Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen

doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P5157-cd

Risk, uncertainty, decision and stakeholders - best practice for sustainable outcomes

Martine J Barons

Department of Statistics, University of Warwick, Coventry, UK E-mail: martine.barons@warwick.ac.uk

Quantifying risk and uncertainty and decision modelling have a great deal in common, and in particular that they are focussed on a main stakeholder or decision-making panel who stands to benefit from the utility they have defined. In every case, to achieve the objectives of the exercise, an essential starting point with any problem is to interact with problem-owners, their advisers, experts and close stakeholders to understand their perspectives, views, values, uncertainties, worldview, etc. In this paper we demonstrate the vital steps to be taken in achieving a high-value outcome, from discovering the purpose of the modelling, through engaging relevant stakeholders to delivery of a sustainable and requisite model.

Keywords: decision making under uncertainty, decision-maker, decision analysis, structured expert judgement, expert, deep uncertainty.

1. Introduction

Sutherland and Burgman urge us to use experts wisely (Sutherland, 2015). In risk management and sustainability management, reliance on experts is central, as these concepts cross multiple domains, often with subtle differences in meaning. Management of risk - potential for harm and its expected loss - for sustainability purposes is growing in importance, particularly in the natural environment (Barons et al., 2021; Barons and Shenvi, 2023) but also for businesses, research communities and government departments (Barons and Aspinall, 2020; Barons et al., 2021).

There is, of course, the temptation to hand a problem over to the analysts to work on in expert mode, ‘in which the analysts essentially take the problem away and conduct the analyses based on standard models’ (French, 2022). However, there is a need to recognise that decisions are framed and defined by their external context (Constable et al., 2022); analysts are unlikely to be sufficiently well-versed in the domain area to be able to provide robust and actionable solution options. Each analyst and expert is typically a product of a single signature pedagogy (Barons and Kleve, 2021), especially in knowledge codes where the acquisition of specialist knowledge is emphasised as the basis of achievement (Maton and Chen, 2019). They use the language, methods and assumptions normative in their own discipline, simply because this is how they have been trained to work. These can lead to problems with working in other domains, for example, mathematicians making the simplifying assumption that an object is a unit sphere because that makes the analysis tractable. A far more productive approach is to work in ‘facilitated modelling mode in which analysts and problem owners, accompanied maybe by some experts and stakeholders, meet in one or more workshops to “solve” the problem’ (French, 2022). However, the chief challenge here is the requirement for humility and a willingness to learn from others (Barons and Kleve, 2021).

This paper draws on research and experience of analysis working with diverse stakeholders and their expert advisors to make evidence informed decisions which take them into a desired future. As with any science, standards of ethics and replicability (Fidler and Wilcox, 2021; Gundersen, 2021; Lim, 2019) must be maintained, both for the justifiability of the decision to auditors and to demonstrate the sustainability of the actions toward the desired end.

This paper adds to the existing literature by providing a summary of best practice that is widely applicable across domains.

2. Modelling for decision-making

The first step in working with decision-makers is often some form of modelling. In this context decision makers may be single individuals or, more commonly, decision making panels or even society itself (Walton et al., 2022), hereinafter called problem owners. However, what constitutes modelling and its purpose in the problem resolution space varies widely between domains. Models are reduced representations of the system being studied, and necessarily omit many details, but seek to indicate broad relationships between entities, issues, processes, behaviors that confront the problem owners in addressing the challenge at hand (French, 2022). Model can carry a plethora of meanings, depending on domain; there is often a distinction made between quantitative an qualitative models, but this is not as clear as might first appear (see (French, 2022)). Qualitative and quantitative models are recognised as working in partnership (Marttunen et al., 2017). Beyond its ability to serve the purpose for which it is employed, the model should enjoy the confidence of the problem owners, and, ideally, their expert advisors and other stakeholders.

The purposes of modelling include sense-making (issue formulation, context setting, surfacing values, setting objectives, problem structuring), analysis & exploration (quantitative analyses, sensitivity and robustness, validation), interpretation & implementation (communication with stakeholders, audit and risk management, building consensus, checking any analysis is requisite) (French, 2023; Phillips, 1984; Argyris and French, 2017). It is important to be clear on objective before committing to models and analysis, i.e. to employ value focussed thinking (Keeney, 1988). Whilst modelling for decision making goes through these three broad stages, it is not, typically, a linear process. At each stage, the discussions around the problem can surface previously unexplored aspects, new information, or new relationships between entities. It is a cyclic process of eliciting the problem owners' perspectives, perceptions of cause and effect, their values, the data and expertise available, sources and nature of uncertainties and their knowledge - understanding relevant to the context - both explicit (scientific) and tacit (skill-based) (French, 2022; Barons et al., 2017) p453.

It is clear that the problem owner needs to be involved with the analyst to produce relevant and actionable solution options. The question then becomes how and when to involve them and how to go about it.

3. The Decision-maker

The decision-maker and their advisors, trusted experts and other stakeholders are involved throughout. Whilst there are stages in the process when expert mode is applicable, these tend to be elements in an overall process conducted in facilitated modelling mode.

The first stage is the soft elicitations stage where the analysts can start to become familiar with the domain, its conventions, language, and sources of authoritative expertise (French, 2022).

Model building depends on the soft elicitation, surfacing the models which may be useful and any adaptations or developments which may be required, should standard models prove to be a poor fit.

Model quantification is required if the solution options are to be compared or if they involve a quantitive measure as an output. In most cases, the purpose of the analysis to aid human decision-making and not to automate decisions; parts of the outputs are often natural language explanations indicating why some solution options are preferred to others (Leonelli and Smith, 2015, 2013).

Evaluation and feedback allow it to be understood and operable by the domain decision-makers. This can involve a lot of tacit knowledge about how information is typically presented, conventions in language and graphical displays.

Another consideration here is the development of sustainable decision support software that can be updated and extended as required.

Finally comes launch and adoption. If the system is envisioned to be in place for many years, those who have not been involved in its design and development will necessarily be less familiar with its workings and the assumptions and simplifications that have been employed in its development. Communicating the features and limitations of the system, and ensuring it is used as intended and not applied beyond its original remit without careful consideration of the reliability of the solution options in the new application, is vital.

3.1. *Soft elicitation*

An essential starting point with any problem is to interact with problem-owners, their advisers, experts and close stakeholders to understand their perspectives, views, values, uncertainties, worldview, and preferences. Elicitation seeks knowledge in a reflective process that enhances their self and shared knowledge (French, 2022). In addition, preferences are often constructed in the process of elicitation (Slovic, 1995). Those contributing knowledge will make a judgement on what is relevant, so the reasoning behind judgements and contributions also need to be recorded (French, 2022).

The elicitation process itself is often a series of facilitated workshops. A good facilitator will enable all participants to contribute. The Cynefin Framework, which categorises systems into clear, complicated, complex and chaotic, can be a useful tool in discussions (Mark and Snowden, 2017).

Where data are available, exploratory data analysis (EDA) (Tukey, 1977) can identify potentially interesting features which can be discussed to ascertain whether they are truly relevant.

There are a number of cognitive biases pertaining to elicitation exercises, which are well-described in the structured expert judgement elicitation literature (see, for example Hanea et al. (2018); Gosling (2018)) and a good facilitator will be aware of biases and take relevant steps to reduce and record them.

Elicitation to structure the problem may involve a small group consisting of the problem owner and perhaps a few key advisors. This group will identify the problem to be solved as they currently see it. Then the processes, inputs, outputs, actors in the system need to be elicited.

Next, their perceptions of cause and effect and how the elements interact need to be elicited. Again, judgement and domain knowledge are important, and the process of discussing and agreeing the nature of the (relevant parts of) the system and their relations can increase the problem owners' understanding of the problem and even shift the definition of the problem itself. At this stage, it is of particular importance to address uncertainties and identify whether they are due to inherent randomness in the system (aleatory), or whether they are due to a lack of knowledge (epistemic). Once the problem is clearly defined, it is time to address the availability of relevant expertise and data. The problem owner should have a good idea of where these data and experts can be found, and which are trustworthy and useful. The analyst can assist by leading a discussion on the data generating process, capture any experimental design aspect of data quality. Outputs of any decision supporting mechanism must be comprehensible to the users of that decision support mechanism. The soft elicitations process can provide insight into how relevant outputs, along with their uncertainties, should be presented.

3.2. *Model Building*

Unless the problem owner is convinced by the modelling approach, they are unlikely to use it. They must be confident that the approach selected will satisfy the purpose of the modelling exercise. Selecting an appropriate model and presenting it to the problem-owners can be helpful in challenging thinking and eliciting key issues they thought were irrelevant or struggled to articulate (French, 2022). They need to be appraised of the advantages and limitations of the different candidate approaches, see French and Kleineberg (2019). Choosing between robust approaches is a matter of judgement. Resource availability, including but not limited to data, expertise and computing power, may rule out some modelling approaches.

3.3. *Model quantification*

Having settled on one or more modelling approaches, the data to quantify the model must be obtained. A number of challenges can arise here: that data may simply not exist, it can be of poor quality such as having many missing values, too scant, or out of date. Some data may exist but be unavailable for ethical reasons, such as personal data. Wherever the data comes from, it is important to have clear variable definitions, recognising that words are used differently in disparate academic disciplines (Barons and Kleve, 2021) and business, industry and government (BIG) sectors.

The more granular the modelling, the more granular the data needs to be. Often, the computational time and data requirements for more detailed models can outweigh the additional benefits in reducing uncertainty and precision of decision options.

It may be that there is previous, relevant research and, if relevant, official statistics such as population number and forecasts can be leveraged.

This process will identify the uncertainties coming from data and the data gaps to be tackled. It is a matter of judgement whether to fill those data gaps using modelling or structured expert judgement approaches (Barons and Shenvi, 2023; Barons et al., 2021). It is important that experts are able to envisage each scenario well enough to allow elicitation of their uncertainties in a robust and valid fashion (French, 2023; Hanea et al., 2018; Gosling, 2018).

The impact of model choice on the eventual identification of actionable solution options should not be underestimated (Vassoney et al., 2021). Replicability of the analysis is non-trivial, but important (Barons et al., 2025; Fidler and Wilcox, 2021; Gundersen, 2021; Lim, 2019).

3.4. *Evaluation / feedback*

Once a model is quantified, it needs to be evaluated, and the problem owner and their advisors employed to identify whether the model behaves as expected, based on their experience of the sector. Problem owners tackling issues of importance to them will react quickly against models and analyses that do not reflect their understanding and perceptions (French, 2023). Finally, evaluation of the outputs and their usefulness to the intended users should be considered and adjusted as required. There should be extensive sensitivity and robustness studies (French, 2023) to address both the optimality of the solutions and the effect of differing opinions of the problem owner, their experts and stakeholders and explore the behaviour of the model more widely to assess its validity (French, 2003).

3.5. *Software engineering*

When a decision support model is to be used for a one-off decision, there is little incentive to consider matters of sustainability of the underlying code. However, for most applications where the extensive time investment described here is considered worthwhile, it is anticipated that the model will be used by many users or over significant time periods. In this case, careful consideration of the robustness of the software is required.

Software needs to be appropriately designed, with relevant commenting and an eye to future uses and adaptations. The implementation needs to be tested to ensure it is error-free and is a faithful representation of the mathematics in the model design. Consideration needs to be made of the maintenance of the software, the resolution of bug reports, and so on. The model needs to be adequately documented so that future users and software maintenance are appraised of the intentions, processes and dependencies of the model-building. Its usability, endurability, adaptability, interoperability must be appropriate.

Ethical use of data also appears in the consideration of the software piece, especially in the case of interaction with other digital systems - data that is secure in a stand-alone system may be less secure in a networked system. As well as data protection regulations, there may be accessibility regulations that apply to the outputs and other parts of the model, which need to supported in the software implementation (see (Jumping Rivers, 2021; The National Archives, 2021) for an example).

3.6. *Launch & Adoption*

Finally, the model is ready for launch and adoption. From here on, it is vital to ensure the users are appraised of the underpinning assumptions of the model, the modelling choices made, the meaning of the visualisations and the other information they receive. Vitally, the uncertainty must be identified and its impact on the model outcomes made cognitively meaningful to the problem owners, allowing them to move forward with one or more of the actionable solution options. A valid and meaningful way of weighting or comparing the actionable solution options is required (Stewart et al., 2013). In particular, the range of uncertainties that remain or were excluded from the analysis is vital in avoiding giving overconfident advice to the problem-owner (Spiegelhalter, 2017; Liu et al., 2017)

3.7. *Summary*

The section headings above can be used as a checklist for those less familiar with working across specialities and conducting analysis with domain experts and problem owners. However, uncertainty has been referred to but not yet been defined and the next section seeks to briefly discuss this vital aspect of analysis to produce actionable solution options for a decision-maker.

4. Uncertainty

Uncertainty - the inability to answer questions precisely - can be categorised in many ways, (Groothuis-Oudshoorn et al., 2017), but there is no real agreement on how to do so. In general, modelling to produce actionable solution options needs a careful consideration of the sources and types of uncertainty that impact the communication of a fair and balanced assessment of uncertainty facing the problem owners (French, 2023). Uncertainty must be addressed within scientific approaches and faithfully communicated to those who are designing, implementing and affected by response measures.

Some uncertainties can be modelled but others cannot be quantified easily; clarity and values need to be resolved by discussion (French, 2003). Deep uncertainty, when decision makers and stakeholders do not know or cannot agree on how likely different future scenarios are, is often addressed by considering scenarios. However, the appropriateness of the range of scenarios is also open to question.

The nine types of uncertainty suggested here fall into three broader groups: stochastic, actor and epistemic uncertainties relate to the external world, i.e. scientific uncertainty relating to the external consequences of the decision; judgemental, computational and model uncertainties relate to modelling and analysis; ambiguity, lack of clarity, value, ethical and depth of modelling uncertainties reflect the confidence the decision makers have in their perceptions, judgements and the decision taken.

4.1. *Uncertain knowledge of the external world*

Stochastic or aleatory uncertainty is natural variation or randomness. We cannot predict an outcome with certainty so we use probability, long run relative frequencies (Frequentist), propensities to adopt different states, and subjective degrees of belief in different outcomes (Bayesian).

Epistemic uncertainty relates to lack of knowledge, for example, we may know a patient has cancer now, but not when the cancer began or its causes. Innovation in novel territory can sometimes encounter situations where an interdisciplinary group of specialists meets an unanticipated and entirely inexplicable situation, in which their expertise does not allow them to grasp what the problem is, let alone how to resolve it. These ‘epistemic breakdowns’ require dialogue to integrate knowledge in the face of epistemic uncertainty (Mengis et al., 2018).

Actor uncertainty relates to how other actors will behave, often modelled using probability models, which assume that over a population, variations in how people act can be described stochastically (French, 2022). But humans do not behave randomly. Different players may adopt different levels of ‘rationality’; human behaviour may not be truly rational, but it is directed.

4.2. *Uncertainty due to modelling and analysis*

Judgemental uncertainties come from uncertainties about which computational models and algorithms to use, what parameter values to use, what data sets to draw on, what assumptions are embedded within model code etc. Sensitivity and robustness analyses may provide ways to investigate such uncertainties (French, 2023)

Computational uncertainties arise from the fact that computers use numerical approximations, compounded when there are multiple calculations or iterations. Some computations are infeasible in useful time frame, so further approximations are made, e.g. Gaussian Processes (Williams and Rasmussen, 1995).

Model uncertainty is the gap between the selected model and reality. Models need to be accurate enough for the task at hand and whilst data models can address modelling error via inflated variances, not all model uncertainty can be so easily captured.

4.3. *Internal uncertainties about ourselves*

Ambiguity and lack of clarity characterise one uncertainty abut ourselves. Some of it is linguistic e.g. lack of clear understanding of some wording such as 'health effects'. Data variable definitions can vary widely. Facilitated workshops are used to eliminate or reduce this type of uncertainty

Value, social and ethical uncertainty asks whose values should dominate - the decision-maker, the government, or society? There are social uncertainties about how expert recommendations are implemented in society and ethical uncertainties about acceptable levels of risk and who bears that risk. Where questions clearly require value judgements for their resolution, these need to be resolved by thoughtful deliberation, perhaps supported by sensitivity analysis, since precision is irrelevant when there is no effect on the ultimate choice. Value uncertainties introduce social responsibilities and ethical concerns, particularly when acting on behalf of stakeholders (French, 2022).

Depth of model uncertainty asks are the models or analyses requisite, i.e. good enough? Is the modelling at the appropriate scale? Is there an urgency that means there is not time to analyse or model more finely (even though this would be ideal)?

4.4. *Communicating Uncertainty*

It is clear that, when problem owners are relying on analysis to produce actionable solution options, that a clear communication of the handling or modelling of uncertainty is provided and any residual uncertainties are unambiguously communicated. With chains of models, model combinations, model stacking, disparate data sets, approximations, multiple calculations, judgements, and pragmatism there are multiple contributions to uncertainty in scientific work. Some are difficult to quantify and will not be fully represented in uncertainty bounds on plots produced. All need to be communication to those relying on them, so they have a full understanding of the uncertainty they face. Under-reporting the overall uncertainty to the decision-makers, risks making them overconfident in their decision (French, 2022).

Some uncertainties may be deep; i.e. arise in circumstances in which data are too sparse, or decision-makers, stakeholders and experts disagree too much to quantify the uncertainty convincingly in the time available (Walker et al., 2012). Moreover, sensitivity analysis may suggest that many actions may become optimal in variations across the range of the deep uncertainties (French, 2023) i.e. a decision for reasonable worst case may be suboptimal for much more likely events e.g. too expensive or disruptive or wrong action altogether.

4.5. *Communication*

The communication of risk and uncertainty is a study in itself. To do this well requires understanding audiences, identifying decision-makers and stakeholders, which may include the general public, communities, special-interest audiences and individuals. Selecting a communication approach, from decision support to storytelling, for these disparate audiences is a skill (Walton et al., 2022)

5. Discussion

The World is facing many complex, possibly existential issues, e.g., in recovering from the pandemic, the Ukrainian War and Climate Change. It is an understatement to suggest that addressing these will involve many conflicting objectives and many stakeholders (Walton et al., 2022; Wallenius and Wallenius, 2022). How the qualitative understanding of issues help to structure an appropriate quantitative model is not well researched (Pidd, 2004)

The iterative nature of elicitations and modelling exercises mean that if the participants of one exercise then seek to analyse the same set of issues using a different methodology, they do so from a different starting position in terms of their beliefs and preferences. Any conclusion, be it the same or different, may simply reflect their learning from the first analysis (French, 2023).

For decisions in the BIG space, decision analysts are seldom present with the problem owners when decisions are finally made. Typically, they provide reports that feed into the final deliberations ; those facing major decisions are usually provided with many reports, some specially commissioned, some from independent stakeholder and pressure groups. These are often based on different framing assumptions, even different sciences and dogmas (French, 2023; French and Argyris, 2018).

Best practices for sustainable outcomes in risk, uncertainty and decision-making under uncertainty are complex, time-consuming and expensive, but making a significant decision without the relevant investment in analysis can be worse.

6. Conclusions

In the complex landscape of sustainability risk management, it is no longer appropriate for analysts to sit in siloed scientific communities. A strongly interdisciplinary approach which incorporates a robust interaction with problem owners is required. Here we provide a summary of good practice in engaging problem owners which can be used as a checklist for those form expert domains where interactions are not commonplace and do not feature in standard pedagogical training.

Acknowledgement

This paper began as a presentation at Prof Jim Q. Smith's 70th birthday conference held in May 2023 at the University of Warwick. Many thanks to participants who encouraged me to write tit up as a paper. Thanks also to Jo Kukuczka for interesting discussion on epistemic clashes and to Harriet Richmond for discussion on integrating knowledge in the face of epistemic uncertainty.

References

Argyris, N. and S. French (2017). Behavioural issues and impacts in nuclear emergency decision support. *European Journal of Operational Research 262*, 180–193.

Barons, M. J. and W. Aspinall (2020). Anticipated impacts of brexit scenarios on uk food prices and implications for policies on poverty and health: a structured expert judgement approach. *BMJ open 10*(3), e032376.

Barons, M. J., W. Aspinall, S. Brewer, and P. Crosskey (2021). Brexit and food security: long-term implications for public health. *BMJ Open*.

Barons, M. J., T. C. Fonseca, H. Merwood, and D. H. Underdown (2021). Safeguarding the nation's digital memory: Bayesian network modelling of digital preservation risks. In *European Consortium for Mathematics in Industry*, pp. 501–508. Springer.

Barons, M. J., A. M. Hanea, S. Mascaro, and O. Woodberry (2025). Reporting standards for bayesian network modelling. *Entropy 27*(1), 69.

Barons, M. J. and S. Kleve (2021). "mastering another language" – a case study in interdisciplinary teaching and learning on food security across two countries and two universities. *Warwick Journal of Education - Transforming Teaching*. Accepted.

Barons, M. J. and A. Shenvi (2023). Where the bee sucks: a dynamic bayesian network approach to decision support for pollinator abundance strategies. *Journal of the Royal Statistical Society Series A: Statistics in Society 187*(2), 393–409.

Barons, M. J., S. K. Wright, and J. Q. Smith (2017). *Eliciting Probabilistic Judgements for Integrating Decision Support Systems*, Volume 261 of *International Series in Operations Research Management Science*, Chapter 17. Springer International Publishing, Switzerland.

Constable, A. J., S. French, V. Karoblyte, and D. Viner (2022). Decision-making for managing climate-related risks: Unpacking the decision process to avoid "trial-and-error" responses. *Frontiers in Climate 4*, 754264.

Fidler, F. and J. Wilcox (2021). Reproducibility of Scientific Results. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy* (Summer 2021 ed.). Metaphysics Research Lab, Stanford University.

French, S. (2003). Modelling, making inferences and making decisions: the roles of sensitivity analysis. *Top 11*, 229–251.

French, S. (2022). From soft to hard elicitation. *Journal of the Operational Research Society 73*(6), 1181–1197.

French, S. (2023). Reflections on 50 years of MCDM: Issues and future research needs. *EURO Journal on Decision Processes 11*, 100030.

French, S. and N. Argyris (2018). Decision analysis and political processes. *Decision Analysis 15*(4), 208–222.

French, S. and J. Kleineberg (2019). Decision support tools for complex decisions under uncertainty. *A publication of the Analysis under Uncertainty for Decision Maker s Network*, 34.

Gosling, J. P. (2018). Shelf: the sheffield elicitation framework. *Elicitation: The science and art of structuring judgement*, 61–93.

Groothuis-Oudshoorn, C. G., H. Broekhuizen, and J. van Til (2017). Dealing with uncertainty in the analysis and reporting of MCDA. *Multi-criteria decision analysis to support healthcare decisions*, 67–85.

Gundersen, O. E. (2021). The fundamental principles of reproducibility. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 379*(2197), 20200210.

Hanea, A., M. McBride, M. Burgman, and B. Wintle (2018). Classical meets modern in the idea protocol for structured expert judgement. *Journal of Risk Research 21*(4), 417–433.

Jumping Rivers (2021). Diagram: A shiny app for the national archives. `https://www.jumpingrivers.com/case-studies/shiny-react-github-national-archives/`. Accessed: (17th February 2025).

Keeney, R. L. (1988). Value-focused thinking and the study of values. *Decision making: Descriptive, normative, and prescriptive interactions*, 465–494.

Leonelli, M. and J. Q. Smith (2013). Using graphical models and multi-attribute utility theory for probabilistic uncertainty handling in large systems, with application to the nuclear emergency management. In *29th International Conference on Data Engineering Workshops (ICDEW)*, pp. 181–192.

Leonelli, M. and J. Q. Smith (2015). Bayesian decision support for complex systems with many distributed experts. *Ann. Oper. Res. 235*(1), 517–542.

Lim, K. T. K. (2019). *Statistical practice and reproducibility in behavioural science*. Ph. D. thesis, University of Warwick, UK.

Liu, X., J. Stoutenborough, and A. Vedlitz (2017). Bureaucratic expertise, overconfidence, and policy choice. *Governance 30*(4), 705–725.

Mark, A. and D. Snowden (2017). 15 cynefin: situating the problem in sense-making framework. *Applied Systems Thinking for Health Systems Research: a Methodological Handbook*, 76.

Marttunen, M., J. Lienert, and V. Belton (2017). Structuring problems for multi-criteria decision analysis in practice: A literature review of method combinations. *European journal of operational research 263*(1), 1–17.

Maton, K. and R. T.-H. Chen (2019, November). Specialization codes: Knowledge, knowers and student success. In J. R. Martin, K. Maton, and Y. J. Doran (Eds.), *Systemic Functional Linguistics and Legitimation Code Theory*, Legitimation Code Theory, pp. 35–58. Milton Park, Abingdon, Oxon: Routledge.

Mengis, J., D. Nicolini, and J. Swan (2018). Integrating knowledge in the face of epistemic uncertainty: Dialogically drawing distinctions. *Management Learning 49*, 595–612.

Phillips, L. D. (1984). A theory of requisite decision models. *Acta psychologica 56*(1-3), 29–48.

Pidd, M. (2004). *Systems modelling: theory and practice*. John Wiley & Sons, Inc.

Slovic, P. (1995). The construction of preference. *American Psychologist 50*, 364–371.

Spiegelhalter, D. (2017). Risk and uncertainty communication. *Annual Review of Statistics and Its Application 4*(1), 31–60.

Stewart, T. J., S. French, and J. Rios (2013). Integrating multicriteria decision analysis and scenario planning—review and extension. *Omega 41*(4), 679–688.

Sutherland, W., B. M. (2015). Policy advice: Use experts wisely. *Nature*, 317–318.

The National Archives (2021). Diagram - the digital archiving graphical risk assessment model. `https://nationalarchives.shinyapps.io/DiAGRAM/`. Accessed: (17th February 2025).

Tukey, J. W. (1977). Exploratory data analysis. *Reading/Addison-Wesley*.

Vassoney, E., A. Mammoliti Mochet, E. Desiderio, G. Negro, M. G. Pilloni, and C. Comoglio (2021). Comparing multi-criteria decision-making methods for the assessment of flow release scenarios from small hydropower plants in the alpine area. *Frontiers in Environmental Science 9*, 635100.

Walker, W. E., R. J. Lempert, and J. H. Kwakkel (2012). Deep uncertainty. *Delft University of Technology 1*(2), 1.

Wallenius, H. and J. Wallenius (2022). How can decision sciences and MCDM help solve challenging world problems? In *Intelligent Decision Support Systems: Combining Operations Research and Artificial Intelligence-Essays in Honor of Roman Słowiński*, pp. 59–71. Springer.

Walton, J. L., P. Levontin, M. J. Barons, M. H. Workman, E. Mackie, and J. Kleineberg (2022, October). Communicating climate risk: A toolkit. License CC BY-NC-SA 4.0.

Williams, C. and C. Rasmussen (1995). Gaussian processes for regression. *Advances in neural information processing systems 8*.