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ORIGINAL ARTICLE

From soft to hard elicitation

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ABSTRACT
At the outset of an analysis, there is a need to interact with the problem-owners to understand their perspectives on the issues. This understanding leads to the construction of one or more models to reflect their views, their values and their uncertainties. Some models are qualitative; others, quantitative. Quantitative models need populating with numbers, either from data or from further judgements elicited from the problem-owners, their stakeholders or their experts. The model(s) may then be analysed to provide feedback to the problem-owners on the possible resolution of the problem. In practice, the process may iterate, cycling through more sophisticated models, which require further inputs from the problem-owners. This paper discusses the elicitation processes involved, arguing that the current literature has developed if not in silos, then in pockets of activity that do not reflect the more joined up processes that often take place in practice. Furthermore, it is suggested that potential psychological and behavioural biases that may occur in quantitative elicitation are reasonably well understood and guarded against, whereas less attention has been paid to similar biases that may affect more qualitative model building.

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1. Introduction

An operational research (OR) analysis passes through many stages from sense-making and problem formulation through analysis to resolution, the taking of one or more decisions and their implementation. Almost all writers on OR methodology describe this process, emphasising that it may pass though several iterations with some cyclic diagram (see, e.g., Keys, 1995; Tomlinson & Kiss, 2013). The pages of the *Journal of the Operational Research Society* and the earlier *Operational Research Quarterly* have seen many discussions – too many to cite fully here – from many disciplinary and philosophical standpoints (e.g., Keys & Midgley, 2002). My own perspective developed from discussions with Doug White (French, 1995, 2015; D. J. White, 1985). It is commonly recognised that the OR process has both qualitative and quantitative aspects; though this was not always so. Some developments in the 1980s and 1990s often seemed to eschew quantitative modelling, perhaps because of the then over-simplified, naïve reliance on mathematically sophisticated quantitative analysis to 'solve' problems (Ackoff, 1977, 1979a, 1979b). Since the turn of the century, however, qualitative and quantitative analyses are recognised as working in partnership, the former serving to structure and formulate the problems for the later (Marttunen et al., 2017; Pidd, 2004; Shaw et al., 2006, 2007)[1]. Qualitative analyses also provide the relevant contexts in which to communicate the results of quantitative analyses (French et al., 2005). More recently, behavioural perspectives have been emphasised and added to our overall understanding of OR problem solving (Becker, 2016; Hämäläinen et al., 2013; L. White, 2016). Terminology has evolved: soft systems methodology (SSM), cognitive mapping, the strategic choice approach, hypergames and many other techniques of qualitative analysis being grouped first under the term *soft-OR* and, more recently, *problem structuring methods* (PSMs).

In this paper we shall argue that the almost dichotomous separation between qualitative and quantitative analyses is unhelpful. There is a simple continuum of increasing understanding as we move from qualitative models, a few bullet points, maybe a picture or two into more structured representations such as cognitive maps or a stakeholder plot, then into more and more sophisticated quantitative models, from simple belief nets, perhaps, to a much more complex chain of models. We shall emphasise this continuum, arguing that there is no clear point of demarcation at which a qualitative model becomes quantitative.

OR is not the only discipline to look at this process of modelling: similar discussions have taken place in other disciplines, though usually with different terminologies. While we talk about soft OR and PSMs:

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- information systems engineers often use SSM as part of a wider process of *systems analysis*;
- knowledge and artificial intelligence (AI) engineering studies discuss *knowledge elicitation* and, perhaps, *sense-making*, *creativity* and *innovation*;
- management consultants have a whole host of model structures that can catalyse sense-making discussions, such as *PESTEL*, *7 S's* and *Porter's 5 Forces*;
- mathematicians often refer simply to *model building*;
- risk analysts have a range of tools to help them in *hazard* and *risk identification*;
- statisticians use *exploratory data analysis* (EDA), *structural learning* and techniques such as *multivariate statistics* and, nowadays, *data-mining* and *machine-learning*.

There is a significant literature in psychology and behavioural science on *sense-making*. Despite the commonalities, discussions have unfortunately largely remained within disciplines without much cross-fertilisation. It is interesting that Cooke (1994) remarks "Information on knowledge elicitation methods is widely scattered across the fields of psychology, business management, education, counselling, cognitive science, linguistics, philosophy, knowledge engineering and anthropology," but does not mention OR, mathematics or statistics or any of the quantitative modelling sciences.

Coming from a background in OR and decision analysis, I find it more natural to refer to an analysis as ending in a decision and its implementation. But statisticians, information system engineers and others may not find this so acceptable, preferring to call the endpoint a *solution*, *result* or perhaps *design*. Here I shall tend to use *decision* or *solution*.

Throughout an analysis, there is a need to interact with the problem-owners, their advisers, experts and close stakeholders to understand their perspectives on the issues. These interactions begin with general discussion of their views, their conception of the world and the issues, their values and their uncertainties. Early interactions are as much about their general worldview, i.e., their *weltanschauung* (P Checkland, 2001; P Checkland & Howell, 1997), and values, as about the specifics of their current concerns. There is a need for broad context before turning to their more specific concerns:

- What are the entities – i.e., processes, inputs, outputs, actors etc. – in the situation before them?
- How do they interact?
- What are the specific uncertainties, challenges, and objectives for the analysis to address?

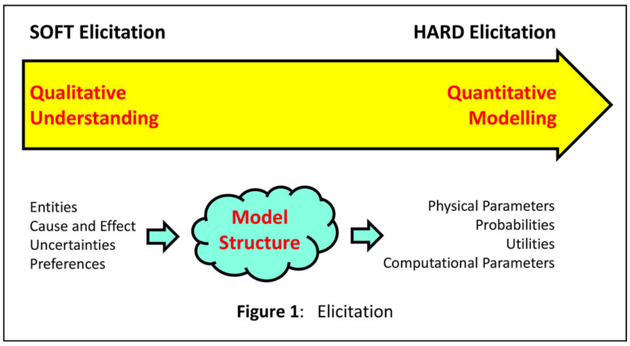

Figure 1. Elicitation.

- How might these be modelled?
- What relevant data and expertise are available?

Gradually a model is structured, capturing – sometimes helping them understand and shape – their perception of cause and effect, their uncertainties, their values, etc. Only at this point might numbers enter the analysis, either from data or by working with them to encode their uncertainties, values and knowledge quantitatively. I discuss this process in more detail below and propose that *all* these interactions are termed: *elicitation*. I suggest that the early qualitative ones are called *soft elicitation* and the later quantitative ones, *hard elicitation*. Though I am not suggesting a dichotomy, rather a process of increasing precision (Figure 1). Despite the visual linearity of this figure, elicitation is an *iterative* process, as some remarks and insights cause the problem-owners to reflect on and revise earlier statements. Moreover, as the wider process of analysis iterates, there will be a need to return to, reflect on and perhaps revise some of the entities and quantities already elicited.

Many would perceive the arguments below as promoting multi-method approaches in which many different investigative, analytic and modelling tools are brought to bear in a single study: and I am. I have seldom been involved in any 'single' method studies. Whether conducting a data analysis, risk assessment or decision analysis, I have almost invariably used many different modelling and analytic tools to look at the issues from different perspectives, seeking mutual support from them and building a broader understanding. However, my perspective relates to the modelling stages of multi-method approaches not the later stages in which analyses need to be drawn together and interpreted.

In the next section, we discuss modelling processes and the role of elicitation. Sections 3 and 4 review, respectively, the literatures on soft and hard elicitation. We then turn to psychological and behavioural perspectives on elicitation, paying particular attention the potential for biases unless elicitation processes are carefully designed and conducted. In Section 6 we discuss a range of issues, arguing that a broader perspective on elicitation would benefit the processes of OR analysis. The final section draws together some conclusions.

2. On modelling and elicitation

Model is a much-used word with a plethora of quite different meanings. In pure mathematics, model theory is a branch of logic with very precise definitions. Many management models, which can often be as simple as three intersecting circles, cause wry smiles across operational research and the mathematical sciences where complex formulae are usually the building blocks of models. In the physical sciences, a model, usually algebraic, seeks to represent the actual world, whereas a decision or risk model may include possible futures, some of which will never have a reality and might be counterfactual (French, 2020). A computer model is an encoding of an algebraic model in a programming language. In ethics, a model can represent ideal behaviour and will very seldom have any algebraic or graphical form. Engineering models used to have a solid three-dimensional form, but now are more likely computer-generated virtual objects that can be viewed from all perspectives and dissembled in many ways. A model in art is not an image of the real person, but quite the reverse: he or she is the real person being portrayed. Here I shall use the terms 'model' and 'modelling' in ways that are common in the OR literature, leaving the reader to discern my particular meaning from the context.

I shall not discuss the possibility and means of validation of different types of models here, but simply assume that the models used in any analysis are trusted by the analysts, problem-owners, experts and stakeholders to provide meaningful and informative results that will help them in reaching a solution.

The adjectives *qualitative* and *quantitative* are often used to qualify models[2]. It is easy to think of a quantitative model as one with numbers in it or, perhaps better, one that can be used to calculate numerical outputs given numerical inputs, with such numerical inputs and outputs being interpretable and informative to the user. Qualitative models would then seem to be those which do not process numbers: e.g., a rich picture diagram or a management model such as Porter's 5 forces (Van den Berg & Pietersma, 2015). But things are not that easy. A cognitive map (Eden, 1988) can look like a simple pictorial network connecting concepts; surely a qualitative model? But it can embedded in software to ease its drawing and modification. Within the computer it will be a quantitative model, one that invites checks to ensure some rationality of connectedness, maybe to be fuzzified (Konar & Chakraborty, 2005). It can develop into a simulation, system dynamics, or an agent based model (Macal, 2016; Morgan et al., 2017; Wainer, 2017); and eventually perhaps into a full multi-criteria decision analysis (Marttunen et al., 2017), a Bayesian belief net or influence diagram (Marcot & Penman, 2019; Shachter, 2007; Walshe & Burgman, 2010). When did the modelling become quantitative? Moreover, in a simple model, a parameter may approximate the average effect of a submodel, which would be part of a more complex model. So the quantitative parameters and the qualitative structure of a model, so easy to distinguish when considering just that model at a moment in time, become intricately related and hard to separate conceptually over the entire modelling process.

It is informative to look to measurement theory, the body of knowledge that clarifies how behaviours in a quantitative model reflect qualitative behaviours in some system (Krantz et al., 1971; Luce et al., 1990; Roberts, 1979; Suppes et al., 1989). Essentially, a measurement theoretic approach sets up a series of axioms that describe the behaviour of relations between entities in the system: e.g., 'is heavier than', 'is worth more than', and 'is more likely than'. These relations may be binary, ternary, quaternary or whatever. They may be objective or subjective. They may be *descriptive* in reflecting how the world is or might be, or *normative* in reflecting how one would like it to be. Further axioms introduce what are effectively measurement tools – metaphorically, rulers – to introduce numerical properties into the system and develop a homomorphism or, in lay terms, an identification between the system and a numerical model. From this perspective, the distinction between qualitative and quantitative models is somewhat illusory. French (2020) illustrates the use of measurement theory to explore the assumptions inherent in scenario-focussed decision analysis.

Quantification simply reflects qualitative properties in a system, but it describes those relationships more precisely. Thus Figure 1 does not represent a qualitative-quantitative dichotomy, but a scale of increasing precision, building on qualitative understanding and representing a system more precisely as details and interactions within a model become intricate. Elicitation – the process of interaction with problem-owners and experts – reflects this and becomes more precise and numerical from left to right. There is no simple dichotomy between eliciting perceptions of systems, entities and relationships and eliciting the numerical attributes of these. Moreover, certain aspects of their perceptions might be represented in different ways: sometimes qualitatively, sometimes quantitatively. For instance, logical parameters can be used to turn on or off behaviours of submodels; or, as noted earlier, a submodel may be replaced by a parameter representing its average behaviour, in some sense.

Franco and Montibeller (2010) suggest that OR studies tend to be conducted in one of two modes.

- The *expert* mode in which the analysts essentially take the problem away and conduct the analyses based on standard OR models. Such studies are common in solving operational and some tactical problems in the Cynefin Known and Knowable spaces (French, 2013). Because such problems occur commonly, well-structured models are relatively easy to build. The analysts' task is mainly to run sophisticated computer codes to explore and analyse the system. Elicitation occurs mainly at the outset of the project and occasionally at interim reporting meetings. The majority of the elicitation will relate to numerical quantities with relatively little to more qualitative issues needed to formulate models.
- The *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. Such studies are common in tackling strategic and some tactical issues, and in responding to crises, i.e., contexts lying in the Cynefin Complex and Chaotic spaces. Elicitation in such studies takes place throughout the analysis. Initially the emphasis is on understanding the perceptions of the group on what is happening and identifying possible strategies that may be taken up in response, and on the values that will drive their decision-making. Later, as quantitative models are built to capture these, there will be a need to elicit numerical inputs for these for those quantities that cannot be inferred from 'objective' data.

This rough dichotomy is an oversimplification; many studies involve elements of both. Large projects dealing with complex issues may begin with several facilitated workshops to explore and identify issues, creating a series of questions. These questions are then explored through sophisticated modelling studies carried out in the expert mode. Later, there may be a return to facilitated modelling to share what has been learnt and evaluate possible strategies, providing guidance to the decision-makers. Elicitation occurs throughout, iterating between soft and harder phases. Some or all of the workshops might be conducted as face-to-face events or remotely (Coakes et al., 2002; French et al., 2009; Nunamaker et al., 2014; Pyrko et al., 2019).

Despite my view that there is a continuum between soft and hard elicitation, the next two sections review these separately, simply because the literature is so divided. These are high-level reviews: details of individual techniques and methodologies being left to the cited literature. Subsequently, we shall draw these together somewhat, though part of the thrust in this paper is to recommend a more thorough effort at synthesis.

3. Soft elicitation

At the start of an analysis, there is a need to make sense of the issues, to structure them in some way, so that they can be addressed. Across the disciplines, many tools and processes are suggested to provide the basis for exploring issues and building models to analyse. In French et al. (2009, Chapter 9), we categorised these under six headings:

- *check-lists*: essentially verbal prompts that can be dropped into a discussion and might stimulate a change of perspective or memory of a forgotten issue;
- *simple two-dimensional plots*: plotting aspects of the problem against qualitative axes can separate them into clusters that can be useful in structuring the issues;
- *trees and networks*: graphs that connect entities according to certain relationships between them;
- *management models*: simple pictorial representations of management theories can help structure issues and challenge thinking;
- *rich picture diagrams*: sometimes the issues can be presented pictorially capturing their essence in a transparent way;
- *scenarios*: encourage the problem-owners to create several alternative futures against which their plans can be discussed and tested.

Such tools have developed somewhat independently in different disciplines. We begin with developments in OR.

3.1. Soft or and problem structuring methods

Soft elicitation has a long history within OR. Recently Harwood (2019) questioned whether the methods were as much used as they had been, but an almost immediate response suggests otherwise (Ackermann, 2019; Ackermann et al., 2020; Lowe & Yearworth, 2019). Rosenhead (2006), Ackermann (2012) and Checkland (2019) provide brief histories of and personal reflections on developments in the area. For descriptions of some of these methods, see: cognitive mapping and SODA (Eden &

Ackermann, 1998); drama theory, hypergames and metagames (Bennett, 1977; Bryant, 2007; Howard, 1971); mindmapping (Buzan, 2005); strategic choice method, (Friend & Hickling, 1997); and SSM, (P Checkland, 2013), along with other systems approaches (Holwell, 2000; Reynolds & Holwell, 2020). More general surveys are offered by Mingers and Rosenhead (2004), Rosenhead (1989), Rosenhead and Mingers (2001), Shaw et al. (2006), and Shaw et al. (2007). Within my home discipline of decision analysis, we emphasise the importance of value-focused thinking in the initial stages of soft elicitation: i.e., being reasonably clear on objectives before committing to models and analysis (Keeney, 1992). The simple process of trying to draw a decision tree or influence diagram can be very catalytic to thought (Wells, 1982; Wilkerson & Smith, 2021). All these writings make clear that to use these methods one has to think as much about process and dialogue as the tool itself (see also, Slotte & Hämäläinen, 2015). Over the decades, these tools and processes have become known within OR first as *soft OR* and later as *problem structuring methods* (PSMs).

3.2. Soft systems and information systems

Since the development of computers after the Second World War and the inception of LEO at J.Lyons & Co. in 1951 to run its orders for its cafes and coffee houses, information and communications technologies have changed governments', organisations' and our everyday lives; but not always with immediate success. There have been many development hiccoughs and more widely published debacles (POST, 2003; Yeo, 2002), and the promise of the technology has not always been delivered in full (Brynjolfsson et al., 2017; David, 1990). To understand these failures, the multi-disciplinary subject of *information systems* (Pearlson & Saunders, 2009) has developed alongside more technology-focused *computer science*. Structured processes of system design and development have grown up, ranging from the highly formalised SSADM to agile development (Kendall & Kendall, 2019; Martin, 2002). All begin with – and often return to – requirements analyses which seek to understand the proposed information systems objectives and context (Mumford, 1995; Pickering, 2004). Within these there is much soft elicitation. SSM is often used, along with other variants of systems thinking, other prompts and simple models to elicit information to shape the design (P Checkland & Howell, 1997; Frank, 2013; Kawalek & Wastell, 2002; Letier et al., 2005; Luna-Reyes et al., 2008).

3.3. Knowledge elicitation

Elicitation seeks *knowledge* from problem-owners, experts and stakeholders in reflective process that enhances their self and shared knowledge. The *Knowledge Management* literature, not surprisingly therefore, contains much on elicitation. Similarly, AI systems embody much domain knowledge, which needs to be elicited from experts, though some may be learnt from training data sets (see Section 3.7). Thus the AI literature also contains much on knowledge elicitation. Paucar-Caceres and Pagano (2009) provide an interesting discussion of knowledge management practices and systems thinking, relating the literatures of knowledge management, information systems and OR. Jashapara (2011) is a broad introduction to knowledge management, while Cooke (1994), Hoffman et al. (1995), Shadbolt et al. (2015) and Sharma and Pandey (2019) discuss knowledge elicitation in AI.

Knowledge may be divided into two forms: *explicit* and *tacit*. Explicit knowledge (e.g., a scientific law) can be written down and hence stored and shared through libraries, etc. Tacit knowledge (e.g., the skill of playing a piano) is more difficult to articulate and needs to be shared by mentoring and 'showing', a process termed socialisation (French et al., 2009; Nonaka & Toyama, 2003). Eliciting explicit knowledge is, not surprisingly, easier. One might simply conduct a literature review (see Section 3.8) or ask an expert. However, when asking an expert, he or she will be making a judgement on what is relevant. So the reasoning behind that judgement needs to be elicited as well. Questionnaires are often used, though more carefully evaluated information may be gained from more structured processes such as the Delphi Method (Dalkey & Helmer, 1963; Linstone & Turoff, 2011; Rowe & Wright, 1999). Aspects of tacit knowledge elicitation are discussed by Chervinskaya and Wasserman (2000), Ford and Sterman (1998), Friedrich and Van Der Poll (2007) and Zou and Lee (2016).

Innovation and creativity techniques are often discussed along with knowledge management (Newell et al., 2009; Nonaka & Toyama, 2003; Rickards, 1997; Schiuma et al., 2012). They create knowledge obviously; but they also fit naturally into knowledge-based perspective on business (Boisot, 1998). Keeney (2012) discusses creativity techniques in the context of decision analysis.

As with all soft elicitation, the *process* of knowledge elicitation is as important as the particular *techniques* used. Workshops are commonly used; cf. facilitated modelling (Section 2). There have been interesting developments of ways of designing such processes using *thinklets* (Briggs et al., 2003; De Vreede & Briggs, 2019; Knoll & Horton, 2011).

3.4. Management Models

I have a well-thumbed early edition of *Key Management Models* (ten Have et al., 2003; Van den Berg & Pietersma, 2015), which I use during the early stages of a project. It covers many models that indicate broad relationships between entities, issues, processes, behaviours, etc. that commonly confront managers in developing strategy, planning operations and solving problems: from SWOT, PESTLE and 7S's to Porter's 5 Forces and Hofstede's Cultural Dimensions. Selecting an appropriate model and presenting it to the problem owners can be helpful in challenging their thinking and eliciting key issues that they struggle to articulate. Management theorists may look at their models as encoding their own knowledge of processes, behaviours, etc.; but, as many consultants know, they are also very effective tools in eliciting relevant perspectives on the issues of concern.

Management consultants often use scenario planning in their work to elicit understandings of what might happen and their clients might respond (van der Heijden, 1996; Wack, 1985a, 1985b). Scenario development is an effective tool to draw out knowledge and understanding, having close relationships with soft systems modelling (Burt, 2011; Powell, 2014). Currently many are investigating the integration of scenario planning and decision analysis in circumstances of deep uncertainty (French, 2020; Marchau et al., 2019; Montibeller et al., 2006; Wright & Goodwin, 1999).

3.5. Mathematical Model building

Mathematics is the discipline that provides the structures and tools that underpin quantitative analysis. Yet looking back on my education – I took a degree in mathematics, albeit half a century ago – I was taught little about the *process* of mathematical modelling. The same was true of my earlier education and seems to be true the handful of mathematics degree programmes that I have explored in writing this. Courses on the process of mathematical modelling are very few. Primary and secondary education does seem to have changed a little: in the UK, key stages provide for much more exploration of the links between mathematics and the real world. A brief literature review suggested that while there is a wealth of material on specific mathematical models, there seems to be few papers or books on the *process* of mathematical modelling. Certainly, I have found nothing like the literatures in other disciplines. That is not to say that mathematicians are not interested in modelling. Applied mathematicians do it all the time and there are challenging series of workshops such as the European Study Groups with Industry[3]. But as a profession, mathematicians seem to gain their modelling skills by socialisation (Nonaka & Toyama, 2003); it perceived as a mainly tacit skill that learnt by working with more experienced modellers. Soft elicitation tools and interventions that might catalyse the articulation of understanding into models are not discussed.

3.6. Risk and hazard identification

Risk management requires that hazards and risks are identified and analysed so that appropriate monitoring and responses can be planned (Aven, 2008; Galante et al., 2014). The identification techniques and processes share much with other soft elicitation processes (Chapman, 1998; Crawley & Tyler, 2003; Glossop et al., 2000). There are many formalised structured procedures to ensure that best practice is followed: e.g., hazard and operability analysis (HAZOP) (Chartres et al., 2019; Dunjó et al., 2010). Questionnaires and procedures such as Delphi are used to gather information on potential hazards and how they relate to work and operating practices (Linstone & Turoff, 2011; Schmidt et al., 2001). Also drawing a fault or event tree is not simply a technical task; it encourages problem owners and experts to think carefully about failure paths and initiating events. Similarly, developing scenarios to form a backdrop to policy conversations about risk can surface many issues and features that need to be addressed in modelling (Hughes & Strachan, 2010; Høyland & Wallace, 2001).

3.7. Exploratory data analysis (EDA)

At first sight, EDA would seem to have little to do with elicitation. Introduced by Tukey (1977) over half a century ago, it refers to a range of tools and techniques to explore data. Originally based around 'quick and dirty' data plots performed on paper, EDA has become computer-based with statistical software offering many exploratory plots. Multivariate statistics offers further ways of exploring data and identifying potential relationships. Many data-mining and machine learning techniques are effectively automated EDA, in which potentially interesting features of a dataset are identified (Baesens et al., 2009; Bendoly & Clark, 2016; Ferreira de Oliveira & Levkowitz, 2003; Klosgen & Lauer, 2002; Rogers & Girolami, 2015). EDA, however, does have much to do with elicitation. Firstly, to undertake EDA, the data sets have to be identified and that takes the judgement to suggest what might be relevant – and what might be relevant if it could but be found (Hand, 2020). More importantly, once the EDA has been conducted and potentially interesting features found, these have to be assessed for whether they are truly informative. For instance, interpreting factors output by a factor or principal component analysis requires broad knowledge of the context. Similarly, if a belief net has been machine-learnt from a dataset, the potential conditional dependencies and independencies need to be examined to see if they make sense. This requires that the analysts work with the problem owners to interpret and assess the EDA. Such discussions almost inevitably elicit much soft information.

3.8. Literature Reviews and horizon scanning

Before beginning any investigation, it is essential to explore what is known, to identify models and analyses that have been applied in similar cases, and to learn of what pitfalls were encountered. Sound modelling and analysis begin with a review of the current academic, professional and grey literatures. This avoids the re-invention of well-worn wheels and ensures, if new wheels are needed, that they are as round as possible given current knowledge. There is also a need to explore discussions of relevant futures, i.e., for horizon-scanning. What do the engineering, environmental, marketing, political, scientific and other relevant communities expect to be happening in the coming months and years (Miles et al., 2016)?

At the outset of a study, a literature review needs to be open, broad and allow the investigators to explore where seems fertile. In some projects and studies, there can be a false imperative to begin with a tightly structured literature review. Much research today, particularly in the medical sciences, builds on meta-analyses of previous empirical research (Borenstein et al., 2009; Hartung et al., 2008; Sutton & Abrams, 2001). To ensure common standards, the process for identifying appropriate studies to include in a meta-analysis requires precise *a priori* criteria for what should be included. Such standards are needed to conform to the assumptions of the statistical meta-analysis. Unfortunately, such tight structuring seems to have spread into many studies that do not use meta-analyses. In particular, in soft elicitation such tight structuring is quite inappropriate. The process of formulating issues and moving from qualitative discussion to quantitative models is a very creative one. It is important that one is allowed to 'follow one's nose' in exploring past literature, a process absolutely forbidden in an over-structured literature review. That said, *if* meta-analysis is used later in the study, e.g., to identify parameters for use in the analysis of a model, then there may be a need for a structured literature review at that point.

Literature reviews are a source of potential models that might be used, but their use also risks substantial errors if their assumptions are not appropriate to the current context. Thus, it is important that the review also identifies their assumptions (Saltelli et al., 2020). A similar point may be made about scenarios. It is common in some domains to repeatedly use a set of scenarios built to explore some aspect of possible futures to explore many others. But it is seldom the case that the 'interesting' futures that they 'spanned' for one problem are entirely appropriate for another. For example, it is questionable whether the FES scenarios built by National Grid[4] are entirely suitable for the purposes for which many others in the UK energy industries use them.

3.9. Sense-making

Over the years, behavioural scientists, organisational theorists, psychologists and others have discussed how individuals and groups make sense of an evolving situation or pattern of novel observations, often stemming from the work of Weick (1995); for a critical review, see Mills et al. (2010). How one makes sense of a situation is shaped by their personal, organisational and societal language and culture (Du Toit, 2003). Sense-making under pressure in crises has also been a concern (Muhren & Van de Walle, 2010; Weick & Sutcliffe, 2001). Snowden's Cynefin model provides many useful perspectives, describing how sense-making transitions into more formal analysis and response (French, 2013; Hasan & Kazlauskas, 2009; Snowden, 2002). Sense-making is a creative process and there are many parallels with the literature on creativity (Rickards, 1997). Sense-making leads us to form mental models. There are processes for eliciting these that we may add to our tools of soft elicitation (Cox et al., 2003; Granger Morgan et al., 2002).

The facilitated modelling mode of analysis invariably involves phases of sense-making (Franco & Montibeller, 2010). One of the tools used by the facilitator is gentle, sometimes perhaps not so gentle, challenge. Challenge stimulates thought and reflection, and can avoid groupthink and related biases: see Section 5. The early phases of modelling and analysis should encourage divergent thinking so that the later modelling and analysis have as much chance as possible of including all relevant issues in their more convergent deliberations. Nonetheless, some may be missed. So it is important that sense-making continues after the early phases of modelling to explore whether there are systematic differences between the problem-owners' and stakeholders' perceptions and any model output. This exploration may be informal or driven by sensitivity and robustness studies along with statistical residual analysis.

4. Hard elicitation

Soft elicitation provides the knowledge to build a quantitative model; Section 6 provides further discussion. That model needs to be populated with numbers, i.e., numerical values for its parameters. For parameters that relate to models of the external world as opposed to, say, a decision maker's risk attitude, it may be possible estimate these statistically from data. However, for some parameters there may be no suitable data. Then it is necessary to ask experts to give values using their knowledge and judgement.

The simplest way to elicit numbers from someone is to ask him or her. To do so, however, risks a variety of behavioural biases: see Section 5. Moreover, the simple answer of a number does not capture any idea of the confidence that should be placed on it nor the reasoning behind it. Hence, many methodologies of parameter, probability and preference elicitation have been developed to counter biases and assess the uncertainty in responses. Recent reviews are provided by Burgman (2015), Dias et al. (2018), Edwards et al. (2007), Hanea et al. (2021) and O'Hagan et al. (2006). For seminal references, see Cooke (1991), Farquhar (1984), Merkhofer (1987) and Raiffa (1968, 2006).

Methodologies for eliciting parameters with associated uncertainties are now well established in risk and decision analyses. Several methods exist for combining the estimates from several experts: some such as SHELF use behavioural methods (Gosling, 2018); others use mathematical algorithms (R. M. Cooke, 2007; French, 2011); and some a combination of both (Hemming et al., 2018). Organisations such as the European Food Safety Authority have now adopted a range of expert knowledge elicitation procedures into their standard working practices (EFSA, 2014). Applications in many other domains are reported (Dias et al., 2018; Hanea et al., 2021). When the parameters concerned relate to probabilities or probability distributions, it is possible to use any of the methods just discussed; but there is also a long literature on probability elicitation in risk and decision analysis (Hora, 2007; Lichtendahl & Winkler, 2007; O'Hagan et al., 2006; Staël von Holstein, 1970). Correlations are less easy to elicit and the means of doing so is an active research area (Werner et al., 2017).

Alongside model parameters, one should recognise that many models are solved using complex computational methods and that these methods need their own set of parameters to drive them. In ideal circumstances, these parameters would be set by a mix of experience and experimentation *in the context of the problem being solved*. In many cases, though, computer code is taken off the shelf and run with default parameters along with half an eye on convergence plots and other criteria. Either way the computation contributes to the uncertainty in the results. Elicitation of computational parameters is not a particularly well-studied topic, although approximations used in and convergence of algorithms are.

In most problems there is also a need to elicit preferences and values to define the objective function or, in decision analytic terms, the utility function. The process of elicitation here is subtly different from the elicitation of parameters and probabilities. Those quantities relate to the external world and, however much the problem-owners and stakeholder might wish, they cannot by an act of will change those and hope to achieve a valid representation. Preferences and values are different. Problem-owners and stakeholders can change their mind about what they want. Indeed, part of the purpose of a decision analysis is to help them contextualise their broad preferences and values, e.g., "I want good health," to the specifics of the issue before them, e.g., "now I have this disease, how do I want to live the rest of my life?" Thus, elicitation becomes a more constructive process helping the participants think through what they want (Abbas & Howard, 2015; French et al., 2009; Keeney & Raiffa, 1976).

It is tempting to think of hard elicitation as being all about 'getting the numbers', but that is far from the case. One should never elicit a quantity without asking for and recording the reasoning behind that judgement. Not only does that provide a sound audit trail, but it also can stimulate fresh qualitative thinking, as further relationships become understood; there really is no real dichotomy between soft and hard elicitation.

It is worth remarking on the role of sensitivity and robustness analyses. Many see these as occurring at the end of the process as a check that the results are not spuriously related to precise numerical values of the inputs. Given the uncertainty in the inputs, other results may be quite as justifiable. However, sensitivity analyses should permeate the process from the moment quantification begins, arguing that (hard) elicitation should be driven by sensitivity and robustness calculations which help identify what needs to be elicited and how accurately (French, 2003). Too often, the analysts may drive for – and the problem-owners expect – greater precision than is strictly necessary; or they may focus their efforts on what is a seemingly important parameter, but which actually has little effect.

5. Behavioural issues in elicitation

Analysts are well aware of potential psychological and behavioural biases that may occur in hard elicitation and these are reasonably well guarded against in the procedures that they use (Dias et al., 2018; French et al., 2009; Kahneman, 2011). We know that in articulating their judgements as numbers, experts, problem-owners and stakeholders may, *inter alia*:

- *anchor* their judgement to some number they have just seen or heard;
- base their judgement too much on some immediately *available* data;
- be biased by the *framing* of the question or context, including interpersonal or political pressures;
- be *overconfident*.

Although these and other biases apply to *quantitative* judgements, they may conceptually apply to more *qualitative* responses. Do experts *anchor* their advice on some assumption or theoretical construct in the question? Do they base their advice or comments too much on some discussion on a similar topic that they engaged in recently or some research result that they have just seen? Does the framing of the general context affect experts' advice on modelling or stakeholders' articulation of their preferences and values? Organisational or political pressures, real or perceived, may bias or quieten advice from some experts or stakeholders. There is a huge literature on overconfidence (see, e.g., Burgman, 2015; Liu et al., 2017), some suggesting that, as in the case of other heuristics and biases, it may have brought an evolutionary advantage, but no longer does so in our complex world with many intangible risks (Johnson & Fowler, 2011). Overconfidence may apply just as much in recommending the use of a particular model or data set as to an assessment of a parameter. Intransitivities have been observed in judgements (Tversky, 1969). They might occur, e.g., when experts have to rank the appropriateness of several models to a particular context. Confirmation bias, in which evidence to confirm not refute is sought, is clearly a potential issue in seeking advice from experts, e.g., in developing a risk monitoring strategy (Nickerson, 1998).

There is, of course, the question of how we recognise – measure – biases in qualitative judgements provided by experts. Calibrating quantitative judgements to assess biases is relatively straightforward. Conceptually, one simply compares an elicited numerical judgement with its actual value. Of course, in practice the actual value is usually unknown, but there are ways of estimating the calibration (Clemen & Lichtendahl, 2002; R. M. Cooke, 1991; French & Hartley, 2018). But how do we assess the calibration of a qualitative judgement? The literature on metacognition, i.e., an individual's awareness and understanding of his or her own thought processes, may offer a route forward (Flavell, 1979; Heyes et al., 2020; Kavousi et al., 2020).

Much elicitation is conducted with groups of problem-owners, experts or stakeholders. There are many examples of unproductive, biasing behaviours observed in groups, ranging from free-riding to groupthink (Baron & Kerr, 2004; French et al., 2009; Turner & Pratkanis, 1998). To counter these, many facilitation techniques have been develop, most of which bring an element of challenge into group discussion to catalyse thought, draw out evidence and make reasoning explicit (L. D. Phillips & Phillips, 1993; Slotte & Hämäläinen, 2015).

Thus, it is reasonable to be concerned about whether biases arise when we ask an individual or a group for their beliefs, preferences, knowledge and advice in order to structure a quantitative model. Those of us involved in facilitated modelling are aware of the potential for bias. We do not simply question decision-makers, experts and stakeholders; the process is far more subtle and challenging to encourage reflection. But do we know that this works? How can we be confident that the model[5] represents the issues and concerns of the problem-owners and stakeholders? In hard elicitation we have a range of approaches to deal with behavioural biases and, where appropriate, recalibrate the numbers. Are there current practices fit for a similar purpose in soft elicitation?

- Statisticians have long discussed model uncertainty after data analysis, including such issues as model choice and validation. But how do we assess models that have been built using expert advice and judgement to determine whether they are sufficiently meaningful and trustworthy that they provide the basis of a solution for the problem-owners? There will be insufficient data to validate them; otherwise, we would have taken a statistical route to achieve that. What about the residual uncertainty that remains from the soft elicitation of the model?

- How do we aggregate the advice and softer judgements from different experts? There are many theories for aggregating quantitative judgements (Dias et al., 2018; Hanea et al., 2021); but much less attention has been paid to weight that we should put on different models that have been advised by different experts.
- Stepping back, we might ask the same questions about the choice of scenarios, which can shape analyses as much as models. Many analyses facing deep uncertainty analyse options against different scenarios (French, 2020; Stewart et al., 2010). What behavioural biases might affect the development of scenarios? How is the choice of scenarios made?

In a sense, I am asking – or, perhaps better, shading – the question of how we recognise that an overall analysis is *requisite* (French et al., 2009; L D Phillips, 1982, 1984). The overall question asks, are the problem-owners comfortable enough with the analysis to move on to take some action. But the subsidiary question here is whether they understand the overall uncertainty that remains from the soft elicitation of knowledge on which the analysis is founded. Do our soft elicitation practices recognise and seek to exhibit that? Indeed, do we have enough understanding of the behavioural processes that contribute to that uncertainty?

6. From soft to hard: An art?

There is an 'elephant in this room', represented by nebulous cloud in Figure 1: how do we move from qualitative to quantitative modelling? How does soft elicitation help us build the models which eventually will be populated with numbers, some from data analysis and some from hard elicitation? There is very little guidance in the literature. Pidd (2004) and the project reported therein made a start, but only a start. Marttunen et al. (2017) provide a review relating to multi-criteria decision analysis. Keeney (2012) describes how he uses value-focused thinking to structure a set of issues and build a rough quantification. Xin et al. (2017) present a case study in which scenario analysis is used to develop a hazard analysis that leads into a risk analysis using Bayesian networks. But most of these reports use a very few methods, often just one, of soft elicitation before a quantitative model becomes apparent. Cawson et al. (2020) describe using several soft elicitation methods, but do not really move on to producing one or more quantitative models.

My own experience lies mostly in decision analysis, usually in facilitated modelling studies. How do I move through the process of developing a quantitative decision model using soft and hard elicitation? The first thing to say is that I have a very broad, open and inclusive attitude to soft elicitation. Whereas some of the methods surveyed in Section 3 are often promoted as complete methodologies, sufficient in themselves, I see them all as just collections of tools and I will use whatever tool seems effective at the time. On many occasions I have combined tools: e.g., mind-mapping the consequences at the end of each branch of an outline decision tree. During problem formulation meetings with problem owners, stakeholders and experts, I begin with some open-ended question such as: "What are the issues concerning you?" I let the discussion flow, learning their language/jargon and accumulate brief summaries of the issues on flip-charts. Gradually I will use various prompts to stimulate discussion: some as simple as PESTLE, others more complex such as Simons (1995) Levers of Control. I find the Cynefin model particularly helpful, categorising as it does knowledge of cause and effect (French, 2013). As an elicitation tool, it helps identify important characteristics of the problem's context and hence what forms of analysis might be most appropriate.

When we have listed a wide range of issues and no new perspectives are emerging, I begin to categorise issues under various headings, driven by my decision analytic perspective: values and objectives, uncertainties, stakeholders, possible actions, potential consequences, context and assumptions, etc. This almost inevitably stimulates discussion of further issues and interactions. We will move towards quantitative models, perhaps during the initial meeting or maybe in later more focused meetings with experts and stakeholders. This step is shaped by the perspectives and tools used within decision analysis (see, e.g., Abbas & Howard, 2015; French et al., 2009; Gregory et al., 2005). Three aspects of decision modelling are particularly relevant (French, 2003):

- *Value and Utility models*. Value-focused thinking is an important driver of decision analyses so a key aspect of the modelling is to develop an attribute/objectives hierarchy and build value and/or utility functions on this. The rough list of objectives and values built up in discussion with the problem-owners and stakeholders provides a start. Grouping these and building a hierarchy will usually catalyse discussion, clarify and redefine meanings and identify any preferential dependencies or independencies (Keeney, 1992; Keeney & Raiffa, 1976).
- *Consequence models*. These predict the outcome of different actions given a set of external circumstances, i.e., a state of the world (French,

2015). Since one possible action may be to do nothing, a consequence model may simply predict the current future. As such it might be a simple linear model, a complex network of economic, environmental, physical, health and other models, or anything in between. The initial value and utility modelling will have identified the important attributes in describing the consequences. The problem-owners, stakeholders and particularly the experts involved may advise on appropriate models to use. If they cannot, then consultation of further experts and/or a literature review may be necessary.
- *Uncertainty models*. The consequence models will make many uncertainties apparent. Parameters may be unknown; indeed, the form of some functional relationships may be unclear. Some uncertainties may be modelled probabilistically (Abbas & Howard, 2015; Smith, 2010); others may be deep and need to be addressed through several parallel analyses in different scenarios (French, 2020).

While I have described these steps linearly, there will be much iteration and revision as each step reflects back to earlier ones. This modelling provides a decision model for data analysis or hard elicitation may provide the various parameters and numerical quantities needed.

That, very roughly, outlines my approach to elicitation and modelling; but I am not sure if other decision analysts approach problems in the same way, because we seldom observe each other and, as I have said, case studies and texts are remarkably light on such details. Away from decision analysis in more mainstream OR, I have even less idea of the processes.

Problem formulation involves many tacit skills and much creativity. It is important that these are understood and the best methodologies and tools used. Until the majority of analysts are skilled in soft elicitation techniques, there are significant risks of that many quantitative analyses will be based upon models that do not recognise – and so do not allow exploration of – significant features. My recent experiences in the *Analysis under Uncertainty for Decision Makers network*[6], particularly in scenario-focused discussion sessions, suggests that many simple techniques, even PESTLE, are quite novel to some of the audience. Within our education system, soft elicitation techniques are seldom emphasised. They may rely on tacit skills that are difficult to teach, especially in the format of a lecture. But they can be taught. Alliance Manchester Business School (AMBS) has long used action learning in the *Manchester Method* (Dewick & Paraskevopoulou, 2008; Drinkwater et al., 2004; Revans, 2011). Active discussion of hypothetical scenarios can be useful (Ackermann et al., 2020; French & Maule, 1999, 2010).

Research is also needed. At the basic level, we need to pull together what is understood across the disciplines. Section 3 points to *some* of the literatures to explore; but my review has barely scratched the surface. Good reporting of experiences in moving from the initial pressures to address a set of issues through modelling and analysis to their resolution will provide a basis. But many more studies are needed of the move from soft elicitation to hard, from qualitative to quantitative modelling.

Moreover, we *need* comparative studies otherwise we will only learn about what works and what does not; and that does not provide the evidence to identify best practice (cf. Bayley & French, 2011). Running parallel studies will be necessary. French et al. (2007; 1998) describe studies based around hypothetical scenarios, but these did not go forward to full quantitative modelling.

7. Conclusions

Perhaps the strongest point that I am seeking to make in this paper is that soft elicitation has developed in parallel in a number of disciplines. Doubtless more than I have touched on here; one might also look to reliability analysis, design science, research methodology and policy sciences, for instance. There is potentially much to be gained by drawing experiences and ideas from across as wide a range of disciplines as possible. The world faces more and more complex problems that require modelling well if we are to solve them to the best of our ability. If knowledge and expertise exist in silos, we risk poor solutions. The OR, other problem-solving and modelling communities need to share ideas; and there is a need for a much more substantial literature review to draw out parallels.

Secondly, while there has been much research into the behavioural issues that that lead to biases in any numerical quantities that are elicited, there has been less of a focus on eliciting soft information that structure the models into which the numbers are input. The potential for biases arising from the modelling itself is surely as great.

Thirdly, the model building that drives the transition from soft to hard analysis may involve many tacit skills, but that does not absolve us from trying to understand these better and share them with, i.e., educate, others. We need to study and document those skills better so that we can identify good practice.

Fourthly, I am implicitly suggesting a change of terminology from, in our case, soft OR and problem formulation to *soft elicitation*. Indeed, we should drop the 'soft'. We need to recognise that *elicitation* is a continuous process that begins with issues and hints of knowledge and continues through to analysis of quantitative models from which conclusions may be drawn.

Notes

1. Ackermann (2012) and Checkland (2019) also reflect on the long debate between soft and hard OR.
2. Pidd (1996) used the terms *interpretive* and *mathematical/logical* for qualitative and quantitative, respectively.
3. https://ecmiindmath.org/
4. https://www.nationalgrideso.com/future-energy/future-energy-scenarios
5. In many complex cases there will be several models either networked together or run in parallel. But that does not change the fundamental question here.
6. http://au4dmnetworks.co.uk/

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