









# **TOOL 2: DEALING WITH AMR DATA**

Central to all AMR surveillance activities is collecting, analysing and reporting data. Highquality data is needed to design effective, evidence-based policies and interventions to control and reduce AMR. However, it can be challenging to understand how common AMR is and where it occurs in a country, because AMR data is often collected, analysed and reported in different ways at local levels.<sup>14</sup>

Many countries also lack laboratory and data management capacities to support effective surveillance.<sup>15</sup> Epidemiological skills are important for analysing and interpreting AMR surveillance data, yet few professionals receive formal training in epidemiology. AMR and surveillance activities are often affected by validity and bias; however, these limitations are not commonly understood or reported.<sup>16</sup> To obtain high-quality AMR data, professionals involved in surveillance activities must understand their role in collecting, recording, analysing and reporting data. Therefore, this tool is designed to help professionals develop the epidemiological skills needed to participate in national AMR surveillance activities.

**PROBLEM:** Many professionals involved in AMR surveillance do not have the necessary epidemiological skills to record, analyse and communicate findings accurately.

**OBJECTIVE:** This tool aims to help professionals understand their contribution to data collection and management within AMR surveillance systems and provides opportunities for teams to identify improvements in their workplace. Professionals using this toolkit will also have an opportunity to build on their understanding of bias and validity and the interpretation of data from AMR studies.

#### **MATERIALS NEEDED IN TOOL 2**

In-person meeting:

- Flipchart paper
- Marker pens
- Adhesive (to hang paper on walls)
- Laptop, projector and internet connection (for PowerPoint slides; alternatively, use an overhead projector and printed transparencies of slides)
- Printouts of figures and tables, depending on the task

Online meeting:

- Internet access and broadband speed
- PC, laptop, tablet or mobile phone
- Videoconferencing tools (such as Zoom, MS Teams, Skype, Cisco Webex, Whereby or Google Meet)
- Access to online whiteboards (such as Google Jamboard, Miro, MS Teams whiteboard or the Canvas Chrome app)

<sup>14</sup> Ashley, E.A., Shetty, N., Patel, J., van Doorn, R., Limmathurotsakul, D., Feasey, N.A., Okeke, I.N. and Peacock, S.J. (2019) 'Harnessing alternative sources of antimicrobial resistance data to support surveillance in low-resource settings', *Journal of Antimicrobial Chemotherapy*, 74(3), pp. 541–6 [online]. Available at https://doi.org/10.1093/jac/dky487 (accessed 18 August 2021).

<sup>15</sup> Hay, S.I., Rao, P.C., Dolecek, C., Day, N.P.J., Stergachis, A., Lopez, A.D. and Murray, C.J.L. (2018) 'Measuring and mapping the global burden of antimicrobial resistance', BMC Medicine, 16(1), 78 [online]. Available at https://doi.org/10.1186/s12916-018-1073-z (accessed 18 August 2021).

<sup>16</sup> Rempel, O., Pitout, J.D.D. and Laupland, K.B. (2011) 'Antimicrobial resistance surveillance systems: are potential biases taken into account?', Canadian Journal of Infectious Diseases and Medical Microbiology, 22(4), pp. e24–8 [online]. Available at https://doi.org/10.1155/2011/276017 (accessed 18 August 2021).

#### Task 2.1: The information cycle and the flow of data for AMR surveillance

Time: about 90 minutes

 $\label{eq:Group size} \textbf{Group size}: five to eight participants and a facilitator$ 

Seating arrangement: in a group, pairs or individually

In this first task, participants will have an opportunity to build on their understanding of how information on AMR is obtained through collecting, managing, analysing and reporting data, and how this information becomes the basis for designing interventions and formulating policies. Participants will identify their own and their team's role in the flow of data for AMR surveillance. This task will require approximately one hour.

 Ask participants to work in groups of two or three people to create a list of all the possible sources of AMR data in their workplace. When describing the sources of data, they should also identify the types of data they deal with, such as clinical patient or animal data, specimen data, laboratory data, pharmacy data, etc. Ask them to consider the following questions:

- What data do you collect (or generate) yourself?
- Is any data is being collected as part of an ongoing surveillance task?
- Do you collect data from alternative sources, such as scientific papers, other research activities, etc.?
- Are there any data sources that are not currently available to you to access? Or are there teams/units etc. in your workplace that you did not previously think of as potential sources of AMR data?

If you are meeting in person, participants can use paper or a whiteboard to write down their responses. If you are meeting remotely, online whiteboards may be a helpful tool to write down everyone's ideas.

#### **Facilitator notes:**

AMR surveillance data can be obtained in two ways: (1) directly from primary sources, such as clinical examination or laboratory testing, or (2) from secondary sources, by gathering data from national surveillance data programmes or research.

Some of the categories and types of data collected for AMR surveillance are as follows:

- Clinical (patient or animal) data (demographic data or metadata): unique identifier; age; gender; healthcare/ veterinary facility; date of admission; presenting symptoms.
- Sampling data (for surveillance): unique identifier; species; breed; gender; sampling site (e.g. slaughterhouse, market); specimen site; specimen type; previous history, etc.
- Antimicrobial data: antimicrobial used; dosage; dosage interval; start/end date; history of antimicrobial treatments, etc.
- Laboratory data: data of receival; culture and ID methods; isolate identifier; antimicrobial susceptibility test (AST) method; species and serotype; quantitative AST result (e.g. minimum inhibitory concentration (MIC), zone diameter (ZD)); qualitative test result (S, I, R); genotypic test, etc.

If participants are working in laboratories or clinical settings, did they consider data sources other than primary sources? What about policy-makers? These participants are likely to access data from several different sources to help inform their decision-making.

- 2. Now that participants have identified the data they collect, get them to think about the other stages of the information life cycle. To get the discussion started, show the group Figure T2.1. Then, as a group, discuss turning data into information and the steps go through along the way. Prompt the group with the following questions:
- a. What do we do with data? (How do we manage/ process and analyse data? At this point, data is converted to information.)
- b. How do we present information for example, visually (tables, graphs), in reports, etc.?
- c. How do we use information? (Interpretation, decision-making, etc.)

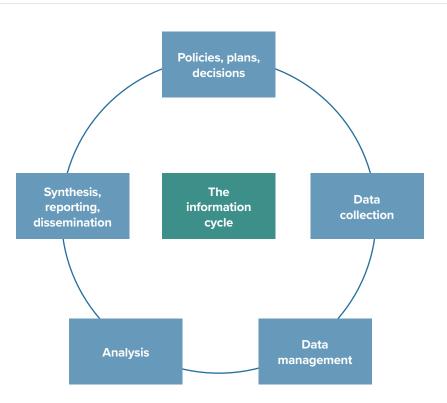


Figure T2.1 The information cycle (Ausvet).

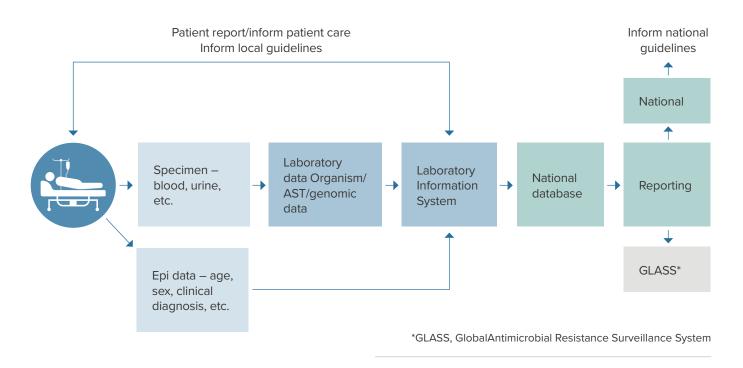
- 3. Ask participants in pairs to sketch out the flow of AMR data in their workplace: specifically, where or how the data comes into the workplace, what happens with data in the workplace, and where data goes out of the workplace.
- Display the participants' diagrams on the wall (or share them online). Also, share the data flow diagrams provided: Figure T2.1 is for human health professionals, and Figure T2.2 is for animal health professionals.
- Ask the participants to compare their diagrams with each other, and with Figure T2.1 or Figure T2.2. Can the group identify how data moves through their workplace?

### **Facilitator notes:**

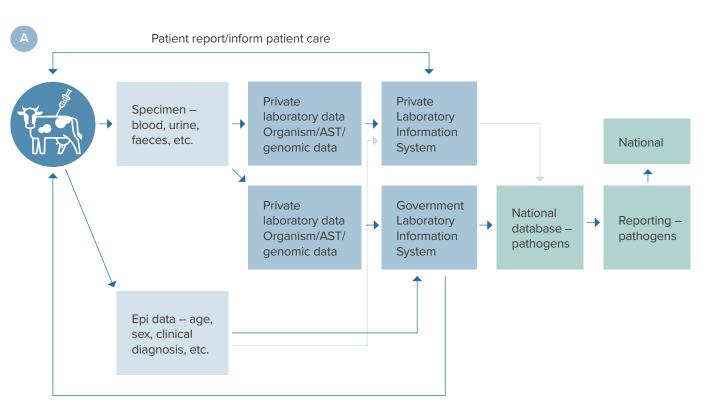
For human health, the ideal data flow situation is local-level data (such as patient data from a hospital and microbiological data generated in a laboratory) moving from the patient care setting to national and global reporting systems.

At the local level, AST results are used to inform treatment decisions about an individual patient, and AST data from all patients in a hospital or local area are used to develop empirical prescribing guidelines. National government agencies may collect data from the local level to develop national prescribing guidelines for surveillance (for example, to report rates of resistance and track changes over time) and to develop intervention programmes. Finally, local-level data may be used to report to global surveillance initiatives such as GLASS.

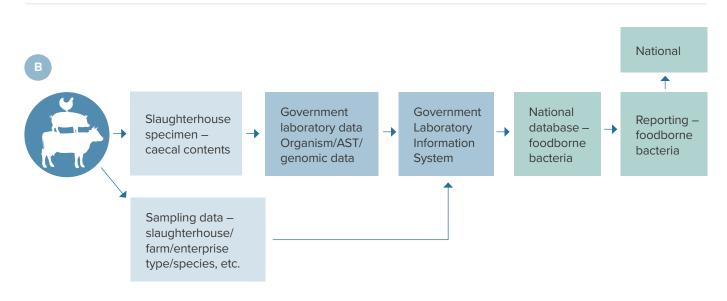
In contrast to human health, much of the AMR data used for surveillance of animals comes from healthy animals. This data flows directly into national databases, often from national reference laboratories or well-supported provincial laboratories. However, some AMR surveillance data in animal health may come from sick animals. If this data is collected, then the flow of data is like that in human health settings. However, accessing AST data from sick animals can be challenging, because the data may come from privately run laboratories.



**Figure T2.1** The flow of AMR data from clinical surveillance of hospitalised patients in a human health setting (Ausvet). (Note that 'GLASS' is the Global Antimicrobial Resistance Surveillance System.)



Patient report/inform patient care



**Figure T2.2** Clinical surveillance of sick animals in an animal health setting and active surveillance of food animals in animal health setting (Ausvet).

5. When data management and data quality procedures are not clear, there is a risk that poor-quality data will be submitted, or that data will not be generated regularly or on time. This affects the flow of data through the AMR surveillance system. Still in their pairs or groups of three, ask the participants to identify any challenges they experience with AMR data flow in their workplace. They should write down these challenges on paper or on a whiteboard.

#### **Facilitator notes:**

Challenges may include inadequate laboratory capacity, a lack of electronic databases, poor linkages between clinical and laboratory data, etc. For example, a participant may be a microbiologist who is responsible for generating and recording AST data, but they work under significant resourcing pressures (such as no time, broken equipment, etc) that affects their ability to perform laboratory tests to as high a quality as they would like.

Alternatively, a participant may be a policy-maker who is reliant on data from the national database and other sources, but there is not enough good-quality information available. The policy-makers rely on this data to develop and implement interventions to control AMR. Some of these interventions may significantly impact members of the community: for example, banning certain antimicrobials in food animals can affect farmers. Without good evidence to demonstrate otherwise, a ban on an antimicrobial agent may negatively impact the health and welfare of animals. Therefore, accurate information is needed to ensure that interventions are necessary and effective.

Ask the participants to report back to the group on their challenges with the flow of AMR data in their workplace. Discuss these challenges as a group and identify practical solutions to some of the problems.

#### **FOLLOW-ON ACTIONS**

As a team leader or manager, you may be able to fix some problems with the way that AMR data flows through your workplace. Reflect on the practical solutions your team may have come up with during this session and think about whether some of these can be implemented. Review these activities regularly.

#### Task 2.2: Data management for AMR surveillance

Time: about 90 minutes

Group size: five to eight participants and a facilitator

Seating arrangement: in a group, pairs or individually

Data management is the next step on the information cycle after data collection. It refers to a set of processes to prepare data for analysis. Without good data management, errors can occur when data is entered, analysed and interpreted; this in turn affects the truthfulness of the information communicated about AMR in a population. Therefore, good-quality data management is an essential component of any surveillance system. In this task, participants will reflect on their understanding of database management principles in their workplace. This task will require approximately one hour.

 As a whole group, ask the participants to identify data management processes required for an AMR surveillance programme. Write these down on paper or a whiteboard.

### **Facilitator notes:**

If needed, you could help to start the discussion by mentioning some of these processes, such as:

- data entry, checking for errors, other quality assurance measures
- determining the essential data set
- creating indicator variables
- integrating two or more data sources
- structuring data within the database structures
- data storage and archiving
- data governance policies and procedures for access, sharing, confidentiality
- data security and protection systems.
- 2. Next, ask the whole group to identify and write down what they think are the best practice characteristics of a good data management system for an AMR surveillance programme.

#### **Facilitator notes:**

If needed, you could help to start the discussion by mentioning some of these characteristics, such as:

- a single validated source of information
- privacy and confidentiality (such as 'de-identifying' patient data)
- adaptive and responsive database systems
- a well-structured and compatible IT system
- user-friendliness
- electronic databases where possible (avoid paper-based forms)
- recording raw (quantitative) results, such as MIC, zone diameter measurements

 Now work through a scenario of what poor data management practices could look like and what can be done to improve them. In this scenario, Ani, an employee of the Ministry of Health, is responsible for putting together all the information required to report to GLASS. Share Figure T2.4 with participants and work through the steps Ani that has to go through to submit data to GLASS, the global AMR surveillance system managed by the World Health Organization (WHO).

#### **Facilitator notes:**

While this scenario is related to participants who work in human health settings, it is also relevant to those who work in animal health settings.

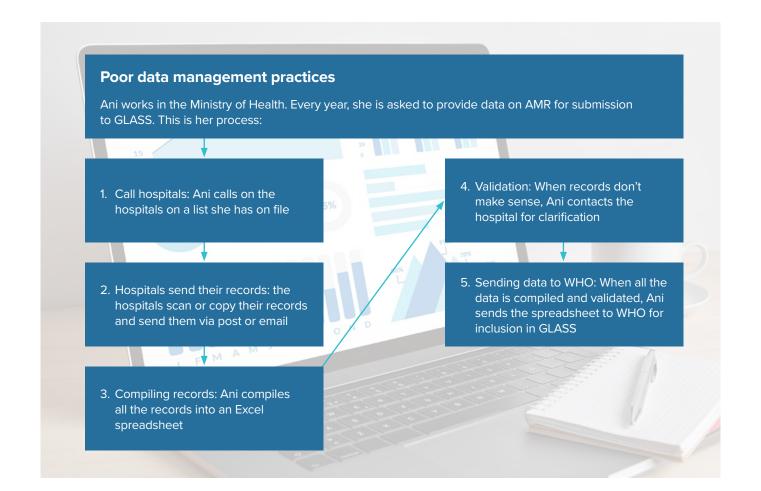


Figure T2.3 Examples of poor data management practices for reporting to GLASS (Ausvet).

4. Now work through what best practice data management looks like for Ani. Ask the group to identify best practice options at each step, and briefly discuss before revealing the answer. Be sure to discuss what best practice is if the group has been unable to determine this before sharing Figure T2.5.

#### Best practice data management processes Ani works in the Ministry of Health. Every year, she is asked to provide data on AMR for submission to GLASS. This is her process: 4. Validation: inbuilt validation in the 1. Ani has a data management system data management systems. These that is automatically linked to all systems automatically query any hospitals on her list data inputs that seem unreasonable. Ani can still contact the hospitals to query any errors not picked up by automatic validation 2. Hospitals provide their records: a data management system that collects all hospital data 5. Sending data to WHO: Ani's data automatically management system aggregates results into an output compatible with GLASS reporting requirements for submission to WHO 3. Compiling records: all the hospital data management systems are compatible, so they automatically provide the outputs Ani requires. The report she generates include all the fields WHO needs automatically

Figure T2.4 Examples of best practice data management for reporting to GLASS (Ausvet).

5. Now that participants know what best practice looks like, ask them (either individually or in small groups) to identify how the data management system used in their current job compares with best practice. Ask them to refer to the lists of data management processes and best practice characteristics that they created in Steps 1 and 2, and to make a note of the strengths and weaknesses of the data management system in the workplace.

#### **Facilitator notes:**

Be sure to share the lists from Steps 1 and 2 so that they can refer to them during this exercise.

- 6. Following on from Step 5, ask the participants to work in groups to identify where data management practices can be improved in their workplace to:
  - a. improve the quality of the data contained in the database (such as minimising data entry errors, using electronic records, etc.)
  - b. improve data flow through the workplace (for

example by using a central database)

c. meet reporting requirements set by their workplace, government agencies, and international programmes such as GLASS or OIE (whether the data is standardised, or if there minimum essential data sets).

#### **Facilitator notes:**

If required, resources on the reporting requirements for GLASS and OIE can be found at the end of the toolkit to inform the discussion.

Ask each group to present these ideas back to the main group for a general discussion. As a group, help to identify how data management systems can be improved within the workplace.

#### **FOLLOW-ON ACTIONS**

Think critically about the challenges that participants have reported during the discussion about data management. Can you implement improvements in data management processes? Support staff to adopt new data management processes.

### Task 2.3: Understanding error, bias, and validity in AMR data for interpretation

Time: about 90 minutes

Group size: five to eight participants and a facilitator

Seating arrangement: in a group, pairs or individually

#### **Facilitator notes:**

Here's a quick recap (if you need one) on error, bias, and validity. When conducting surveillance to determine the frequency of AMR in a population, we are always aiming to find the 'truth'. Deviation from the truth may be due to random or systematic errors. Systematic error (also known as bias) is the most important error associated with AMR data. **Bias** occurs when the samples collected are from patients or animals that are not representative of the population (selection bias). Bias also occurs because of problems with diagnostic or laboratory equipment, for example a mis-calibrated instrument causing repeated measurement errors.

#### Validity

Describes the extent to which a study measures what it intends to measure without systematic bias. It is divided into two parts: (1) **internal validity**, which describes how representative study results are of true study population values, and (2) **external validity**, which describes to what extent study results can be extrapolated to the target population.

The participants have now worked their way around the information cycle to data analysis and interpretation. For this task, participants will have an opportunity to understand common sources of error and bias, and limits to validity of AMR data – and how these affect data interpretations. After this task, participants should critically appraise sources of error and bias in AMR data and determine if the results are valid for the population.

1. Selection bias task: Start this task by watching <u>a</u> two-minute YouTube video on selection bias.<sup>17</sup> (This video was part of a task in the module Fundamentals of AMR data, from the Tacking antimicrobial resistance online course.) After watching it, ask the group to identify examples of selection bias that may occur in their workplace or in AMR surveillance in general. The participants should write down these limitations or challenges.

#### **Facilitator notes:**

Participants may identify forms of error or bias that are not selection bias. If this occurs during the discussion, note these biases and inform participants what type of bias they have identified.

In human health settings, selection bias can occur when only specimens from hospitalised patients who do not respond to first-line treatment are collected and submitted ASTs. If there is no AST data from patients who are successfully treated with the first antimicrobial prescribed – that is, patients who are less likely to have resistant infections – then the results from surveillance may overestimate the prevalence of AMR in the human population.

In animal healthcare settings, selection bias can occur when only healthy animals are sampled. For example, broilers (meat chickens) are sampled at slaughterhouses for national surveillance of AMR in foodborne bacteria. However, only healthy chickens are sent to the slaughterhouse – sick chickens may die or are euthanised before reaching the end of the production cycle. Sick birds may be more likely to have a resistant infection that did not respond to antimicrobials. This means that the results of a study of AMR in foodborne bacteria from healthy broilers at slaughter may underestimate the prevalence of AMR in broilers overall. However, if the objective of surveillance in food animals is to estimate the prevalence of AMR in animals that enter the human food chain, then this bias is not really a problem, because sick birds do not generally enter the food chain. Instead, separate surveillance activities can be conducted on sick animals. In this case, the objective of surveillance in sick animals would be to detect changing or emerging resistance mechanisms.

 As a whole group, look at an example of selection bias as shown in Figure T2.6. In the example, a researcher investigates the prevalence of methicillin-resistant Staphylococcus aureus (MRSA) in people in Indonesia. Work through the steps that the researcher takes to determine the prevalence of MRSA in Indonesian hospitals.

#### **Facilitator notes:**

While this scenario is related to participants who work in human health settings, the concepts are also relevant to those who work in animal health settings.

<sup>17</sup> If you cannot access YouTube in your organisation, share the link of the video with the participants and ask them to watch this prior to the team meeting.

#### **Selection bias: Example**

A researcher designs a study that aims to report the prevalence of methicillin-resistant *Staphylococcus aureus* (MRSA) in Indonesia. The research steps include:

	1. The researcher has a friend working in a surgical ward of a hospital in Jakarta
۲ ه	2. The friend downloads all the AST results for post-operative patients on the ward in the past 12 months
	3. Over 1000 AST results were available, so the researcher is very pleased with the sample size, which minimises random error
O Y	4. The researcher analyses the data
	5. The results show that 72% of S. aureus samples are resistant to methicillin
	6. The researcher concludes that MRSA is very common in Indonesia

Figure T2.5 An example of selection bias in an AMR study in human healthcare (Ausvet).

Now ask the participants the following questions:

a. What is wrong with this study?

#### **Facilitator notes:**

The researcher's target population was the whole of Indonesia, but the population sampled was just selected from post-operative patients in one surgical ward of a hospital in Jakarta. Post-operative patients are more likely to be exposed to MRSA than the general population. Also, the patients selected were only those where doctors have requested AST. It is likely these patients had AST performed because they had failed antimicrobial therapy.

b. Should the researcher abandon the study and start again?

#### **Facilitator notes:**

The study can still provide some useful information – on the prevalence of MRSA in post-operative patients in a hospital in Jakarta, for example. However, it cannot answer the original research question: 'What is the prevalence of MRSA in Indonesia?'

#### **Facilitator notes:**

The data should not be used alone to measure the prevalence of MRSA in the Indonesian population, because it only describes the prevalence of MRSA in post-operative patients at a hospital in Jakarta. However, in combination with data from other hospitals and outpatient settings, this data can contribute to understanding AMR in Indonesia overall.

- 3. Validity task: Start this task by watching a two-minute YouTube video on external validity. After watching it, ask the participants to think about their work and the populations they sample. Prompt the discussion with the following questions:
  - a. What samples does your workplace collect or process? Are the samples from healthy animals, sick people, etc.?
  - b. What are the implications for external and internal validity in interpreting and reporting on AMR from these samples?
  - c. What can be done in your workplace to address the validity problems?
- 4. Next, ask the group to examine the validity problem in AMR surveillance which is this:

In most cases we want to answer the question 'What is the prevalence of resistance to antimicrobials in a population in Country X?' but the activities that generate data used in surveillance can usually only answer the question 'What is the prevalence of resistance to antimicrobials in the bacterial isolates tested?' When the sample is not representative, as is the case in most AMR surveillance, the information from AST cannot be easily extrapolated to the wider population. Prompt the discussion by asking the group the following:

- a. What are the limitations of AMR data and how do they affect what we know about AMR overall?
- b. How can we make samples more representative in human health and animal health?
- c. If the challenges are too great to achieve representativeness in AMR studies, what else can be done to manage validity and the appropriate reporting of AMR data?

#### **Facilitator notes:**

some suggestions for improving validity include:

- making sure you are sampling representative data points for example, don't just sample broiler chickens reared in a large commercial farm if you want to learn about AMR in chickens in a country where smallholders raise most chickens
- evaluating the validity of a study when interpreting its results
- not making conclusions at the population level if the study is based on a biased, non-representative sample
- educating yourself and colleagues on the importance of validity in surveillance.

## **FOLLOW-ON ACTIONS**

As individuals, reflect on the following when participating or reviewing data arising from AMR studies or surveillance activities:

- Is the design of the task appropriate for the research or surveillance objective?
- Do the sampling units (people or animals sampled) differ systematically from the general population that is being examined?
- Is the way that AMR is measured susceptible to measurement or misclassification errors?
- Is the interpretation of results appropriate? For example, are the report authors wrongly implying that the results can be extrapolated to the general population?

# Additional resources on the collection of AMR and AMU data for international reporting requirements (GLASS and OIE)

### WHO/GLASS

- Global Antimicrobial Resistance Surveillance System: Manual For Early Implementation (WHO, 2015)
- Global Antimicrobial Resistance and Use Surveillance System (GLASS) Report: Early Implementation 2020 (WHO, 2020)
- WHONET: microbiology laboratory database software

#### OIE

- <u>'Monitoring of the quantities and usage patterns of antimicrobial agents used in food-producing animals</u>', Chapter 6.9 of the Terrestrial Animal Health Code (OIE, 2019)
- 'Guidance for completing the OIE template for the collection of data on antimicrobial agents intended for use in animals' (OIE, 2020)
- Template for an AMU survey
- OIE Annual Report on Antimicrobial Agents Intended for Use in Animals: Better Understanding of the Global Situation, fifth report (OIE, 2021)

#### Tackling antimicrobial resistance online modules

- Fundamentals of data for AMR https://www.open.edu/openlearncreate/course/view.php?id=6554
- Processing and analysing AMR data <a href="https://www.open.edu/openlearncreate/course/view.php?id=6556">https://www.open.edu/openlearncreate/course/view.php?id=6556</a>
- Sampling (human health) https://www.open.edu/openlearncreate/course/view.php?id=6550
- Sampling (animal health) https://www.open.edu/openlearncreate/course/view.php?id=5624
- Introducing AMR surveillance systems <a href="https://www.open.edu/openlearncreate/course/view.php?id=6548">https://www.open.edu/openlearncreate/course/view.php?id=6548</a>

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