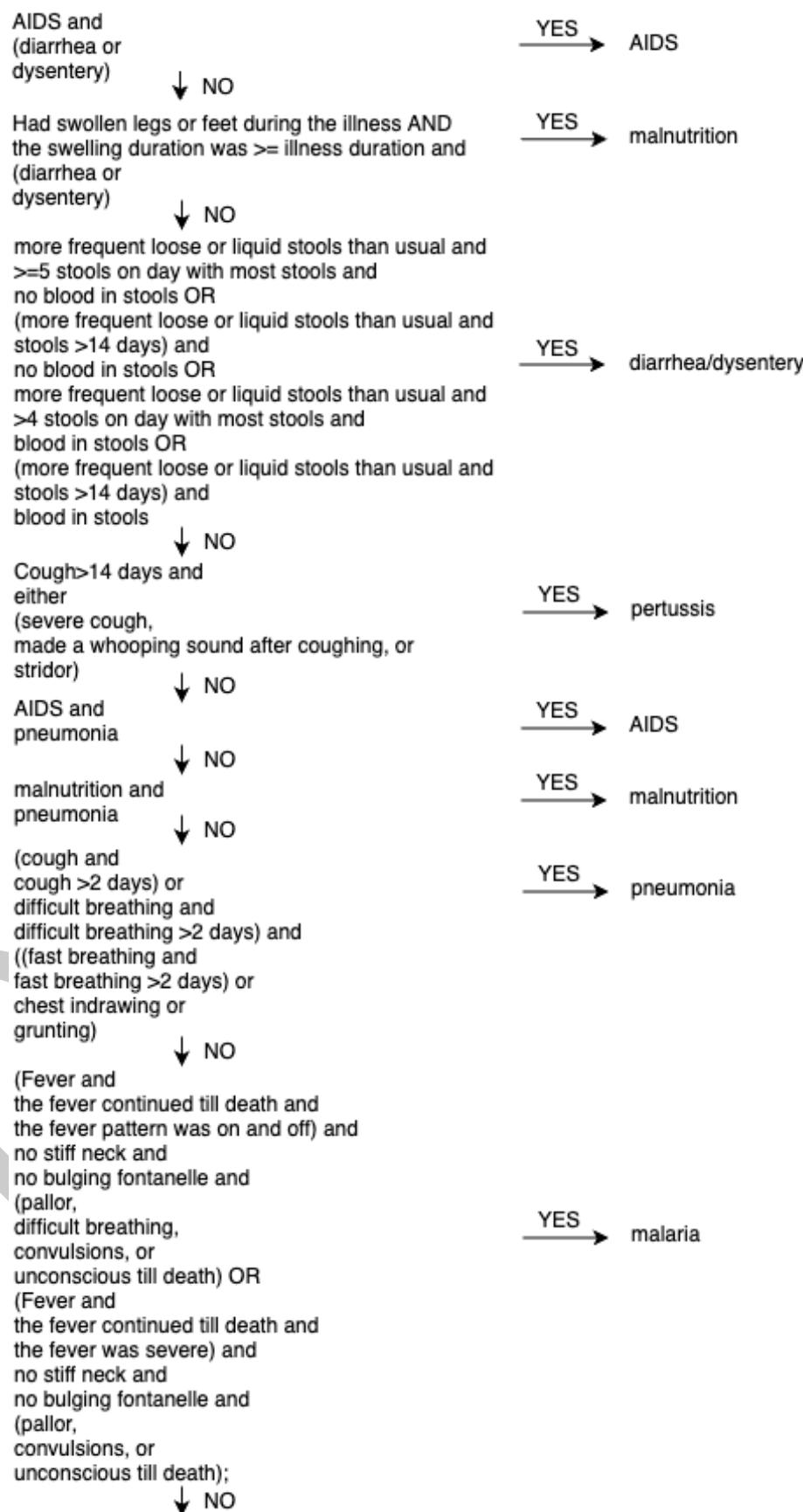
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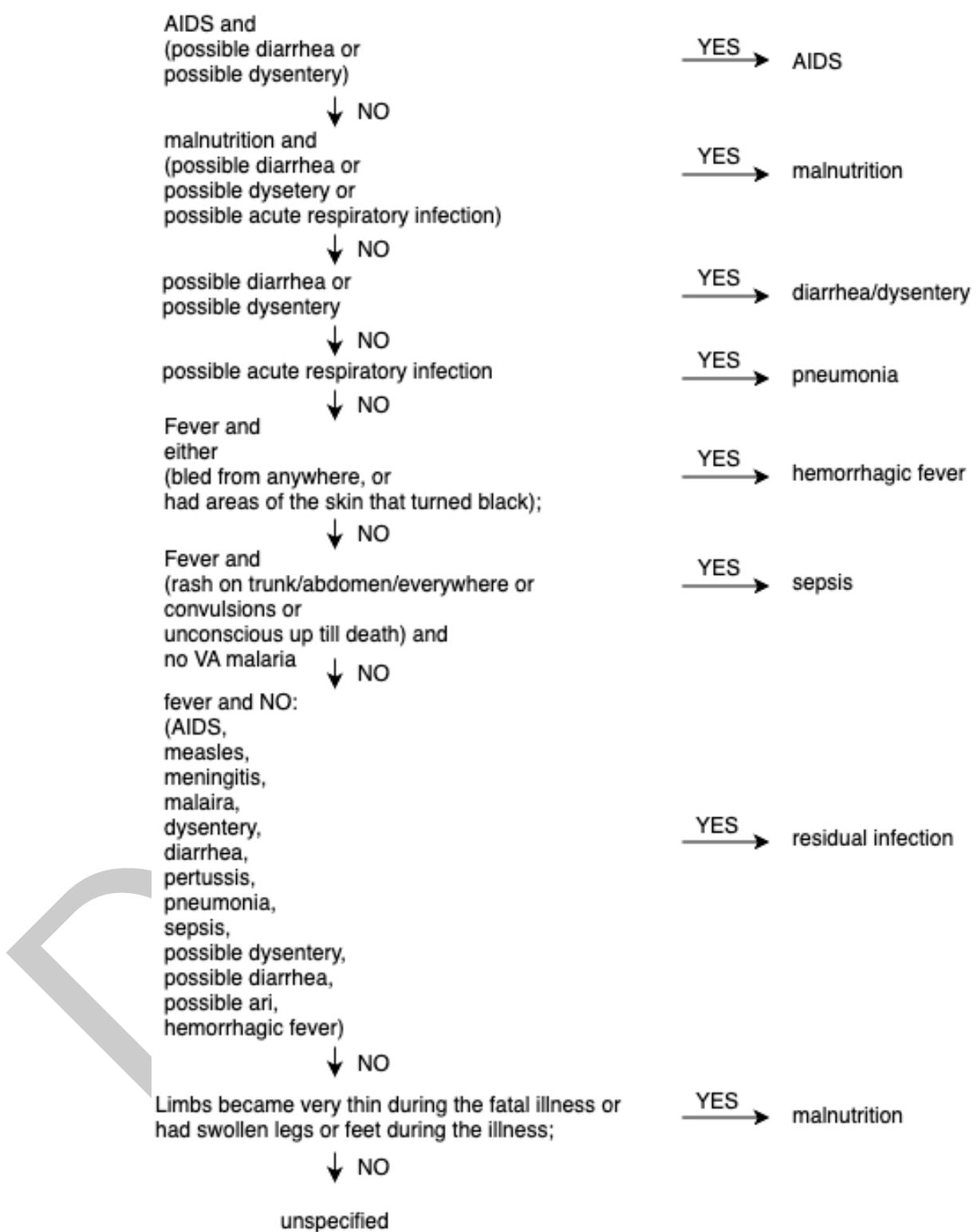


<sup>84</sup> **Appendix 2: deterministic hierarchical algorithm to reach a single  
cause of death in children 1-to-59-months-of-age**





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