Expert knowledge elicitation: Accessing the big data in experts' brains

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Abstract

A vast amount of expert knowledge currently remains inaccessible to digital information systems. Expert knowledge elicitation is a systematic approach to accessing and synthesizing the insights of subject matter experts, especially when accessible objective data are incomplete. In plant pathology, expert knowledge elicitation is valuable for addressing urgent, uncertain, and/or future challenges, such as emerging disease threats, complex epidemiological systems, knowledge gaps when resources are limited, and future scenarios. This perspective explores when expert knowledge elicitation is most effective for addressing plant health challenges, emphasizing its role in informing timely, expert-based decisions. We discuss lessons learned from real-world implementations across diverse regions and pathosystems, highlighting strategies for eliciting, structuring, and interpreting expert-derived data, as well as associated caveats. We frame expert knowledge as a form of “big data,” and outline two complementary approaches: (i) how existing big-data streams (e.g., remote sensing, crowdsourced reports, and digital surveillance) can inform expert judgements; and (ii) how outputs from expert knowledge elicitation can be captured as scalable datasets (text, tabular, audio, and video) that enable AI-supported synthesis. Also, we illustrate how expert knowledge can be integrated in Bayesian analyses, providing a transparent and rigorous approach to understanding uncertainty and improving inference. Finally, we outline future opportunities, including integration with artificial intelligence, to scale and strengthen expert knowledge elicitation in support of global plant health.

Keywords: Prior knowledge, Bayesian update, decision support, epidemic modeling, expert opinion, knowledge gaps, future scenarios, expert elicitation, big data, artificial intelligence, natural language processing

Expert Knowledge Elicitation: Transforming Expert Insight into Data

In plant pathology, not all knowledge is accessible in digital information systems, such as peer-reviewed publications or public databases. Experts in plant pathology who, for example, work with growers and perform experiments throughout a region, acquire extensive knowledge from their field experience and informal observations that often remains unpublished (Fig. 1). The 'file drawer problem,' where lower priority results are filed away and known only to collaborators, is a common issue across scientific disciplines (Scherm et al. 2014). Expert knowledge can be thought of as big data based on common "3V" definitions (Kitchin and McArdle 2016; McAfee and Brynjolfsson 2012; Table 1) due to its high volume, velocity of acquisition and updating, and variety of topics (Bargmann and Marder 2013; Bazinet et al. 2023).

Big data in plant pathology span genetic sequence repositories, unstructured text in scientific articles, readings from remote sensors (satellites, drones, smartphones), and high-resolution meteorological data (e.g., forecasting). Disease-forecasting tools illustrate velocity by processing near-real-time information to support day-to-day decisions (Mueller et al. 2024). Advances in data collection and artificial intelligence facilitate processing of expert knowledge into structured information for integration with other data types to address key problems in plant pathology. When objective data are scarce, costly, or not readily available in digital form, structured expert knowledge elicitation is a pathway to access expert knowledge. Digitization into tangible data like audio and video represents a promising avenue to improve reproducibility.

Considering expert knowledge as "big data" emphasizes the scale, richness, and rapid updating of human information processing. Humans have substantial long-term visual memory capacity, with experiments documenting storage of detailed representations of thousands of images (Brady et al. 2008; Wang et al. 2003). Experts can process visual information rapidly (e.g., plant disease images) and base their opinions on patterns they have observed. In practice, expert knowledge may be updated almost in real time and at regional scales, for example, through scouting and consultations. This makes experts “walking databases” of diverse, often unpublished epidemiological information accumulated over years of experience.

Expert knowledge elicitation (Table 1) is a systematic process to gather expert knowledge and opinions, and to synthesize these perspectives (Hadjigeorgiou et al. 2022). It may address specific system traits – such as yield loss and management adoption rates (potentially as model parameters for follow-up studies) – or more strongly subjective judgements, such as preferences and opinions about future scenarios (EFSA Panel on Plant Health (PLH) et al. 2018; Hadjigeorgiou et al. 2022). Expert knowledge is particularly useful when objective data from field, lab, or greenhouse experiments are limited (Costa et al. 2017; EFSA Panel on Plant Health (PLH) et al. 2018). As we discuss below, one important aspect of expert knowledge elicitation is incorporation of methods to minimize the effects of bias and address other challenges inherent to expert judgements.

Existing big-data streams inform expert judgments, and better integration can improve elicitation design. For example, satellite or drone imagery could help contextualize expert-estimated rates of pathogen dispersal. Leveraging crowdsourced disease reports and social-media signals can be complementary to expert perceptions about disease occurrence (Bock et al. 2020; Mahlein 2016). Conversely, expert-elicited information may be transformed into tangible big data, like audio or video from interviews or text from narrative responses and surveys. This information could be captured via platforms such as REDCap/Qualtrics and archived for re-use, enabling replication, sensitivity analysis, and meta-analyses (Patridge and Bardyn 2018).

The *first* objective of this Perspective is to synthesize how expert knowledge elicitation has been used in plant pathology and its potential for new applications. The *second* objective is to review methods in expert knowledge elicitation that provide structured and scalable information, while considering the limitations associated with interpreting this data. *Third*, we illustrate how expert knowledge can be integrated as informative priors (Table 1) or data in a Bayesian update, and how updating these priors, as new data become available, supports evidence-based practices. *Finally*, we consider the future potential for expert knowledge elicitation, including integration with artificial intelligence.

Expert Knowledge Elicitation in Plant Pathology and other Fields: Uses and Impact

Expert knowledge elicitation is an emerging tool in plant pathology, providing valuable information for decision-making to address plant health issues. Collective expert knowledge is often a primary source of unpublished information that is used for pathogen prioritization (McRoberts et al. 2016). Expert judgment is commonly used to quantify the risk of the introduction of plant pathogens to a new region (Arndt et al. 2022). In practice, determining priority locations for pathogen surveillance across a region (e.g., a state or province) often depends on the multi-criteria knowledge of experts (Bouwmeester et al. 2023; Hughes and Madden 2002).

Some studies have highlighted the complementary value of expert assessment in estimating key parameters in epidemiological models (Chen et al. 2019; Hughes and Madden 2002). These applications build on foundational epidemiological frameworks developed for the study of plant disease epidemics (Jeger et al. 2018; Madden et al. 2007). In other cases, decision-support systems for plant diseases have been strengthened or validated through shared expert judgment (Chen et al. 2019; Motisi et al. 2022). Expert knowledge elicitation has helped characterize geographic risk factors contributing to the spread of plant pathogens (Andersen Onofre et al. 2021; Etherton et al. 2025; Thomas-Sharma et al. 2017).

At larger geographic scales, expert knowledge has been used to understand the impacts of plant pathogens on global ecosystems (Acuña et al. 2023; Savary et al. 2019). In policy development, the U.S. Environmental Protection Agency (EPA) uses balanced expert assessment (Table 1) when reviewing the impacts of insecticides, fungicides, and rodenticides on human health and the environment (U.S. Environmental Protection Agency 2004, 2009, 2024). Expert knowledge elicitation has been applied to support decision analysis across the science of plant health: for a range of plant pathogens, across host plants, and in high-, middle-, and low-income countries (Table 2).

Use of expert knowledge elicitation in other disciplines illustrates the potential for new applications in plant pathology. Many areas of plant pathology can benefit from expert knowledge methods applied in pest biosecurity (EFSA 2014). Plant pathology commonly has data requirements to understand pathways of transmission, uncertainty, and how to address newly emerging problems. These applications map onto complementary modeling approaches that have different strengths and data needs (Table S1A). Models of human health have used expert knowledge to adjust the modeling process for estimating the burden of communicable diseases (Mangen et al. 2013). Conservation biology uses expert knowledge elicitation to address the common need to make decisions with incomplete information (Petracca et al. 2018; Runge et al. 2011), an issue for many questions in plant pathology. Expert opinions have also helped to characterize the effects of technologies on progress toward the Sustainable Development Goals (Herrero et al. 2021), illustrating the potential for using expert reasoning to evaluate future scenarios. In agricultural economics, Bayesian updates have been used to integrate objective data with expert opinions (Mkondiwa et al. 2024). Integrating these data types can help bridge evidence gaps, improve uncertainty quantification, and support more informed decisions, for example, for farm input subsidy programs.

When, Where, and Why to Use Expert Knowledge Elicitation in Plant Pathology

Types of uncertainty: In general, three key considerations can help plant pathologists determine whether expert knowledge elicitation is useful to address a problem in plant health science (Fig. 2). The first consideration is the level of uncertainty associated with the plant health problem in question. Uncertainty can arise from a relative lack of knowledge (epistemic uncertainty - Table 1) or the inherent randomness in a system or process (stochastic/aleatoric uncertainty - Table 1) (Kiureghian and Ditlevsen 2009). Both types of uncertainty are often an issue for questions in plant pathology. One source of epistemic uncertainty is confounding factors; for example, when assessing the use of a fungicide for disease management, it is difficult to have full knowledge about the trade-offs of economic risks and environmental risks (such as fungicide resistance development) (U.S. Environmental Protection Agency 2004, 2009). Another key example of epistemic uncertainty is limited information about the informal trade of planting material in a region (Table 1: 'informal planting-material exchange') (e.g., Andersen Onofre et al. 2021; Etherton et al. 2025; Mouafo-Tchinda et al. 2024), where informal trade is currently difficult to track through objective approaches in most countries. Stochastic uncertainty is generated by system elements that are inherently difficult to predict. Examples include weather conditions years in the future that will influence epidemics, or yield losses at a national or global scale (Savary et al. 2019).

Expert knowledge elicitation can support decision-making when there is a substantial degree of uncertainty in the target problem. If a problem is too uncertain, experts may lack sufficient relevant information to address the problem (Morgan 2014). For example, accurately anticipating the timing and geographic location for the introduction and establishment of a new pathogen species in a country is a particularly complex problem; the utility of expert opinion may be limited in the face of such high uncertainty. However, biosecurity experts might have unpublished information about geographic factors driving the general introduction patterns of plant pathogens at a particular location (a less uncertain problem), and good foundational knowledge of pathogen biology. This expert knowledge could provide valuable information for addressing the problem. If solving a problem depends on information that is already certain or readily predictable, tools other than expert elicitation can address the problem using available information.

Data availability: A second consideration is whether objective data are currently lacking or digitally inaccessible (Fig. 2). For example, a practical issue in plant pathology is the prioritization of pathogen species in biosecurity programs to prevent introduction and establishment in a country. How do policymakers effectively establish priorities quickly if essential epidemiological information is typically lacking for new pathogens? Similarly, when addressing large, complex systems, such as value chains (Table 1) or landscape-scale cropping systems, objective data may not exist, may be sparse, and may be difficult to combine in models lacking interoperability. Expert knowledge elicitation can serve as a quick approach to acquiring this relevant information in a structured format, using proven methodologies for data collection, calibration and analysis (Aspinall and Cooke 2013; Morgan 2014), as discussed in more detail below. Another useful outcome from expert elicitation can be identifying which information needs to be collected through objective data-acquisition tools in the long term.

Cost-effectiveness: A third consideration is the cost-effectiveness of expert knowledge elicitation given resource constraints. Plant pathologists have used expert knowledge elicitation when acquiring data with 'gold-standard' technologies is challenging (e.g., when implementing new field experiments is not practical). For example, expert elicitation has been applied in African agricultural systems, where expert elicitation provided the first quantitative comparisons of organic and conventional agriculture performance (Andriamampianina et al. 2018). Expert elicitation can serve as a relatively rapid data-acquisition tool when these other technologies are too costly (Arndt et al. 2022), time-consuming (Chen et al. 2019), or not feasible (e.g., quickly documenting informal exchange of planting material (Andersen Onofre et al. 2021)). The flexibility of expert elicitation may be seen as both a strength and weakness; while methods may be difficult to standardize and field-specific protocols are scarce, this malleability allows for a set of methodological adaptations based on time, budget, and locational constraints (Hemming et al. 2018). Software such as Elicitator (Allan et al. 2010) can make analyses more straightforward; in general, open-source software can streamline the formalization of elicitation protocols, and collection and processing of data, a priority in time-sensitive situations (Aspinall and Cooke 2013; Knol et al. 2010). However, expert knowledge elicitation alone is clearly inappropriate for providing definitive evidence to address a new biological hypothesis, such as satisfying Koch's postulates or confirming the presence of a new pathogen species in a country.

Expert knowledge elicitation is generally cost-effective for addressing problems in plant pathology where substantial uncertainty, lack of objective data, and resource constraints converge, especially when information is needed quickly. Expert knowledge elicitation offers additional benefits beyond data collection. When experts interact directly, such as drawing experts together in meetings, expert elicitation can facilitate interactions that may develop into future projects, encourage the creation of collaboration networks, develop innovative ideas, and foster knowledge transfer across domains. There are opportunities to better integrate expert elicitation with existing big-data resources (e.g., remote sensing layers or gridded weather data), which may increase cost-effectiveness. by providing context that speeds convergence and supports validation of elicited quantities. Framework selection can be guided by precision, scalability, interpretability, and data requirements; Table S1A summarizes these trade-offs to support method choice.

How Expert Knowledge Is Collected and Translated into Usable Data

There are generally four steps to conducting expert knowledge elicitation: i) defining the project objectives and determining what data to elicit to meet them, ii) designing the elicitation process, iii) implementing the elicitation, and iv) translating the data obtained into quantitative information to inform decision making (Martin et al. 2012). The first step is to define the purpose of the information gathered through elicitation. The kind of data to be obtained, the nature of the models used, and decisions to be made will determine whether a research question warrants the use of expert knowledge elicitation. Information elicited from experts is most useful when uncertainty affects a final model or decision, or improves the performance of the model or decision being made (Bojke et al. 2021).

The second step is to determine the specific type of information required, for example by choosing models or parameters, and approaches to quantifying uncertainty. At this stage, research organizers formulate the questions experts will answer. It is important to include in the organizational team an array of end users, such as modelers and people knowledgeable about the system being targeted. This team will discuss data formats and use in a model/decision, and alignment with the resources available for processing data and modeling. This team also selects and invites experts to participate in the expert knowledge elicitation, considering factors such as expert reputation, experience, publication record, and availability (Bojke et al. 2021). The European Food Safety Authority (2014) discuss an expert as being someone whose judgement is deemed worth eliciting; in expert knowledge elicitation supporting plant pathology, experts may also come from complementary fields such as crop breeding, economics, and entomology.

The third step involves choosing or designing the elicitation instrument, including methods for measuring uncertainty and processing data. European Food Safety Authority (2014) provides an in-depth discussion of the design, implementation, and aggregation of elicited information. There are two common approaches to data collection. In direct elicitation (Table 1), experts are asked to communicate knowledge in terms of quantities that will be used by the analyst. For example, experts directly provided estimates for the onset date of initial symptoms of grape downy mildew in France (Chen et al. 2019). In indirect elicitation (Table 1), experts provide personal opinions or describe experiences, which the analyst processes to derive the needed quantities (Martin et al. 2012). For example, experts characterized potato seed exchange networks in Ethiopia, which were later used to simulate the potential spread of seedborne pathogens (Etherton et al. 2025); modeling the movement of informal seed would often be impractical without expert input (McGuire and Sperling 2016).

Elicitation methods exist on a spectrum of synchronicity and expert engagement, from asynchronous email surveys of experts, to individual interviews, to group discussions. More direct interactions with experts, whether in-person or by phone, are more resource-intensive than emails or pre-made surveys. Protocols such as Delphi techniques and Cooke's model have the potential to provide concise answers to time-sensitive or high-risk issues, such as in the management of invasive pathogens and biosecurity decisions (Table 1). The European Food Safety Authority (2014) and Soares et al. (2024) provide a detailed comparison of the protocols discussed below. Similar procedures with some additional steps to emphasize systematic preparation, customization to the problem, and transparency of outcomes have been developed in environmental health research (Knol et al. 2010). Facilitators and developers of elicitation questions must have a clear idea of how the data they are collecting will be encoded and analyzed, as this strongly influences the choice of methodology, software, and the structure of the questions (Martin et al. 2012).

Delphi techniques are often used to reach a group consensus by pooling inputs after experts hear the anonymized opinions of other experts and update their individual responses accordingly (Linstone and Turoff 2011), without personal identifiers to influence judgements. It is often applied with an equal-weighting aggregation rule (European Food Safety Authority 2014; McBride et al. 2012). Delphi techniques are most useful for discussion of complex questions, accentuating differing viewpoints while gathering knowledge to generate a clearer answer than what individual experts might provide alone (Linstone and Turoff 2011).

Cooke's model is an individualistic approach that limits expert interaction to training and briefing (European Food Safety Authority 2014). Cooke's model involves weighting experts' judgements based on a set of seed or calibration questions and uses their performance to adjust the relative weight of their answers (Cooke 1991). An important advantage of this model is that it allows for validation (European Food Safety Authority 2014), because the approach to mathematical aggregation is auditable and objective. This model is also supported by readily accessible software, such as the Excalibur package (Boutry et al. 2023) and ANDURYL Python-based code (Hart et al. 2019).

The IDEA "Investigate, Discuss, Estimate, and Aggregate" protocol is a variation of the Delphi technique, to provide a reproducible expert elicitation for estimating probabilities and quantities, originally intended to improve biosecurity decisions (Hemming et al. 2018). The "Discussion" portion in this protocol promotes linguistic clarity, critical thinking, and evidence sharing, rather than emphasizing a group consensus (Hemming et al. 2018). Wittmann et al. (2015) provides an example of the IDEA protocol used to forecast carp invasions in Lake Erie based on expert judgments.

The Sheffield elicitation framework (SHELF) uses behavioral aggregation to reach a consensus distribution (Gosling 2018; Williams et al. 2021). SHELF focuses on variable and fixed interval methods for expert elicitation and is compatible with Bayesian applications. SHELF has a corresponding R package for fitting distributions and illustrating expert judgements in real-time during discussions (Gosling 2018; Soares et al. 2024).

After implementing the elicitation while making sure all questions are clear to the experts, the last step is the translation of the elicited knowledge into quantitative information to inform decision-making or modeling. A common goal of expert knowledge elicitation is integration of data types. For example, expert-based parameter estimates can be combined with epidemiological models (Etherton et al. 2025; Motisi et al. 2022). Table S1A synthesizes how expert-elicited information contributes to priors, parameters, constraints, and validation across Bayesian, mechanistic, and machine-learning frameworks. Daee et al. (2017), Martin et al. (2005) and Rose et al. (2023) exemplify key applications of these frameworks when combined with expert elicitation, highlighting more opportunities for plant pathology than currently applied. Notably, artificial intelligence (e.g., transformer-based sentence embeddings and large language models, or LLMs) provides innovative ways of coding narrative responses, clustering themes, and linking qualitative rationales to quantitative parameters (e.g., Bojanowski et al. 2017; Devlin et al. 2019; Team Gemini et al. 2025). Interactive machine learning offers additional opportunities to integrate expert feedback loops with model refinement (Daee et al. 2017). Capturing expert elicitation outputs as digital artifacts (audio or video of group discussions, verbatim transcripts, structured survey exports) is key to accelerating this integration (Fig. 1). Digitization of expert knowledge enhances (1) replicability and audit trails; (2) evaluation of variability between responses and origin of disagreements; and (3) systematic bias identification.

Mitigating Bias and Assessing the Quality of Expert Knowledge

Expert-elicited knowledge may be subject to several cognitive biases (Morgan 2014). For example, anchoring-adjustment bias occurs when experts are shown potential answers to the questions being asked, such as mentioning the potential yield loss levels before experts respond. Experts' estimates may be directly influenced by these initial values (anchoring) (Tversky and Kahneman 1974). To reduce this issue, questions can be structured in a non-leading way, beginning by asking for values in terms of extremes or in relation to one another, rather than the best value (Morgan 2014). Anchoring is an important consideration in structuring expert knowledge elicitation, because experts will likely be influenced by the phrasing of questions and influenced if they hear the responses of other experts before formulating their own responses. Structured elicitation case studies confirm that these biases are common in practice but can be mitigated through formal design; the quality of expert information may be improved when experts review each other's estimates and revise their judgments (McBride et al. 2012).

Availability bias results when experts provide a judgement or probability based on how easily they can recall relevant occurrences or information (Tversky and Kahneman 1974). More recent or impactful events are relatively more available in experts' memory, which may influence experts' answers in relation to timing, abundance, or occurrence of certain pathogens. Availability bias should be considered when developing instruments to avoid overlooking relevant information (Tversky and Kahneman 1974).

In plant pathology, selection bias may emerge when experts disproportionally represent specific geographic regions within a country. For some topics, there might be overrepresentation of experts from temperate, high-income regions, and underrepresentation of the tropics (Kowal et al. 2022). Experts may be less familiar with the early stages of an epidemic and its dynamics, resulting in incomplete observations of the system (Battiston et al. 2021; Glennon et al. 2021). Selection bias can be partially mitigated using approaches such as structured recruitment for stratified sampling with pre-set quotas for experts in key sub-groups and/or using weighting of expert responses so experts from groups that better match information needs (or have lower error) carry more influence (Bird and King 2018; O'Hagan 2019). Storing full elicitation traces (timestamps, item order, rationales) and linking them to external big-data covariates (e.g., contemporaneous weather anomalies) can also help diagnose availability.

Expert overconfidence is common across expert knowledge elicitation (McKenzie et al. 2008; Morgan 2014). Several potential explanations include anchoring, experts' perceived pressure to give precise response ranges to fulfill their role as experts, and an instinctive reliance on experts' individual "short-cut" heuristics (O'Hagan 2019).

Since experts vary in their level of knowledge, analysis of data from expert knowledge elicitation can weight the responses of experts based on some measure of their knowledge. One approach to this is to weight expert responses by each expert's years of experience working on the topic being addressed. Another option is to ask experts to rate their confidence in each response, though implementing this effectively demands extra time from experts. A better approach, when practical, may be to assign weights to responses based on the expert's performance on a set of calibration questions in their area of expertise for which the answer is already known (Cooke and Goossens 2004). However, finding appropriate calibration questions is challenging: the questions must be relevant enough to the topic targeted by the elicitation to indicate expert knowledge, yet different enough that they do not influence the elicited answers.

Balancing Challenges and Opportunities for Expert Knowledge Elicitation

As discussed above, there are a number of challenges to implementation of expert knowledge elicitation. In the worst-case scenario, there may be no adequate experts who can provide the information desired, so the results of expert knowledge elicitation would be misleading if there are not adequate checks on data quality (Morgan 2014; O'Hagan 2019). Distinguishing between stochastic and deterministic components in a system can help address aleatoric uncertainty (stochasticity, or inherent system variability), such as in weather-driven epidemics or long-distance pathogen dispersal. Examples include eliciting conditional probabilities (e.g., infection rates given environmental conditions) or using elicited inputs in stochastic models, like weather-dependent SEIR frameworks (Table 1) (Xiao et al. 2022). Reporting uncertainty intervals (e.g., 5th/50th/95th percentiles) instead of point estimates also helps to capture variability (Rongen et al. 2024).

Expert knowledge elicitation can be resource-intensive, requiring travel, coordination, and extensive data processing (Grigore et al. 2017). Remote elicitation techniques, modular instruments, and digital platforms can alleviate these constraints, in addition to supporting reproducibility and streamlined data workflows (Grigore et al. 2017). We provide a comparison of different frameworks that can be combined with expert knowledge elicitation, considering available data, desired interpretability, and computational capacity (Table S1A). To scale up expert knowledge into big data, communities will need information systems with reproducible protocols, role-targeted access, and sufficient storage for mixed data types (audio, video, text, tabular). General data-collection tools (REDCap, Qualtrics, SurveyMonkey) can be adapted to capture expert group discussions, geospatial inputs, and uncertainty quantiles. Exporting data in machine-readable formats (CSV, JSON, raster) will increase compatibility with Bayesian updates and AI models. Bayesian probabilistic sensitivity analysis can systematically evaluate how uncertainty in elicited parameters propagates through complex models (Oakley and O'Hagan 2004).

A Bayesian Framework for Combining Expert Elicited and Objective Data

Bayesian updating (Table 1) provides a structured and transparent framework for integrating expert knowledge with other forms of data (Ikorasaki and Akbar 2018; Garrett et al. 2004; Mila and Carriquiry 2004; Yuen and Hughes 2002) (Fig. 3). Bayesian updating is a useful option in several structured elicitation approaches (Table S1A and S1B), often applied when decisions have significant economic implications or regulatory impact. A distinctive characteristic of Bayesian statistics is that parameters are explicitly treated as having a probability distribution. A Bayesian update starts with a prior probability distribution (or 'Bayesian prior', Table 1) for the parameter of interest that represents existing information (such as expert knowledge and/or previous objective results). The prior distribution is updated when new data become available, obtaining the posterior distribution (Table S1A) (van de Schoot et al. 2021). New data may come from objective measurements (e.g., a pilot trial) or from new expert-elicited data. For example, experts may define the prior distribution that is later updated by field data. Another example is when existing maps or model outputs act as the Bayesian prior that experts later refine (Mkondiwa et al. 2024; Rosace et al. 2024).

Defining the parameter of interest is the starting point of our workflow (Fig. 3)**.** In the example below, field efficacy is a parameter denoted as θ and represents **the probability that a farm using recommended biosecurity methods remains uninfected during a 30-day period.** The posterior distribution combines the prior distribution of θ with evidence from new observations.

Multiple approaches can be used to answer this type of research question, but Bayesian updating provides key opportunities to efficiently integrate a mathematical framework with expert knowledge. Bayesian statistics combines multiple information sources: expert knowledge and objective data. It explicitly measures uncertainty in terms of intervals, not just point estimates. It can adjust the influence of expert input, which is useful when sample sizes are small or conditions differ between regions. However, Bayesian updating also has limits when applied in risk analysis, and complementary perspectives may be needed to adequately capture some broader dimensions of uncertainty (Aven 2020). We therefore treat Bayesian approaches as one option within a broader decision process.

As an example, when local field data are absent, expert judgment can be treated as data by encoding structured responses and, where relevant, using hierarchical models (Table 1) to account for expert-to-expert differences. A simple effective sample size (ESS) (Table 1) cap keeps expert input from overpowering the analysis, managing how strongly the expert data can influence the analysis. Prior-predictive checks (Table 1) then simulate plausible trial results from the prior, to see whether it produces reasonable outcomes (Fig. 3). These steps (encoding, ESS caps, and prior-predictive checks) are extensively implemented in the supplementary notebook in a hypothetical example simulation https://github.com/jrobledob/Expert_Elicitation_in_Plant_Pathology.

When data become available, the same expert information can be blended into the prior and then updated with the new observations. In this example, a power prior weight (Table 1), δ, which is a dial (0–1), sets how much influence the expert information has in the hybrid prior (δ=0 ignores experts; δ=1 takes them fully). By varying δ, a sensitivity analysis (Table 1) makes the impact of expert assumptions transparent and tunable (Fig. 3). This δ-weighting and the update steps are demonstrated in https://github.com/jrobledob/Expert_Elicitation_in_Plant_Pathology

In practice, when priors are neutral/well-calibrated and sample sizes are modest, Bayesian intervals for θ often track frequentist intervals closely, so either summary can be shown alongside the other (Bayarri and Berger 2004). The Bayesian route provides the ability to formally include expert information, quantify its influence, and carry that forward as more data accumulate.

The example uses hierarchical structures when experts differ (partial pooling rather than treating each expert as identical), runs prior-predictive checks to avoid unrealistic priors, and conducts both one-at-a-time (Table 1) and global (Table 1) sensitivity analyses as good practices. It also follows WAMBS-style (“When to worry and how to Avoid the Misuse of Bayesian Statistics”) guidance to document choices and diagnostics. All technical details (formulas, priors, θ summaries, δ-weights, and diagnostics) of this workflow and the example below are in https://github.com/jrobledob/Expert_Elicitation_in_Plant_Pathology. This text focuses on the rationale. Similar workflows have been developed in related agricultural decision contexts (Mkondiwa et al. 2024).

Hypothetical example of Bayesian analysis

Consider the scenario of an invasive pathogen in a new region in the tropics, where the national plant protection organization needs to formulate a strategy but objective data in the country are not available yet. Expert knowledge elicitation provides a structured way to capture informed expectations about the likely performance of biosecurity measures, accounting for local conditions. For example, local experts may judge the likely effectiveness of biosecurity practices in tropical areas by considering field results from temperate regions where the pathogen is already present, taking into account local factors, such as climate or management constraints, that could modify how biosecurity practices perform in the new location in the tropics.

To formalize such expert judgments, they can be incorporated in a Bayesian workflow designed to evolve as new evidence becomes available (Fig. 3). The process begins with an informative and adaptable prior distribution for field efficacy (θ), defined here as the probability that a farm implementing biosecurity procedures remains uninfected over a given period. This prior distribution is based on studies conducted in temperate regions and is represented as a Beta distribution with moderate strength (a prior that nudges but does not dominate; in the code this “strength” is the prior ESS =

α+β, with larger ESS meaning a stronger nudge). Because transportability from temperate to tropical settings is imperfect, we deliberately build in extra uncertainty.

In the absence of trials in the tropical region, expert judgments can be incorporated as small "pseudo-trials," where confidence levels (low, medium, or high) are translated into a corresponding number of notional observations—for example, a high-confidence judgment might be treated as 30 observations, while a low-confidence one is treated as 10. To prevent expert opinion from dominating the analysis, explicit caps can be placed on the total effective sample size, and hierarchical modeling (allowing each expert's estimate to "borrow strength" from the group so no single outlier drives the result) can be used to account for differences between individual experts. This approach yields a posterior distribution for field efficacy (θ) that is already informative for decision-making and can be checked for plausibility using prior-predictive simulations (simulating multiple trials from the prior to see if the outcomes look reasonable before analyzing the real data).

As data from the new location in the tropics become available, the framework adapts. A hybrid prior is created by combining the original prior, based on experiments and results in temperate regions, with expert input, adjusting the weight given to expert opinion through a parameter δ. By varying δ in a sensitivity analysis, we can see how much expert judgment influences the results. This hybrid prior is then updated with trial data from the tropical setting, producing a posterior distribution that reflects both prior knowledge and new evidence. Once the new objective data from the tropics are available, the same trial can also be analyzed using standard frequentist methods. In practice, when priors are well calibrated and sample sizes are modest, Bayesian and frequentist approaches tend to give similar conclusions (Bayarri and Berger 2004), meaning that either approach can be used—depending on whether decision-makers choose to include expert opinion or not.

This workflow is presented as an illustrative example rather than a prescriptive recommendation. A complete technical explanation, with a fully worked simulated example—including simulated data from expert knowledge elicitation, expert knowledge elicitation formulated as a prior, prior-predictive checks, hierarchical expert modeling, sensitivity analyses, and a comparison with frequentist intervals—is provided as supplementary material in https://github.com/jrobledob/Expert_Elicitation_in_Plant_Pathology, together with code.

Lessons Learned from Implementing Expert Knowledge Elicitation in Plant Pathology

We discuss lessons learned for improving implementation, from experience using expert knowledge elicitation to study questions in plant health in Cameroon, Colombia, Ethiopia, India, Nepal, Pakistan, the Republic of Georgia, Tanzania, and the USA (Adhikari et al., in preparation; Andersen Onofre et al., 2021; Mouafo-Tchinda et al., 2025; Plex Sulá et al., in preparation; Robledo et al., in preparation; Thomas-Sharma et al. 2017). Many of these analyses focused on generating geographic data layers of estimated parameters such as yield loss, and networks of informal trade in planting materials as a potential conduit for the spread of seedborne pathogens. A common goal was to provide baseline information about the geographic distribution of pathogens and pests at a national level, and the potential for invasive spread, as input for decision-making by National Plant Protection Organizations. This is in contrast to the above example of Bayesian analysis, which focused careful attention on understanding a single important parameter. That type of focused attention could add another dimension to the national projects discussed in this section, when stakeholders identify key parameters for detailed consideration. Direct elicitation may be used for precise quantities and indirect elicitation when narratives/experiences must be encoded before quantification (Martin et al. 2012).

Continuous instrument improvement

The design and adaptation of instruments was a critical factor influencing the success of expert knowledge elicitation. Adjusting instruments to each country supported local relevance and expert engagement. The approach involved review and adaptation of country- and crop-specific questions with the organizing team, in terms of points such as the relevant pathogen species and relevant yield loss levels to consider, fostering expert engagement (Mouafo-Tchinda et al.). In Thomas-Sharma et al. (2017), experts were asked to provide frequency distributions, such as the distribution of frequencies of grower use of different types of management. However, many experts were more comfortable providing means, especially when questions involved intricate biotic interactions. This indicates the need for compromise between the information that researchers would like to obtain, and what experts can provide, especially given time constraints. It also highlights the need for instruments that facilitate data acquisition, for example by providing real-time and interactive feedback to experts in a summary of their responses (e.g., maps or graphs) and potentially figures indicating the implications of expert parameter estimates. The use of varied question formats addressing the same information could increase confidence and provide measures of uncertainty, if time allows. To reduce anchoring and capture uncertainty, we could use SHELF-style percentile prompts with real-time plots and pre-specified EFSA aggregation, for example, implemented via Elicitator and REDCap/Qualtrics (European Food Safety Authority 2014; Gosling 2018; Morgan 2014; Patridge and Bardyn 2018).

Expert identification

For system-level studies, identifying the right mix of experts with relevant and complementary knowledge is important (Thomas-Sharma et al. 2017). In some cases, participants may have narrow specialization, such as deep knowledge of a single pathosystem or region, but limited awareness of others. This underscores the importance of assembling diverse expert teams to ensure broad and balanced insights for the pathosystems being studied. Confirming instrument content with in-country expert organizers prior to expert knowledge elicitation is important when applying a study across locations, given that pathogen species and other components of pathosystems can vary widely. Expert knowledge elicitation in plant pathology can benefit from incorporating experts in related disciplines—entomology, horticulture, economics—to provide a more holistic estimate of yield loss frequency distributions, for example, and to avoid biases from single-discipline perspectives. Selection bias could be mitigate with stratified recruitment and response weighting, and, when feasible, apply Cooke's calibration using, for example, Excalibur/ANDURYL for performance-based weights (Bird and King 2018; Boutry et al. 2023; Cooke 1991; Hart et al. 2019; O'Hagan 2019).

Participatory elicitation

Access to experts' time may be a limiting factor. In Andersen Onofre et al. (2021), expert knowledge elicitation was structured as a two-day facilitated workshop that included a broad spectrum of stakeholders from the potato value chain. This project made clear the importance of effective facilitators, note-takers, and, when needed, translators. Beyond the structured questions in the instrument, capturing spontaneous discussions among stakeholders can be a valuable source of insights. In Mouafo-Tchinda et al. (2025), in-person workshops enabled real-time discussion and clarification of the instrument and allowed participants to discuss complex issues before answering the questions. This group dynamic significantly enhanced the consistency and clarity of responses, demonstrating the benefit of collaborative, face-to-face formats when feasible. In Thomas-Sharma et al. (2017), expert knowledge elicitation was implemented through paper-based, in-person, and phone interviews. These methods allowed for some direct engagement, but the format could have been strengthened with tools that helped experts visualize answers and that elicited uncertainty. Delphi/IDEA might be used for anonymized iteration toward estimates, and Cooke's model for auditable individual judgments after independent first estimates (European Food Safety Authority 2014; Hemming et al. 2018; Linstone and Turoff 2011; Morgan 2014).

Data analysis and interpretation

Interpreting and integrating elicited data also offered important lessons. For example, if some experts perceive questions to be too complicated (such as the case of asking for frequency distributions of yield losses), data analysis is less straightforward when some experts estimate frequency distributions while other experts only provide an estimated mean (Thomas-Sharma et al. 2017). One solution is to improve instruments for analyzing uncertainty and expert confidence, potentially through synthesizing answers from experts across fields. Integrating expert responses with other data sources, such as analyses of cropland connectivity as a proxy for potential epidemic networks (Xing et al. 2020), can help model pathogen risk and prioritize phytosanitary actions (Andersen Onofre et al. 2021). Finally, transparent documentation of the expert knowledge elicitation process (roles of organizers and experts, assumptions about participation, reviews, and post hoc reflections) is important for building the credibility and reproducibility of expert knowledge elicitation findings. To support data analysis and interpretation you might encode 5th/50th/95th percentiles, use hierarchical models with ESS caps, run prior-predictive checks, vary δ in hybrid priors, link to remote-sensing/crowdsourced/weather layers, and code narratives with embeddings/LLMs (Bayarri and Berger 2004; Bock et al. 2020; Bojanowski et al. 2017; Devlin et al. 2019; Mahlein 2016; Mueller et al. 2024; Oakley and O'Hagan 2004; van de Schoot et al. 2021).

Based on these experiences with expert knowledge elicitation, a curated question catalog, PlantQuest, is being developed to assemble questions that are relevant in plant pathology, along with an associated app to facilitate application of expert knowledge elicitation using the PlantQuest catalog (Fontan et al., in preparation). This catalog incorporates continuous feedback on how best to formulate questions in instruments for expert elicitation, to avoid ambiguities and obtain high-quality data. Having easy-to-use tools for expert knowledge elicitation can facilitate decision-making for common problems in plant pathology, and provides an opportunity for research teams to share a baseline that is interoperable and reusable across applications. PlantQuest can template direct/indirect items, uncertainty formats, and aggregation choices (Delphi/IDEA, SHELF, Cooke) and auto-export for Bayesian updates and AI-supported synthesis (Fontan et al., in preparation).

Potential for plant pathology, future applications and new interfaces with AI

Scope and near-term applications: Expert knowledge elicitation has provided important research results in plant pathology over the past two decades and there are new opportunities in coming decades. For example, expert elicitation can be integrated with scenario analysis to address key problems in complex systems in plant pathology (Savary et al 2017), including scenario analysis of global change (climate, land-use, or irrigation change). Sensor technologies may be integrated with expert perceptions in disease surveillance (Mahlein 2016, Bock et al. 2020). Another important application of expert knowledge elicitation is in the context of disaster plant pathology (Etherton et al. 2024). Before and after disasters such as droughts, floods, and civil conflicts, there is a need for plant disease information, but rapid implementation of new objective studies is often challenging. In practice, information needed from experts after disasters may often be obtained using rushed and casual approaches. Methods in expert knowledge elicitation can improve elicitation of high-quality information from experts using methods that account for the nature of expert knowledge. Together, these use-cases highlight where structured elicitation can supply timely, decision-relevant inputs when conventional data collection is constrained.

Interfaces with AI and data workflows: Expert knowledge elicitation presents valuable opportunities to fill data gaps, promote cost-efficient forecasting, catalyze interdisciplinary collaboration, and support integration with Natural Language Processing (NLP) and other AI-driven models. Expert knowledge elicitation may be especially useful when combined with probabilistic frameworks, such as Bayesian update, which are well-suited to incorporate, quantify, and appropriately propagate uncertainty in a transparent and rigorous manner. Big data can both inform prior acquisition and be generated by expert knowledge elicitation itself. Capturing and analyzing these data with modern AI enables more transparent uncertainty quantification and more actionable plant health decisions. In practice, this means treating elicitation outputs (text, audio, video) as analyzable datasets that can be linked to models and revisited as new evidence is available. New approaches to expert knowledge elicitation that incorporate AI-driven analysis of digital audio and video may make a range of new types of analyses possible, such as the potential to measure expert uncertainty based on analysis of nonverbal cues in videos.

LLMs to support instrument design and synthesis: There are many opportunities for ongoing improvement to methods in expert knowledge elicitation. LLMs may be used to provide an initial summary of experts' answers to open-ended questions and discussion (Kaiyrbekov et al. 2025). Transformer-based models can be used to identify latent themes and quantify agreement and uncertainty. Since LLMs synthesize available literature, they can help formulate questions for elicitation instruments and help identify knowledge gaps. LLMs also have potential for identifying questions that could be used to weight expert responses based on how accurate experts are, as it could synthesize pertinent knowledge and help to identify relevant questions that are of a similar caliber to those in the elicitation instrument. Integrating expert knowledge elicitation methods with digital twins (Table 1) could clarify to experts the implications of their parameter estimates. These supports target two bottlenecks: efficient instrument preparation and scalable synthesis of mixed-format elicitation traces.

A human-AI pipeline vision: In the future, the most effective systems to support plant health will likely have strong integration across new objective observations, expert knowledge input, and modeling input and output, with potentially automated cycling between human and artificial intelligence in a streamlined pipeline that is less dependent on interpretation and less subject to biases (Fig. 1). For example, there is the potential to use LLMs to facilitate eliciting expert estimates of priors in Bayesian updates (Capstick et al. 2024). There are exciting prospects to integrate the most valuable input from each data acquisition component, such as in the context of ongoing development of a national plant health risk analysis (Mouafo-Tchinda et al. 2025). This pipeline emphasizes reproducibility, transparent uncertainty, and the ability to update decisions as soon as new data or judgments become available.

Capacity needs: While advances in LLMs and machine learning may support more effective use of expert knowledge, in the future there may be less expert knowledge available in plant pathology. Underinvestment in research and extension programs may result in fewer experts who have direct experience with plant disease epidemics. Future public and private investments to maintain expertise in plant health would ensure that there is a ‘pipeline’ of new and up-to-date information for integration in human and artificial intelligence. Expert knowledge elicitation can help to optimize data-driven decisions when resources are limited. Sustaining expert capacity therefore remains a prerequisite for realizing the benefits of AI-enabled elicitation.

Acknowledgements

We appreciate very useful recommendations from Phytopathology reviewers. We appreciate support from USDA Animal and Plant Health Inspection Service (APHIS) Cooperative Agreements AP21PPQS&T00C195 and AP22PPQS&T00C133 and the USDA Specialty Crop Research Initiative, project award nos. 2020-51181-32198, 2022-51181-38242 and 2024-51181-43302, from the U.S. Department of Agriculture’s National Institute of Food and Agriculture. We also appreciate support from the CGIAR Seed Equal Research Initiative, USAID Bureau of Humanitarian Assistance (BHA) award number 720BHA22IO00136, and the CGIAR Trust Fund (www.cgiar.org/funders/); we thank all donors and organizations which globally support the work of CGIAR through their contributions to the CGIAR Trust Fund. The opinions expressed in this article are those of the authors and do not necessarily reflect the views of USAID or USDA.

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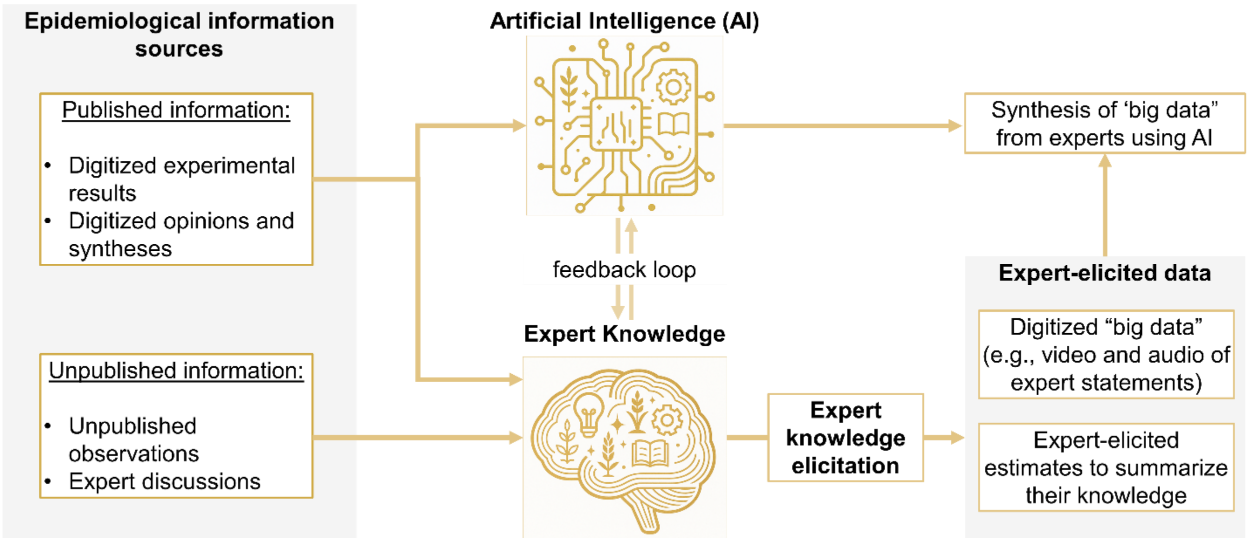

Figure 1. Expert knowledge includes knowledge of unpublished observations and discussions that are not generally available as input to syntheses such as those from artificial intelligence (AI). Experts may also have valuable opinions about future scenarios. Expert knowledge elicitation is designed to optimize the quality of data obtained from experts. Expert knowledge elicitation can generate statistical summaries of expert knowledge provided directly by experts in direct elicitation, or can generate video or audio of expert statements in indirect elicitation. AI can be used to synthesize the results of expert knowledge elicitation and translate the results for different purposes. Expert knowledge can serve as a baseline for decision-making, which can be improved with information from new experiments.

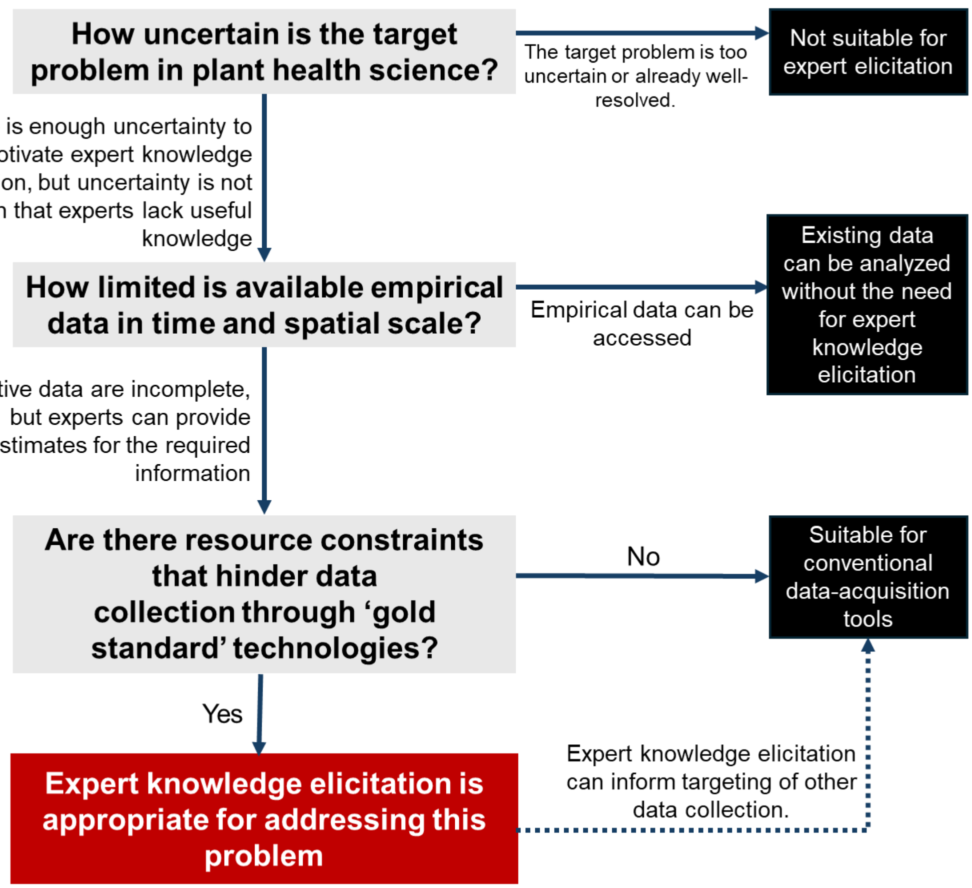

Figure 2. The greatest value of expert knowledge elicitation in plant pathology lies in situations where a 'somewhat uncertain' problem has incomplete objective data, and resource constraints make it difficult to acquire data through 'gold-standard' technologies as part of new field, lab, or greenhouse studies.

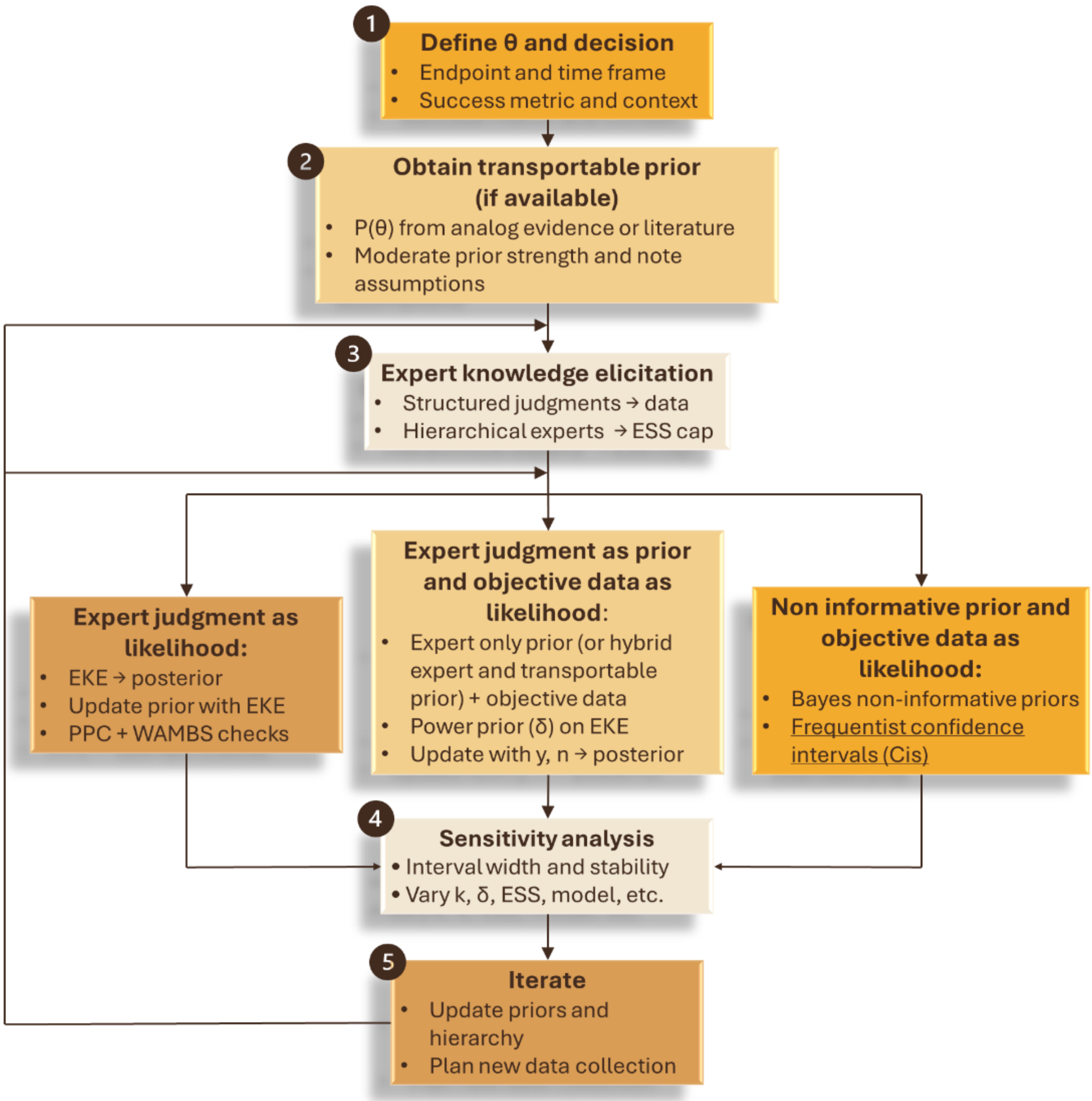

Figure 3. Workflow of an example for combining expert elicitation with Bayesian updating. Step 1 defines the decision and endpoint (e.g., θ - field efficacy: the probability a treated farm remains uninfected during the assessment window). **Step 2** specifies a transportable prior P(θ) based on evidence, with moderate strength (e.g., *k* for a Beta prior Beta(α,β), *k*=α+β reflects the prior's effective sample size [ESS]). **Step 3** elicits expert knowledge and models expert variability with a hierarchical model (e. g.,

partial pooling across experts), including calibration and ESS safeguards (ESS reflects the informational weight assigned to the expert input). Three scenarios can be considered depending on the availability of data, **Scenario A:** updates the prior with expert knowledge treated as data (e. g., when no local trials exist). **Scenario B:** forms a hybrid prior by discounting expert information (e.g., with a power prior weight $\delta \in [0,1]$: higher δ = more weight given to expert input) and then updates with objective data (e. g., *y* successes out of *n* treated units). **Scenario C:** provides a data-only baseline using a Bayesian non-informative prior (e.g., Beta(1,1)) and/or frequentist confidence intervals (CIs) (e.g., Wilson/exact). In **Step 4** Uncertainty and robustness are evaluated via prior-predictive checks [PPC] (simulate plausible data from the prior), WAMBS (“When to worry and how to Avoid the Misuse of Bayesian Statistics”) considerations, and sensitivity analyses (e. g., over *k*, δ, ESS, and modeling choices). **Step 5** The cycle iterates as evidence is available, revising priors and the hierarchical structure.

Term	Operational definition (for this paper)	Primary use in this paper	Related References
Objective data (empirical/observational data)	Direct measurements collected with documented, standardized procedures whose numeric values do not depend on the observer's judgment; independently verifiable and reproducible.	Provides likelihoods and validation targets (e.g., field-trial incidence/severity/yield, diagnostic assay results, surveillance detections, meteorological records, remote-sensing indices, administrative/interception records)	EFSA Panel on Plant Health (PLH) et al. 2018; Jeger et al. 2018; Madden et al. 2007
Expert	An individual with demonstrable, peer-recognized expertise and knowledge relevant to the target questions (e.g., years of practice, professional role, regional familiarity), selected according to pre-specified criteria.	Provides judgments/estimates for expert knowledge elicitation.	Hemming et al. 2018; Knol et al. 2010
Expert knowledge elicitation (EKE)	Structured process to obtain, quantify, and synthesize expert judgments as data to inform decisions under uncertainty.	Data acquisition when empirical data are sparse/slow.	Caley et al. 2014; EFSA Panel on Plant Health (PLH) et al. 2018; Hemming et al. 2018
Elicitation instrument	Protocols, prompts, and procedures (survey/interview/workshop) used to collect expert judgments.	Design/execution choices and documentation.	Hemming et al. 2018; Martin et al. 2012
Big data	Big data often refers to datasets that usually contain a large amount of data, are rapidly updated, and potentially span a variety of data types and topics.	Experts' minds are an important, potentially extensive source of diverse and rapidly updated information.	Sagiroglu and Sinanc 2013

	Some big data sets are so large, fast, or complex that traditional data processing methods are inadequate.		
Bayesian prior (informative prior), prior distribution	Probability distribution representing existing knowledge about a parameter before current data; “informative” when derived from substantive knowledge (e.g., from EKE).	Prior for prevalence and other parameters.	Hartley and French 2021; O’Hagan 2019
Posterior distribution	Updated distribution of a parameter after combining the prior with observed data (likelihood).	Decision-relevant inference after updating.	Mila and Carriquiry 2004; O’Hagan 2019
Epistemic uncertainty	Uncertainty due to limited knowledge or model structure; reduces with additional information.	Rationale for using expert knowledge elicitation.	Kiureghian and Ditlevsen 2009
Stochastic/aleatoric uncertainty	Inherent randomness of the system; not reducible by more information.	Interpreting variability and modeling.	Kiureghian and Ditlevsen 2009
Direct elicitation	Experts provide quantities directly used in analysis (e.g., dates, probabilities).	Method option.	Martin et al. 2012
Indirect elicitation	Experts provide judgments (e.g., rankings, experiences) that analysts transform into required quantities.	Method option.	Martin et al. 2012
Delphi technique	Iterative, anonymous rounds with feedback to converge/clarify group judgments.	Group processes and bias mitigation.	Linstone and Turoff 2011

IDEA protocol	Investigate–Discuss–Estimate–Aggregate: a structured elicitation workflow.	Improving reliability of judgments.	Hemming et al. 2018
Performance weighting (Cooke's method)	Weighting experts by calibration and informativeness on seed questions.	Aggregation of expert inputs.	Colson and Cooke 2018; Cooke and Goossens 2004
Anchoring & adjustment bias	Tendency for estimates to be pulled toward initial values or cues presented before elicitation.	Instrument design and training.	Morgan 2014; Tversky and Kahneman 1974
Availability bias	Judgments influenced by easily recalled or recent events rather than base rates.	Instrument design and interpretation.	Morgan 2014; Tversky and Kahneman 1974
Value chain	Network of actors and flows (materials/info) moving planting material/products.	Framing seed movement examples.	Andersen Onofre et al. 2021
Informal seed/planting-material exchange	Non-formal, often undocumented movement of planting material among actors.	Motivating EKE for hidden flows.	Andersen Onofre et al. 2021; McGuire and Sperling 2016
SEIR model	Compartmental epidemic model with Susceptible–Exposed–Infectious–Removed states.	Example of stochastic modeling with elicited inputs.	Li and Muldowney 1995
Bayesian hierarchical prior	Prior that shares information across experts/groups while allowing group- or expert-specific parameters.	Modeling heterogeneous experts.	McGlothlin and Viele 2018
Balanced expert assessment	Use of diverse, balanced expert panels/procedures in regulatory assessments.	Policy examples (e.g., EPA guidelines).	(U.S. Environmental Protection Agency 2004, 2009, 2024)
Hierarchical models	Statistical models that share information (partial pooling) across groups/experts while	Encode expert-to-expert variability; borrow strength across	Gelman & Hill 2007; McElreath 2020

	allowing group-specific parameters, improving estimates when data are sparse or heterogeneous.	experts/regions in Bayesian updates.	
Effective sample size	The amount of information a prior contributes, expressed as the number of data points it is roughly equivalent to.	Cap prior influence from expert inputs so elicited information cannot dominate new data.	Morita, Thall & Müller 2008; Neuenschwander et al. 2009
Prior-predictive checks	Simulating plausible data from the prior (and model) to assess whether assumptions could have generated reasonable observations before seeing the data.	Screen/eliminate unrealistic priors before updating with trial data.	Gelman et al. 2013; Gelman et al. 2020
Power prior weight	A tuning parameter (0–1) that raises the likelihood of historical/expert data to a power δ to control how much those data inform the prior.	Build a hybrid prior that transparently dials the influence of expert information; run δ-sensitivity.	Ibrahim & Chen 2000; Ibrahim, Chen & Ghosh 2015
Sensitivity analysis	Systematically varying inputs/assumptions to assess their impact on model outputs and conclusions.	Report robustness of inferences to prior choices, δ, and model settings.	Saltelli et al. 2008; Oakley & O'Hagan 2004
One-at-a-time sensitivity analysis	Varying a single input while holding others fixed to see its individual effect on outputs.	Quick, interpretable checks of key assumptions (e.g., δ alone, prior ESS alone).	Saltelli et al. 2008
Global sensitivity analysis	Exploring the output response to simultaneous variation of multiple inputs over their joint ranges (often variance-based).	Quantify joint uncertainty propagation for priors/parameters; identify most influential assumptions.	Sobol' 2001; Saltelli et al. 2008
WAMBS	"When to worry and how to Avoid the Misuse of Bayesian Statistics" — practical guidance	Document modeling choices/diagnostics and improve transparency/reproducibility.	van de Schoot et al. 2021

	and reporting checklist for Bayesian analysis.		
Digital twins	Virtual, updateable representations of real systems that mirror key processes to test scenarios and visualize implications of parameter choices.	Communicate to experts how elicited parameters affect epidemic dynamics/decisions; support interactive “what-if” exploration.	Grieves & Vickers 2017; Tao et al. 2019

Above:

Table 1. Operational definitions of key terms used in this manuscript.

Below:

Table 2. **Where elicitation becomes data:** representative plant-health applications showing what was elicited (e.g., pathogen lists, detection probabilities, adoption rates, network structures, efficacy and process parameters), why EKE was required (scarce/inaccessible objective data, time/budget constraints), at what scale (country to global), and with whom (panel size/discipline mix), across crops and pathogens. These cases span categorization/prioritization, global burden estimation, seed-system epidemiology, risk mapping, sampling design, forecasting tool calibration/validation, early warning, and national policy evaluation.

Topic addressed	**Information acquired**	**Rationale for use of expert elicitation**	**Spatial coverag e**	**Experts included**	**Targeted crop(s)**	**Targeted pathogen(s)**	**Reference(s)**

Pathogen categorizatio n	1. A list of quarantine pests 2. A list of regulated non-quarantine pests	Emerging, new, and invasive pathogens have little published information.	Europea n Union	Many experts	Many crops	Many pathogens	EFSA Panel on Plant Health (PLH) et al. 2018
Pathogen prioritization	A list of select agents in the United States of America	Selecting among tens of thousands of plant pathogens is not an easy task.	United States of America	Many experts	Many crops	12 exotic plant pathogens	McRoberts et al. 2016
Global plant health assessment	1. Plant health status 2. Plant health trends	Not specified	Global	80 experts	16 plant systems	Not pathogen specific	Acuña et al. 2023
The global impact of plant pathogens	Magnitude and frequency of crop losses per each pathogen species	Accurate quantificatio n of pathogen impacts is difficult at a global scale	67 countries	219 experts	5 major crops	137 pests and pathogens	Savary et al. 2019
An integrated seed health strategy	1. Seed exchange between stakeholders 2. Adoption rates of potato varieties 3. Estimates of disease prevalence	Disease reports were sporadic, and pathogen distribution remains	Republic of Georgia	15 experts	Potato	6 diseases	Andersen Onofre et al. 2021

		understudied.					
Seedborne pathogen movement through seed systems	1. Characterization of seed trade networks 2. Characterization of farmer communication networks	There were no formal reports on the geographic exchange of seed and information.	Ethiopia	20 experts	Potato	Bacterial wilt (Ralstonia solanacearum Phylotype II sequevar 1)	Etherton et al. 2025
Mapping continental risk of a disease	Vulnerability scores for 1. Dominant Musa genotype 2. Altitude 3. Temperature variability 4. Precipitation 5. Connectivity to infected areas 6. Distance to infected areas	Importance of each risk factor was not available on the continental scale	Africa	Not specified	Bananas	Banana bunchy top disease	Bouwmeester et al. 2023
Cluster sampling for disease incidence	Estimation of sample size	Anticipated values of the targeted parameter is usually unknown.	Not applicable	1 hypothetical expert	Not applicable	Not applicable	Hughes and Madden 2002
Advisory system for fungicide application	Estimates for the date of initial symptoms appearance	Weekly scouting of symptoms by every	France	29 experts	Grapes	Grape downy mildew (Plasmopara viticola)	Chen et al. 2019

		farmer is time consuming.					
Validation of a forecasting tool (ExpeRoya)	Estimates for the efficacy of 1. Fungicides 2. Spore dispersal 3. Spore wash-off 4. Infection 5. Leaf emergence Latent period	Scattered published knowledge of a complex pathosystem	Central America	17 experts	Coffee	Coffee leaf rust (Hemileia vastatrix)	Motisi et al. 2022
Early warning of pathogen incursions	Probability of disease detection	Budget constraints: Direct detection experiments are expensive for every disease.	Australia (Victoria)	157 experts	11 grain crops	14 exotic pests and diseases	Arndt et al. 2022
Risk assessment of seed degeneration	Estimated adoption rates of management options	Limited information was available for low-income countries	Africa and India	25 experts	Potato	No pathogen specific	Thomas-Sharma et al. 2017
National risk assessment	Estimates for 1. Crop yield losses 2. Certified seed use	Nationwide estimates of each factor was not available	Pakistan	28 experts	Bread wheat	33 diseases and pests	Plex Sulá et al (Unpublished)

	3. Informal seed movement 4. Information exchange	from formal reports.					
Policy effectiveness assessment	Estimates for 1. Movement of planting material 2. Movement of personnel	Nationwide estimates of each factor was not available from formal reports.	Colombia	127 experts	Bananas	Fusarium wilt (Fusarium oxysporum f. sp. cubense tropical race 4)	Robledo et al (Unpublished)