BARD: A structured technique for group elicitation of Bayesian networks to support analytic reasoning

Ann E. Nicholsona,∗, Kevin B. Korbā, Erik P. Nyberga, Michael Wybrowa, Ingrid Zukermana, Steven Mascaroa, Shreshth Thakura, Abraham Oshni Alvandi4, Jeff Rileya, Ross Pearsoana, Shane Morrisb, Matthieu Herrmanna, A.K.M. Azada, Fergus Bolgerd, Ulrike Hahne, David Lagnadoe

aMonash University
bBayesian Intelligence
cAutomatic Studio
dUniversity of Strathclyde
eUniversity College London
fUniversity of London, Birkbeck

Abstract
In many complex, real-world situations, problem solving and decision making require effective reasoning about causation and uncertainty. However, human reasoning in these cases is prone to confusion and error. Bayesian networks (BNs) are an artificial intelligence technology that models uncertain situations, supporting probabilistic and causal reasoning and decision making. However, to date, BN methodologies and software require significant upfront training, do not provide much guidance on the model building process, and do not support collaboratively building BNs. BARD (Bayesian ARgumentation via Delphi) is both a methodology and an expert system that utilises (1) BNs as the underlying structured representations for better argument analysis, (2) a multi-user web-based software platform and Delphi-style social processes to assist with collaboration, and (3) short, high-quality e-courses on demand, a highly structured process to guide BN construction, and a variety of helpful tools to assist in building and reasoning with BNs, including an automated explanation tool to assist effective report writing. The result is an end-to-end online platform, with associated online training, for groups without prior BN expertise to understand and analyse a problem, build a model of its underlying probabilistic causal structure, validate and reason with the causal model, and use it to produce a written analytic report. Initial experimental results demonstrate that BARD aids in problem solving, reasoning and collaboration.

Keywords: Probabilistic reasoning; probabilistic graphical models; causal reasoning; collaborative process; Delphi process.

1. Introduction
In many complex, real-world situations, problem solving and decision making require effective reasoning about causation and uncertainty. The effectiveness of human reasoning in these cases is limited: it may handle simple, quasi-linear cases well, but in complex or non-linear cases it is notoriously prone to confusion and error (Kahneman et al., 1982; Hahn & Harris, 2014; Newell et al., 2015). One way to handle such reasoning more effectively is to employ Bayesian Networks (BNs) (Pearl, 1988; Korb & Nicholson, 2011) which are an Artificial Intelligence (AI) technology that models uncertain situations, supporting probabilistic and causal reasoning and decision making.

∗Corresponding author
Email address: Ann.Nicholson@monash.edu. Phone: +61 448 019 439 (Ann E. Nicholson)
BNs have been deployed for this purpose in diverse domains such as medicine (Sesen et al., 2013; Flores et al., 2011), education (Stacey et al., 2003), engineering (Bayraktar & Hastak, 2009; Choi et al., 2007; Misirli & Bener, 2014), surveillance (Mascaro et al., 2014), the law (Fenton et al., 2013; Lagnado & Gerstenberg, 2017), and the environment (Chee et al., 2016). Furthermore, BNs have been used to analyse common fallacies in informal logic (Korb, 2004); analyse and assess a variety of arguments in criminal law, exposing some common errors in evidential reasoning (Lagnado et al., 2013; Fenton et al., 2013); analyse human difficulties with reasoning under uncertainty (Hahn & Oaksford, 2006; Hahn 2014), and proposed as a general structured method for argument analysis (Korb & Nyberg, 2016).

BNs take advantage of the natural ability of humans to reason and build causal models about the world (Lagnado & Sloman 2004; 2006; Sloman & Lagnado 2015; Bramley et al. 2017). However, for domain experts to construct their own BNs, current software usually requires substantial training, does not provide much guidance on the model building process, and does not provide any support for collaboratively building BNs. Our system addresses these deficiencies. BARD (Bayesian Argumentation via Delphi) combines BNs with a Delphi social process: a systematic method for combining multiple perspectives in a democratic, reasoned, iterative manner (Linstone & Turowski, 1975). The key novel features of BARD, our structured methodology for group reasoning, are: (1) customised Delphi-style BN elicitation; (2) structured, iterative and incremental BN building; and (3) structured, semi-automated narratives.

**Customised Delphi-style BN elicitation.** Analysts in small groups, optionally assisted by a facilitator, are guided through a structured Delphi-like elicitation protocol to consider and represent their problem-relevant knowledge in a causal BN augmented by descriptive annotations. BARD provides tools to assist elicitation of BN structure and parameters, review and consensus building within the group, and evaluation of the results. BARD’s Delphi-inspired social process helps groups of analysts avoid common pitfalls. Analysts are required to first develop an answer on their own, in a private phase, and shows other group members’ contributions after the analyst has published his or her initial attempt. This approach supports an analyst’s modification of their initial models, while maximising the diversity of answers from which the group starts its work. The other major features of Delphi utilised by BARD include anonymity and moderated discussion, both of which help groups avoid being unduly influenced by the opinionated rather than the knowledgeable.

**Stepwise, iterative and incremental BN building.** BARD breaks down a given task into six steps that are performed by the analysts: (1) pre-modelling exploration of the problem to be solved, (2–4) building the components of the BN, (5) exploring the BN’s reasoning on specific scenarios, and (6) report writing with BARD’s support. However, progress needn’t be linear: BARD encourages analysts to incrementally and iteratively build their individual BNs and seek regular feedback through communication with other group members and the facilitator.

**Structured, semi-automated narratives.** BARD guides verbal reporting with an analytical template, designed to elicit relevant points in a logical and thorough way that is consistent with general good reasoning guidelines (e.g., Clapper (2015)). BARD also auto-generates from the BN model many key points, in English, organised according to the same template—such as the diagnosticity of evidence and critical uncertainties—which analysts and the facilitator can easily incorporate into their solutions.

The development of BARD started as part of the CREATE (Crowdsourcing Evidence, Argumentation, Thinking and Evaluation) program funded by IARPA (Intelligence Advanced Research Projects Activity [1]). The CREATE program sought to develop, and experimentally test, systems that use crowdsourcing and structured analytic techniques to improve analytical reasoning, including to help people better understand the evidence and assumptions that support or conflict with conclusions. CREATE’s secondary aim was to aid users to improve their communication of their reasoning and conclusions.

[1]https://www.iarpa.gov/
This included meeting the guidelines for high-quality analytical reports outlined in the Intelligence Community Directive 203 (ICD-203) (Clapper, 2015). Even though BARD aims to improve the quality of analysis using BNs, it is not designed for BN experts. A core purpose of BARD is to make BNs accessible to the uninstructed, so that those outside the BN community can benefit from them.

BARD is based on a novel combination of two techniques: BNs and Delphi (Section 2). The BARD approach presented in Section 3 is the first structured workflow that supports non-BN experts, with a minimal amount of training, to build and reason with BNs, with automated explanations. BARD is also the first BN tool to support a Delphi-style social process that allows participants to collaboratively construct a group BN solution. Section 4 summarises results from empirical studies that provide evidence of BARD’s efficacy as a structured technique for improving group reasoning. Section 5 concludes by summarising the contributions of the paper, and outlines directions for future work.

2. Background

In this section, we provide background about BNs and Delphi elicitation protocols for group decision making.

2.1. Bayesian Networks

BNs are the culmination of a century of research on models formally representing causal relations, beginning with the work of Sewall Wright in the 1920s and 30s on path models (Wright, 1934). This tradition has given rise to structural equation models, which underwrite much of the formal work in economics, psychology and the social and biological sciences. It also led to work on discovering causal relations from data, including work by Herbert Simon and Hubert Blalock on “non-experimental” causal inference (e.g., Simon, 1954; Blalock Jr, 2018). In the 1980s, statisticians and AI researchers developed new techniques for modelling probability distributions, which were codified in Judea Pearl’s text Probabilistic Reasoning in Intelligent Systems (Pearl, 1988). This work launched Bayesian Networks (BNs) as a modelling tool for reasoning and decision-making under uncertainty, and its theoretical underpinnings as a field of study.

A BN is a directed, acyclic graph whose nodes represent the random variables of a problem, and whose directed links (arrows) represent direct probabilistic dependencies between the nodes they connect (Pearl, 1988; Korb & Nicholson, 2011); in so-called causal BNs, these dependencies are also supposed to be causal. Each node at the tail of an arrow is a parent of the node at the head of the arrow (it’s child). The relationship between each child and its parents is quantified, for discrete variables (i.e., with a finite number of possible states), by a Conditional Probability Table (CPT) associated with the child node. The CPTs of a BN jointly give a compact representation of the full joint probability distribution of the variables in the BN. Users can set the values of any combination of variables in a BN, usually on the basis of observed evidence $e$. This evidence propagates through the network, producing a posterior probability distribution $P(X|e)$ for each variable $X$ in the network. There are several efficient algorithms for propagating evidence, supporting a powerful combination of predictive, diagnostic and explanatory reasoning.

Figure 1(b) illustrates a simple BN, where the Drug Cheat variable represents whether an athlete has taken performance enhancing drugs, while Sample A Result and Sample B Result represent the results of a test to detect a performance enhancing drug. Note that the variables are all discrete (Figure 1(a)). The arrow from the Event variable (Figure 1(b)) shows that the probability of Drug Cheat=True is influenced by the event, while the arrow from Taking M879 indicates that the medication M879 may lead to a positive test result. The combination of influences on the test result are quantified in the CPT for Sample A Result, while the different drug cheating rates for different events are shown in the CPT for Drug Cheat (Figure 1(c)). The prior probability for a competitor being a drug cheat, $P(Drug\ Cheat = True)$, is computed to be 2.33%, while the sequence of new probabilities computed by the BN software for Sam the Swimmer is 32.41% after a positive result for Sample A, jumping to 95.79% after a positive
The Drug Cheat Problem (BARD Training Problem)

After competing, a proportion of competitors at the Olympics are randomly chosen for testing for the presence of steroids. Here we’ll consider only competitors from three sports: athletic runners, swimmers and weightlifters. Drug tests conducted in the past indicated that 4% of Weightlifter take performance enhancing drugs, while Runners are half as likely as Weightlifters to take performance enhancement drugs and Swimmers are half likely as Runners. The error rates are 2% false positive and 5% false negative. When an athlete is chosen for drug testing, two samples are taken, the A and the B sample, with the B sample only analyzed if the A sample comes back positive. The threshold for being found guilty, which will result in automatic disqualification and a 2 year ban, is 98%.

Consider the scenario of a swimmer, Sam, who is randomly chosen for testing. Sam returns a positive result for first the Sample A Test, and then the Sample B Test. Sam claims that the positive test result was not caused by a performance enhancing drugs, but by taking a medication, M879, prescribed by her doctor that is on the approved list. M879 has recently been found to trigger a positive result in the test for performance enhancing drugs. Sam’s doctor confirms that Sam did take this medication for a condition that is very rare. Based on the given information and evidence should Sam be found guilty and hence disqualified and banned for 2 years.

![Diagram](image)

**Figure 1:** The Drug Cheat Problem: The BN structure, the CPTs together with base scenario (no evidence) and the updated posterior probabilities for the scenario involving Sam the Swimmer after each new piece of evidence.
result for Sample B, and finally decreasing to 49.24% in light of new information about taking M879 medication.

2.1.1. Probabilistic reasoning errors

As shown in many studies, human reasoning under uncertainty is fraught with cognitive biases, which result in an incorrect update or utilisation of probabilistic information. Some examples are: overconfidence—exaggerating the probability of likely events and the improbability of unlikely events (Lichtenstein et al. [1982], Healy & Moore [2007]); base-rate neglect—ignoring objective prior probabilities (Tversky & Kahneman [1982], Welsh & Navarro [2012]); and anchoring—depending too much on an initial piece of information (the anchor) (Kahneman et al. [1982]). While many structured representations may assist in the avoidance or mitigation of cognitive biases when analysing problems, causal BNs are particularly suited to biases involving probability or causality. By design, BNs only permit logically consistent probabilistic information to be specified in each model, and they provably compute the probabilistic consequences without error or bias. So, if the correct elementary information can be elicited from humans (the arrows, CPTs, and any observational inputs), all the more complex probabilistic calculations will also be correct. Most of BARD’s other features (including stepwise construction and Delphi, both described in Section 3) are designed to promote accurate elicitation. Accordingly, the process of modelling reasoning under uncertainty via causal BNs has been shown to help avoid several common human reasoning fallacies, such as base-rate neglect (Korb & Nyberg [2016]), confusion of the inverse (Villejoubert & Mandel [2002]), the conjunction fallacy (Jarvstad & Hahn [2011]), the jury observation fallacy (Fenton & Neil [2000]) and, most recently, the zero sum fallacy (Pilditch et al. [2019]).

In addition, people often make reasoning errors in relation to causality. For example, people often mistake correlation between events for direct causation, when a hidden common cause may be more likely (Lagnado & Sloman [2004], Pearl & Mackenzie [2018], Kushnir et al. [2010], Gopnik et al. [2001]). Causal BNs discourage such mistakes, partly because analysts are forced to think about and model direct causal relations explicitly. Two examples of causal reasoning phenomena involving indirect causal connections that are difficult for people to handle, but are correctly captured by causal BNs, are: explaining away—when the confirmation of one cause lowers the probability of an alternative cause (Liefgreen et al. [2018]); and screening off—when knowledge of the state of a common cause renders two dependent effects independent of each other (Pearl [1988]).

2.1.2. BN tools

Given these benefits, it is not surprising that BNs have been applied to many application areas, as detailed above, in tandem with the development of BN software tools that allowed technologists to build, edit, evaluate and deploy them. Widely-used commercial BN software tools include Hugin, GeNie, Netica, AgenaRisk and BayesiaLab. In addition, research software and tools include Elvira, R BN libraries (BNT, SamIam, and BayesPy).

2.1.3. Elicitation of BNs

In order to overcome the “knowledge-engineering bottleneck” (Korb & Nicholson [2011]), machine learning methods for learning BNs from observational datasets were invented, with several of these

https://www.hugin.com/
https://www.bayesfusion.com/
https://www.norsys.com/index.html
https://www.agenarisk.com/
http://www.bayesia.com/
http://leo.ugr.es/elvira/
http://www.bnlearn.com/
https://github.com/bayesnet/bnt
http://reasoning.cs.ucla.edu/samiam/
https://pypi.org/project/bayespy/
algorithms (e.g., the PC algorithm (Spirtes et al., 2000), CaMML (O’Donnell et al., 2006) and the R libraries) incorporated into BN tools. However, in the absence of adequate datasets, BNs can be built through elicitation of domain-specific knowledge from experts. (Expert elicitation and machine learning can also be combined.) Proposed methodologies for constructing BNs through elicitation are based on concepts such as building BNs iteratively and incrementally (Laskey & Mahoney, 1997, 2000; Korb & Nicholson [2011] Bonch [2010], breaking down complex models into sub-models or fragments, and building BNs with common structures or elements called “idioms” (Fenton & Neil [2014]). However, none of the commercial BN software packages support the structured elicitation of BNs, or these knowledge engineering principles. Instead, they assume that users understand BN technology, and know how to translate their knowledge of a causal process or argument into a BN. The BARD system is designed to fill this gap.

The various BN elements that need to be elicited during BN construction include its variables, arrows, parameters (conditional probabilities) and their combinations in subnetworks and networks. There is active research in the acquisition of these elements, mostly concentrating on elicitation from domain experts; for example, concept mapping is a popular technique for relating concepts in graphs, which can be used as a preliminary step in building BNs (Novak 2010).

Korb and Nicholson have advocated an iterative and incremental approach to BN construction (Korb & Nicholson [2011] Part III), suggesting that models should initially be built up from a small local structure around a target variable of interest, rather than by attempting to exhaustively consider every possible factor relevant to the target variable from the start. In this approach, subsequent iterations pick up a few additional factors at a time, with validation (e.g., using expert feedback) in each iteration. BARD supports such an incremental and iterative BN construction approach, where the feedback is provided by a group of analysts solving the same problem, instead of an expert. Overall, BARD’s incremental approach belongs to the “spiral prototyping” or “agile model building” family, which adapts ideas long used in software engineering (Boehm 1988).

Probability elicitation has been attacked from a variety of directions. Since users are sometimes uncomfortable specifying exact probabilities, even when they are informed that they needn’t be treated as precise, probabilities have often been replaced by language equivalents (Chris [1987] van der Gaag et al. [1999])—an approach that was also adopted in the ICD-203 mapping of probabilities to English (Table 1). In BARD, we have taken a dual approach, where probabilities may be viewed both numerically or verbally.

Several protocols have been proposed for eliciting probability intervals, such as a 3-pt method (Malcolm et al. 1959; Soll & Kluyman 2004), a 4-pt method (Speirs-Bridge et al. 2010) and the IDEA protocol (Hemming et al. 2018a). These interval protocols have also been used to combine the responses of multiple experts—and one study used a form of Delphi for exact CPT elicitation (Etminani et al. 2013). However, to date, these protocols have not been integrated into any commercial or research BN software tools. Instead, they are applied outside the BN software, and their outcomes are incorporated into BNs by the model builder (Nicholson et al. 2011) van der Gaag et al. 2012] Pollino et al. 2007; Hemming et al. 2018b).

The elicitation of causal structure is a relatively under-explored area. A generic prototyping approach to address this problem has been proposed in (Korb & Nicholson [2011] Part III). Other approaches propose “idioms” (Fenton & Neil 2000), “templates” (Laskey & Mahoney 2000) and “network fragments” (Laskey & Mahoney 1997) to represent common types of causal reasoning to be incorporated into problem-specific models when appropriate. While the BARD training protocol (Section 3.5) introduces these concepts, and describes how BARD can be used to construct models that capture them, there is not yet any explicit functionality to facilitate this in the tool. Serwylo (Serwylo 2015) pioneered using online crowdsourcing and automated aggregation for BN structure elicitation, albeit not in the Delphi style, while Nicholson et al. 2016] explored Delphi elicitation and automated amalgamation of structure and parameters. However, BARD is the first tool to apply Delphi to the full BN model building process.
During elicitation, it is an important but often under-appreciated task to document how the model was constructed, e.g., the sources of modelling elements and their reliability. Although as yet there is no accepted standard for this kind of meta-documentation, BARD offers an initial approach for structured recording of this meta-information (see Section 3).

Validating computer models means testing their accuracy in representing a real-world system. In general, computer models are validated using expert feedback, data or a combination of the two (Flores et al., 2011; Korb et al., 2013). The BN software packages listed above support data-driven validation in several ways, but do not support structured expert validation, such as the validation framework proposed by Pitchforth and Mengersen (Pitchforth & Mengersen, 2013), beyond ad hoc exploration and validation of “what if” scenarios, as does BARD. In the BARD environment, group deliberation offers a further form of validation, i.e., via the social process described in Sections 3.1 and 3.3.

2.1.4. Explaining Bayesian Networks

The automatic generation of explanations from BNs has been investigated since the early 1980s (Boerlage, 1983; Sember & Zukerman, 1989; Suermann, 1992), followed by work conducted by authors Korb and Zukerman (Korb et al., 1997; Zukerman et al., 1998, 1999; Jitnah et al., 2000), and more recently by other researchers (Vreeswijk, 2005; Keppens, 2011). However, automated explanation from BNs has thus far been selective and special purpose, with language tailored to specific variables and subnetworks. The algorithms generated to date have achieved limited success in explaining complex non-monotonic relations. BARD’s explanation-generation component circumvents some of these problems, producing explanations that harness the explicit causal nature of links, as well as common idioms for expressing probabilistic and causal relationships (Section 3.2).

2.2. Delphi protocols for group decision making

There is considerable evidence that decision making by groups (either by reaching consensus or amalgamation) can produce better outcomes than decision making by individuals (Salerno et al., 2017; Kugler et al., 2012; Charness & Sutter, 2012; Straus et al., 2011). However, there are also well-known problems while working with groups, e.g., anchoring on the earliest responses, groupthink, and the excessive influence of higher-ranking members (Kahneman et al., 1982; Stettinger et al., 2015; Mumford et al., 2006; Packer, 2009). Several methods have been developed over the years that attempt to harness the positives of groups, while preempting or mitigating the negatives; one of the most well-established is the Delphi technique (Linestone & Tuoff, 1975; Rowe et al., 1991).

Delphi is an example of a nominal group technique, where the group members never actually meet face-to-face, but interact remotely. Thus, participants need not be present at the same location or make their contributions at the same time—practical benefits when experts are dispersed, perhaps internationally, with limited time and conflicting or busy diaries. Furthermore, the group members don’t even know who their fellow group members are—a deliberate ploy designed to ameliorate cues related to supposed seniority, experience or expertise, which may be unhelpful (as expertise and advancement can often be related to personality or background characteristics, rather than skill or knowledge). Thus, members can focus on the information provided by others, and the undue influence that powerful or dogmatic individuals can have on group judgments is reduced.

These anonymous participants are first asked to provide their own judgement on the issue at hand, before finding out about the responses of others. This increases the independence and diversity of initial responses, reducing social loafing and the premature conformity seen in anchoring and groupthink. The responses are collated by a facilitator, then fed back to the participants for a second round. The participants consider the information (which may simply be the mean or median of the group response when quantitative values are in question, but may also include rationales/justifications for answers), then provide another response, which could be the same as before, or could be an amended one. This encourages participants to rationally reconsider their response in the light of any new information provided by others. Several rounds may take place, continuing until some stability is achieved (although most changes
take place in the second round, and few studies go beyond two or three rounds). This process tends to increase the level of consensus in the group, but the more fundamental aim is to increase the overall quality of the responses. After the final round, the facilitator usually aggregates the responses of the individual members (or collates them, if responses are qualitative in nature), and the resultant answer is taken as the group response. Answers are usually weighted equally, which ensures that the final response reflects fairly the views of all group members. In addition to their benefits for administration and collation, using a facilitator tends to encourage constructive contributions from members and avoid any unproductive, heated arguments.

In summary, the defining characteristics of a Delphi process (Rowe et al., 1991) are: anonymity, iteration followed by feedback, and aggregation (or collation) of group responses, which is often completed by a facilitator. A review in Rowe & Wright (1999) found that, at least for short-term forecasting problems and tasks involving judgements of quantities, Delphi has generally shown improved performance compared to freely inter-acting groups or a statistically aggregated response based on the first-round responses of individual participants. However, Delphi has not previously been tested on complex reasoning problems.

One Delphi variant is a “roundless” version, called Real-time Delphi (Gordon & Pease, 2006), where the iterative process (providing individual responses, viewing information from other participants, and amending responses) is not controlled by a facilitator, and for each participant the transition between steps occurs immediately, i.e., in real-time. This setup is more flexible than regular Delphi in the timing of participants’ contributions, and has the potential to speed up the Delphi process. However, since participants can see any other available responses directly and asynchronously, rather than after amalgamation or collation by a facilitator, some of the biases associated with direct interaction may re-emerge. The social process in the BARD methodology is a version of Real-time Delphi. We discuss our reasons for trading off speed and ease of use against bias in Section 3.1 below.

3. BARD Approach

In the Delphi-style BARD structured group technique, individual group members (called analysts in BARD) submit their contributions to a problem anonymously. A moderator (called the facilitator in BARD) guides and supports the analysts through the process, and ensures an overall group solution is produced. A BARD group consists of a single facilitator and any number of analysts.

3.1. BARD Workflow

The BARD workflow consists of six steps, broken down into three phases, as depicted in Figure 2. The first, the pre-modelling preparatory Step 1, focuses on helping the group understand the problem to be solved and the questions to be answered, along with the main hypotheses and pieces of evidence. The second phase consists of Steps 2–5, where the focus is on building a causal BN that models the
Figure 3: High-level representation of the BARD workflow within a step for analysts (above) and facilitator (below) working in a BARD group.

problem situation and using the causal BN’s reasoning to assist in answering the questions. These steps reflect the natural sequence of tasks in BN construction: selecting the variables (Step 2), determining the network structure (Step 3), parameterising the model by eliciting the CPTs (Step 4), and then exploring the completed model’s reasoning on specific scenarios (Step 5). Step 6 involves production of a structured written report. While there is a natural sequence to the workflow, it is not a one-way street: users can always go back to revise their previous work. This supports building the BN iteratively and incrementally, per best-practice BN construction (Section 2.1.3).

Analysts contribute their individual domain knowledge and problem solving abilities across these six steps of BARD, while the facilitator constructs a Group version for each step, based on the analysts’ work. This is done via a structured workflow within each BARD step. At each step, analysts are required to first work on their own, and then share that initial attempt with the group. After this, they can view other analysts’ work and the current group solution (Figure 3), discuss solutions via the step-specific discussion forum, and move on to the next step whenever they choose (the “real-time” element). Analysts can also move back to an earlier step to revise their work at any time, and then move forward again to any step they previously reached.

The facilitator’s workflow is more flexible than the analysts’, as they can move to any BARD step and can view all analysts’ shared work at any time. It is the facilitator’s role to synthesise the group’s work at each step as necessary to develop a coherent solution that reflects the group’s thoughts. They encourage analysts to resolve any points of disagreement themselves; however, they are empowered to make the final decisions, which may involve either collating different analysts’ work or adopting a single analyst’s work. The facilitator can present the current group solution (for any or all steps) back to the group at any time so that analysts who have shared their work for that step can view it, discuss and provide feedback, and revise their work if they wish.

The social process within BARD’s structured workflow is a flexible variant of Real-time Delphi, arising from our observations during the interactive design and prototyping approach we used during BARD’s development. The BARD refinements of Delphi elements reflect the needs we identified to keep participants in the CREATE program engaged and actively contributing in a modern, online environment, including: (1) the contribution required of group members by BARD—specifically, building and using a BN for relatively complex problem solving—is much more demanding than the tasks typi-
ally considered within a traditional Delphi processes; (2) participants have expectations of significant autonomy (rather than having to wait for others at every step), while still being able to access peer and facilitator support when needed; (3) participants often have a preference for direct engagement with others (rather than having all communications and information come through a moderator/facilitator); (4) the BARD process becomes far too drawn-out with multiple Delphi rounds for each of the six steps, especially when the group is working in a distributed, asynchronous manner and may be spread over different time zones; (5) when one analyst wishes to revise their work from a previous step it is too onerous to require everyone else to return to that step; (6) groups must be allowed to continue operating in the temporary or permanent absence of a facilitator; and (7) not all participants will be equally engaged over the whole problem-solving time period, so to maximise their opportunity to contribute when they are engaged, it is beneficial to allow them to complete and comment on earlier steps others have already passed through and/or later steps others have not yet reached (rather than only accepting contributions to a single, current Delphi round).

A further issue we found is that participants vary in their domain expertise or problem solving ability. Hence, while the workflow must support some form of aggregation or collation, BARD does not enforce traditional Delphi equal weighting of all group member contributions for quantitative judgements. Further, for more qualitative judgements, traditional Delphi allows for further rounds until there is no significant change in opinion. This kind of stopping rule may also be used in BARD, but for our experimentation completion of the workflow was deadline driven, and this is likely to be more applicable to future real-world applications.

Although analysts' real names are concealed, they are assigned pseudonyms that they keep throughout the problem. This helps to identify the work and comments of each analyst in each step, and also relate it to their work and comments in other steps, which makes discussion and comparison far easier for participants.

Although we have deviated from traditional Delphi processes, BARD retains some of the key features that have made Delphi a successful method—anonymity, individual judgement before sharing, iteration and feedback, use of a facilitator—with some aspects supported and encouraged rather than enforced. Hence, we describe the BARD workflow as Delphi-style, rather than the Delphi method per se.

Finally, throughout the six steps, BARD encourages its users to enter a rationale to explain their analysis, making it easier for other group members to understand the solution. This detailed documentation improves the exchange of ideas and provides a basis for discussion on points of disagreement, and hopefully leads to a better understanding of the problem and the resulting solution.

3.2. The Six Steps of BARD

Here each of the six steps are described in more detail.

Step 1: Explore Problem allows analysts to read and examine the problem, review any questions that have been posted, and encourages them to extract key features by identifying (1) the hypotheses suggested by the problem/questions, and (2) the items of evidence most pertinent to those hypotheses. Analysts are also encouraged to provide rationales for the inclusion of each hypothesis and evidence item. The motivation behind this step, as a precursor to the BN modelling, is to have the group gain and record a shared understanding of the problem they must solve, and reach some level of agreement on the key elements that must be included or addressed in BN construction to answer the questions posed.

---

12During BARD’s development, we prototyped and evaluated other versions of Delphi, two of which are still supported and configurable via the administration panel at problem setup time. These are (1) a classic Delphi process, with multiple Delphi rounds for each of the six steps of BARD, analysts all moving to the next step at the same time when the facilitator gives them access, no discussion forums, and where analysts only see the amalgamated group version provided by the facilitator rather than each other’s work directly; (2) a variant Delphi process (sitting between the classic Delphi and the default real-time version) where, in addition to the group solution, analysts can view and discuss other team member’s published work, but with the facilitator controlling access to the next step.
**Step 2: Variables** is where the variables of the BN are specified, with BARD suggesting that analysts consider converting the hypotheses and evidence items from Step 1 into variables. BARD prompts for two kinds of variables: **Target** variables and **Other** variables. Target variables are often the hypotheses or further variables closely associated with the questions to be answered. In BN modelling methodologies, these are also described as “query” or “output” variables, and these modelling methodologies suggest identifying them first and then focusing attention on variables that are either causes or effects of those target variables—the “other” variables in BARD. Target variables are distinguished with a different colour in the Structure visualisation, but all variables (Target or Other) may be the output variables of a scenario in Step 5 Explore Network (see below).

BARD variables must be specified together with their discrete states, which BARD currently supports in four categories: Boolean (with just the two states **True** and **False**) for propositional variables, e.g., *Testing performed* in the Drug Cheat example; Binary (any other two-state variables), e.g., *Taking M989*; Ordered (any multi-state variables with the states in ranked orders), e.g., *(High, Medium, Low)*; and Unordered (any other discrete variable), e.g., the *Event* variable has the states *(Weightlifting, Running, Swimming)*).

Descriptions of the variables and the variable states are solicited, but not required, as are “rationales” for the choice of variables. These meta-data items are intended not only to document the intent and meaning being these modelling elements, but also to stimulate active discussion when other analysts see them and disagree.

**Step 3: Structure** is where the relationships between the variables are specified. In this step, BARD displays each variable as a draggable node (with its name) on a canvas, and prompts analysts to specify the causal structure by drawing arrows between pairs of variables, i.e., graphically specifying relationships to produce a node-link (or “network”) diagram for the BN. Target variables are differentiated from other variables by colour (Figure [1]). Arrows can be readily deleted or redirected to a new variable. Analysts can associate text labels with arrows, as well as create general labels anywhere on the canvas to act as titles or general purpose on-canvas documentation (as standard in most BN software GUIs).

During this step and later steps that display a network view of the BN (e.g., Step 5 as shown in Figure [5]), BARD adjusts the layout of the network to enforce a natural causal “flow” (left-to-right and up-to-down) and to prevent graphical elements from overlapping. This is achieved using a technique called constraint-based layout (CoLa) ([Dwyer et al. 2009](#)). As the analyst specifies arrows, CoLa automatically shifts variables around the canvas to maintain distance between them, prevent variable overlaps and minimise overlap between arrows and labels. One advantage of this automation is reduced effort by the user, but also, it’s easier for users to recognise similarities and differences in other models when they are laid out in the same way. CoLa does allow analysts to reorganise the network layout manually, by clicking and dragging variables around the canvas, while still enforcing some layout constraints.

At this point, the analyst may wish to add additional variables or modify the states or names of existing variables. They can do by returning to Step 2, per the flexible BARD workflow across steps (Figure [2]).

**Step 4: Parameters** allows users to specify the conditional probabilities for each child variable given each joint state of its parents, i.e., the child’s CPT. BARD provides two modes for specifying the conditional probabilities: (1) as answers to questions, one question for each combination of the parent node states; or (2) via a table. In either case, BARD provides two ways of entering probabilities: (1) as percentages; or (2) as English language verbal descriptors, each of which has an associated probability range, as given in ICD-203 ([Clapper 2015](#)) (Table [1]). In combination, this yields four possible input

---

13Currently, the configuration of these layout constraints is done in the software. In future, we plan to make this configurable by the BARD administrator or by users.

14We followed the Netica table layout rather than Hugin/Other software, which reverses the rows and columns, because it makes scrolling vertical rather than horizontal when the table size increases.
Table 1: Mapping verbal probability descriptors to probability ranges, taken from ICD-203 (Clapper 2015)

| Probability Descriptor | Probability Range |
|-----------------------|-------------------|
| No Chance             | $0\%$             |
| Almost No Chance      | $0 < p \leq 5\%$ |
| Almost No Chance      | $5\% < p \leq 20\%$ |
| Unlikely              | $20\% < p \leq 45\%$ |
| Roughly Even Chance   | $45\% < p \leq 55\%$ |
| Likely                | $55\% < p \leq 80\%$ |
| Very Likely           | $80\% < p \leq 95\%$ |
| Almost Certain        | $95\% < p < 100\%$ |
| Certain               | $100\%$           |

Step 5: Explore Network is where the group members can use the BN for reasoning, thus exploring the consequences of steps 2-4. Evidence is added by setting one or more variables to particular states, and the BN reasoning engine computes new probability distributions for the remaining variables. In BARD, each set of evidence is called a “scenario” (following AgenaRisk terminology), and may involve setting values for any number of variables. A scenario may describe a specific situation given in the problem description or just a hypothetical “what-if” scenario that the analyst wants to explore. In BARD, scenarios are named, can be given associated descriptions, and may be shared and discussed. When viewing other analysts’ BNs, a BARD user can’t edit them, but they can explore their consequences by adding new scenarios that are only visible to them. Analysts can always change/extend either their own BN or the associated scenarios, and facilitators can do this for the group’s model. Step 5 always includes a default “base” scenario, which shows the probability distributions for all specified output variables when no evidence has yet been added.

Step 5 is where the group decides whether to continue the spiral prototyping of the BN or, if they are satisfied with it, move on to Step 6 (Report). Scenarios allow an explicit and visual way of investigating the appropriateness of the BN—both its structure and parameters—and determining whether it is giving a reasonable representation of known or hypothetical scenarios. Scenarios can also provide a direct means of answering questions about the confirmatory value of evidence or the final probability of some event given any combination of evidence. More formally, by allowing scenar-
Figure 5: Step 5: Explore Network allows evidence to be added into scenarios in the left panel and the resulting updated probabilities in the right panel. The model in the centre panel provides an overview of the network and highlights the evidence variables in blue. The screenshot above shows the base scenario, along with a scenario after each new piece of evidence is added. Below is summary explanation for the third scenario (with all three pieces of evidence).

ios to be set up, stored and examined, BARD supports the following validation activities (Korb et al., 2013): face validity—checking whether a model captures the known features of a situation; content validity—checking whether the model’s confirmatory or causal relationships capture known relations; case analysis—seeing whether known cases are modelled correctly; sensitivity analysis—determining whether variations in target variables are proportionate to variations in evidence, including examining the confirmatory power of different evidence sets. This is obviously useful for testing whether parameters (conditional probabilities) are sensible, but can also reveal missing causal connections, for example. In the future, we anticipate providing more targeted sensitivity analysis tools, such as reporting Bayes Factors (for confirmation) or causal power (e.g., via the measure in Korb et al. (2011)).

The BARD Step 5 workspace is divided into three panels (Figure 5): the left-most panel contains the scenarios, with the base scenario listed first, and a single active scenario (selected and expanded) at a time; the middle panel shows the BN structure; the right panel shows the output variables (a subset of all the variables in the BN, as selected by the user) together with the computed probability distribution over the states; and a summary explanation is shown below. When a scenario is active, the distribution of non-evidence nodes may be easily examined. If the user wants to compare the outputs of two (or more) scenarios, they can either click back and forth (like AgenaRisk) or open (in another browser window) an additional instance of BARD for the same problem in the same step, to view the two scenarios side-by-side.

BARD Step 5 includes a general-purpose automated BN explanation tool, implementing a mix of traditional and novel natural language generation techniques and taking advantage of the explicitly causal nature of the links and common idioms for expressing probabilistic and causal relationships. The BARD Automated Explanation Tool (AET) can be used by analysts when exploring a complete causal BN, either to critique the model, or to contribute to writing up a report based on the reasoning provided by the BN.

The BARD AET generates both a summary explanation, which is re-generated and displayed each time probabilities are updated during the Explore Network step, as well as a detailed explanation that can be accessed by clicking through to a separate dialog box. For both, target variables and states (specified directly in the Explore Network step) are used to focus the explanation. Probabilities are stated both numerically and with verbal descriptors, following the ICD-203 recommendations (Table I).
The BARD summary explanation provides information about what the model probabilities would be if no evidence were entered, specifying only the target variables and states. If the scenario specifies evidence, additional statements are provided about what the evidence is for the given scenario, and how the model’s probabilities change when we take this evidence into account. An example of the summary explanation is given in Figure 5. The BARD detailed explanation includes multiple elements: the causal structure of the model, the probabilities of the target variables without any evidence and how the target probabilities are related to each other, the general reliability and bias of the evidence sources, why the evidence sources are structurally relevant, the probabilistic impact of the evidence items on each hypothesis (which can be presented in several ways and include additional notes to highlight interactions between them), and the final probabilities of the hypotheses given all the evidence (Zukerman et al., 2019).

The AET has been tested on all ten BARD training problems (Section 3.5), as well as the four problems in the BARD empirical experiments described in Section 4, and in three additional problems developed for CREATE. Overall, it has been shown to produce satisfactory English language descriptions. However, we have not yet empirically tested to what extent the provision of automated explanations, or which elements of them, improve analytic solutions.

**Step 6: Report** provides an environment in which the group can develop a joint written answer to questions raised in the problem statement. In our preliminary testing, we identified that providing a template to assist users in writing effective reports improved their performance. The template encourages analysts to methodically organise and explain their analysis in detail, and prompts them to include various key elements of good reasoning, such as probability estimates for key hypotheses in any BN developed. The Automated Explanation Tool available in Step 5 also provides its detailed output in sections of text aligned with the template sections, which can be used directly or paraphrased to complete corresponding sections of the template.

Step 6 also allows analysts to rate final reports, which will either decide or inform which report is selected as the solution for that problem. This element was added when preliminary usage indicated that discussion forums did not always generate a clear consensus or guidance for the facilitator on the best BN or final report. Furthermore, in some experiments a few facilitators were no longer active at this stage in the process, so analyst ratings allowed the group report to be selected automatically in these cases. Rating is done on a scale from 1 to 10 using a slider. After they have submitted their ratings, analysts can see the average score for each option and how many ratings have been submitted so far, but cannot see other analysts’ ratings.

BARD has a notion of submission for the final group solution. In Step 6, the facilitator can click a ‘submit’ button, which generates a PDF of the group report, and sends it to a nominated electronic location. This is useful for experiments and for usage when there is a hard deadline, but not required. All group members have access to the final published group solution and can download both the written report in PDF format and the BN.

3.3. The BARD Social Process: roles and communications

A BARD group consists of a single facilitator and any number of analysts. The analysts contribute their individual domain knowledge and problem solving abilities across the six steps of BARD and are tasked with producing the best possible solution to the problem the group has been given.

Like the moderator in traditional Delphi processes, the facilitator provides instructions to the group for each step, signals when work is to begin and when responses are to be submitted, reminds analysts of any internal milestones or overall deadlines, presents collated results and other summaries back to the group, and highlights points of interest in those summaries. The collated results are constructed and shared via the dedicated Group workspace at each step, that only the facilitator can edit, but that all analysts can view once they have shared their own work.

The facilitator should incorporate contributions from the analysts to create the group solution, rather than making unnecessary novel contributions themselves. However, the facilitator will make the final
decision on what is included and also have editorial control over how it is expressed in the group’s final report.

BARD provides two main communication channels:

1. **Discussion forums.** There is a separate Discussion Forum for each BARD step. This is where group members can communicate with each other and discuss the challenges for a particular step, gain a better understanding, provide feedback on others’ work, and discuss each other’s ideas to reach consensus. A new discussion on a particular topic can be started by any analyst or the facilitator. Each topic’s discussion is displayed as a single thread, with participants encouraged in the BARD training to use the \texttt{@analyst.pseudonym} convention to indicate when their comment is a reply to another analyst’s comment.

   The provision of a separate Discussion Forum for each step is intended to support the Delphi principle that participants should attempt their own solution before viewing other analysts’ contributions; for example, an analyst may be able to read and contribute to a discussion about the BN Variables (Step 2), but if they have not yet provided their attempt at the BN structure (Step 3), then they can’t see the Step 3 Discussion Forum. Of course, this relies on the analysts following the protocol and not discussing topics in one forum that are related to a different step.

2. **Messaging.** BARD’s chat message channels provide private, two-way messaging between the facilitator and an analyst, and BARD also allows the facilitator to send a single message to multiple analysts. Messages are not associated with steps. Analysts do not see who else the facilitator may have sent the same message to, and they do not see any messages between the facilitator and other analysts. The message sender may optionally elect to generate an email notification for the recipient(s), which is a useful nudge for someone to login again to BARD when it is being used by the group asynchronously. However, BARD does not allow analyst-analyst direct messaging, to reduce private “side” conversations and to encourage a collaborative process where all group members have access to the same information and discussions.

   BARD training advocates that the majority of facilitator communication to the group members should be via the Discussion forum. However, the messaging channel is more suitable for contacting individual analysts who have not been contributing either individually or to discussion; for answering private questions from an analyst about using the BARD application (especially where to find help); and for communicating privately to an analyst regarding inappropriate social behaviour (such as showing a lack of respect for others in the discussion forums). The facilitator is supported in these aspects of the role with an administration panel that shows a summary of each group member’s last BARD access, and the stage they have reached.

   BARD advocates and supports participants using pseudonyms to maintain their anonymity, a key feature of any Delphi process. However, this aspect is managed by the BARD administrator (see Section \ref{sec:admin}) who may choose to have users identified by real names rather than pseudonyms.

   BARD also provides functionality enabling users to automatically incorporate elements of each other’s work into their own solution (if they are analysts) or into the Group solution (if they are the facilitator). This is done in slightly different ways in each step, due to the distinct types of content being incorporated. Copying work can greatly reduce the burden on individual analysts, and make it easier to produce compatible contributions. For example, if one analyst likes some of the variables another analyst has defined in step 2, then they can easily adopt them and proceed to demonstrate a slightly different structure in step 3.

   The problem solution arising from the BARD process is either (i) the amalgamated consensus Group version produced by the facilitator, or (ii) the highest rated individual BN or Report; BARD supports both options.

\footnote{It is difficult to remove all chances of side conversations while enabling public discussion, because analysts could, for example, post their private email addresses onto the forum and set up a conversation outside of BARD.}
3.4. The BARD platform

BARD is a client-server application comprised of a group of cloud-based servers that provide services and resources to connected clients (Figure 6). The main BARD server provides the BARD login, collaboration, problem solving and report generation services, and connects: (1) a Database server, which provides SQL database services; (2) a Bayesian Network server, which provides the back-end reasoning via commercial BN software; (3) an Automated Explanation server running the AET (see Step 5 above), which also utilises the BN server; and (4) a Storage server, which stores items such as images uploaded into discussion forums or the report.

![Figure 6: BARD application architecture.](image)

The BARD platform has an administrator console, which allows the BARD administrator to configure the application process flow, enable/disable certain features (e.g., the version of Delphi), and schedule tasks. The admin console also allows the BARD administrator to manage users, problems and groups, including to: set up problems, optionally with start and end times; create user accounts; create groups to work on a specified problem; allocate users to groups together with (optional) pseudonyms; allocate roles to group members; and download the report from completed problems.

The BARD platform supports an additional role, an Observer, who is assigned to a group and can only observe all stages of the BARD process (in “read-only” mode), without being able to contribute to it (apart from messaging the facilitator). They are able to see all public contributions from their group members and facilitator and all steps at any time. This was originally introduced for the CREATE program, to support ‘reserve’ participants ready to step in as replacements when other participants dropped out of a group during the problem-solving process; but the Observer role has also proved useful for researchers during experiments, and for analysts and facilitators to keep Observer access for all aspects of a given problem once it “closes”.

While BARD has been developed as a collaborative BN tool to improve analytical reasoning, stripping out the collaboration features of BARD still leaves a sophisticated analytical tool for solving problems by an individual: we call this version SoloBARD. It allows an analyst to move through the six steps of BARD without consultation or guidance from anyone else.

3.5. BARD Training

The BARD Platform comes with approximately 4 hours of training, covering all key elements of the BARD approach: (1) causal Bayesian network technology; (2) the BARD workflow including the six steps of BARD and the group interactions; (3) the BARD software tool, from the perspective of both analysts and the facilitator; and (4) writing structured analytical reports, using the BARD templates.

---

16 BARD currently runs with both Netica and AgenaRisk BN servers; we anticipate extending to other widely used BN software.

17 Currently Amazon Simple Storage Service (S3)
This training consists of individual interactive eCourses, produced using the StoryLine 360 tool and hosted on a commercial cloud-based Learning Management System (LMS), called Moodle. The eCourses are all relatively short, from 2–15 minutes, which suits self-paced learning. The LMS allows the BARD training material to be re-packaged into different courses for different purposes, and the training can be partitioned. For example, one of the BARD experiments (see below) presented the training courses to its participants in the following partitions: “required” (approx 1 hr 30 min), “recommended” (approx 1 hr 15 min) and “optional” (approx 1 hr 15 min).

In addition, the LMS is integrated with the BARD software, so that users can visit the LMS at any time from the BARD landing page, and training activity and completion data can be exchanged with BARD, which can then be used for BARD group creation and role allocation.

These LMS-hosted eCourses are further augmented by online help material, which provides assistance and guidance for users within the BARD tool in real time as they work through the BARD process. These embedded help components include: training problems that allow users to work through elements in the BARD approach as an individual analyst, with pre-populated “ideal” solutions available as the group solution; an optional product tour associated with each BARD page, offered on first use and with the ability to revisit; a general Help facility that includes PDF and audio-visual versions of the eCourse material; context-specific help as tooltips, page-based tips, and pop-up help tips; and “What do I do next?” guidance.

4. Evaluation

Here we summarise two experimental studies to test the effectiveness of the BARD approach to problem solving, and their findings; each is reported in detail elsewhere.

SoloBARD Experiment (Cruz et al., 2019). This experiment addressed whether the BARD system improves individual reasoning on three apparently simple probabilistic reasoning problems that each incorporated a tempting qualitative fallacy and also assessed the quantitative accuracy of the answers. These fallacies are discussed in detail in Pilditch et al. (2018); Liefgreen et al. (2018); Pilditch et al. (2019). Individuals in the experimental group (N=29) used the SoloBARD system, which provides the six Steps of BARD without any of the social processes, for constructing BNs to use in reasoning about and solving the problems. The normative solutions could be achieved via BNs with just seven binary variables. The control group (N=30) received generic training based on the CREATE ‘Guide to Good Reasoning’ slides and produced their report using MS Office tools. External raters were recruited to blindly assess the final reports from both groups against problem-specific marking rubrics. Reasoning was assessed on two measures: (1) total rubric score on both qualitative and quantitative questions; (2) score on only the quantitative questions (a subset of the total). On both measures, the group using SoloBARD performed substantially above controls (see Cruz et al. (2019) for details). These results demonstrate that BARD, even when used privately by individual analysts, assists them in producing better reasoned reports for suitable problems.

Groups using BARD End-to-End (Korb et al., 2019). This experiment addressed whether, given similar probabilistic reasoning problems to the previous experiment, groups using BARD submit better reports than individuals using the best available pen-and-paper tools for probabilistic reasoning. The experimental condition consisted of groups of up to eight analysts and a facilitator, using the BARD workflow. The control group consisted of individuals using Google’s online G Suite tools, frequency formats and chain event graphs (see Gigerenzer & Hoffrage, 1995). Using individuals as the control is an acknowledged limitation of the study as it introduces an additional variable that cannot be distinguished from the tools used, i.e., group size. However, this was done to match the similar experiment being performed simultaneously by IARPA, and we were unable to add a third condition of groups using G-Suite due to cost constraints and the difficulty of recruiting and retaining enough participants. External raters were again recruited to assess the final reports from both groups against the
problem-specific marking rubrics. Participants analysed three problems: Problem A in week 1, Problem B in weeks 2 and 3, and Problem C in weeks 4 and 5. The latter two were divided into two stages, partly due to their complexity, but also allowing us to investigate the value of BARD in coping with dynamic problems, where evidence and information are updated and require an analysis to be revised. 198 participants started in the experimental group, with 145 participating in all 5 weeks, while the control group started with 44 and finished with 23 participants. The experimental condition outperformed the control by a significant margin on all problems (see Korb et al. (2019) for details). This provides evidence that BARD groups can also beat individuals in producing better reasoned reports for suitable probabilistic problems, even when the individuals are using the best available pen-and-paper tools.

In addition, participants from the experimental condition were surveyed at the end of the experiment to capture feedback on BARD usability, using the System Usability Scale (Brooke et al., 1996) to give subjective usability ratings, and an open-ended questionnaire. Both the ratings and open-ended comments showed overall positive user satisfaction with the BARD software, although we note that the results were undoubtedly skewed in the positive direction because participants who dropped out of the experiment didn’t complete the survey.

5. Conclusions and Future Work

We have presented a novel structured technique for collaborative reasoning and problem-solving that combines a logical procedure for building causal BNs with a Delphi-style social process. BARD is the first Bayesian network software tool to (1) break down BN construction and reasoning into specific steps that guide relatively novice users through the process, together with minimal upfront training and embedded help, (2) support groups to collaboratively build a consensus BN, partly by implementing the entire process in an online platform, and (3) use the BN to produce a consensus written analytic report, assisted by a reasoning template and automatically generated key points. Initial experimental results, summarised in Section 4, are promising for both the usability and effectiveness of the BARD tool for assisting problem solving and reasoning, by both individuals and groups. The written analytical reports using BARD (29 using BARD individually in one experiment, 145 using BARD in groups in another) were significantly better, assessed against problem-specific marking rubrics, than the controls.

While the version of the BARD tool presented here supports elicitation of all key elements of a BN, it lacks additional features that are available in other BN software packages, such as modelling with continuous variables, learning either the structure or parameters (CPTs) from data, allowing the CPTs to be specified by equations, supporting decision-making more explicitly with decision and utility nodes, and sensitivity analysis. We plan to enhance BARD with these features incrementally, utilising the functionality of the existing BN software used in BARD’s back-end, subject to resource availability. We are also implementing functionality to import and export BNs in the formats used by other BN packages. Beyond industry-standard BN features, we plan to provide more support for BN idioms, such as those already designed for legal arguments. There is also a body of work on the statistical amalgamation of BNs (e.g., Flores et al. (2011)), and group elicitation of parameters (e.g., Hanea et al. (2018)); we plan to incorporate some of these methods into BARD for use by the Facilitator, to further support collaboration.

The BARD platform provides a rich tool for research on how individuals and groups build and reason with BNs. BARD’s configurable constraint-based structure layout will allow us to investigate whether particular enforced BN structure layouts improve understanding of a model and its reasoning, and aid comparisons between alternative BNs. We also intend to improve and test the efficacy of the various elements produced by our cutting-edge Automatic Explanation Tool, and improve their presentation by making individual elements available on demand and combining verbal with visual aids.

\footnote{Netica and AgenaRisk, at time of writing.}
As we discussed, BARD trades off the rigour of traditional Delphi for the flexibility and user-friendliness of a ‘real-time’ version. Piloting suggested that for our participants and tasks the trade-off is worthwhile. We also have some experimental evidence that even a minimal Delphi-style interaction improves the network structures produced by BARD groups (Bolger et al., 2019). Nevertheless, we do not yet have any direct experimental comparison for BARD groups between traditional Delphi, real-time Delphi, and free interaction. So, further research comparing social protocols is needed to optimise overall system performance. This investigation will be facilitated by the configurability of BARD user access, with three different versions of Delphi processes already available. Further possible research on collaboration includes investigating the best group size and the factors that may influence it (e.g., Belton et al. (2019)); how a group may be split across different tasks; and how outputs from multiple groups working in parallel might be considered within a meta-level BARD group.

Acknowledgement

Funding for the BARD project was provided by IARPA through their CREATE project, under contract number 2017-1612200003.

References

Bayraktar, M. E., & Hastak, M. (2009). Bayesian belief network model for decision making in highway maintenance: Case studies. *Journal of construction engineering and management, 135*, 1357–1369.

Belton, I., Bolger, F., Sissons, A., Rowe, G., Hamlin, I., Crawford, M., Taylor-Browne LÅka, C., Vasilichi, A., & Wright, G. (2019). Does size matter? the effect of group size and opinion diversity on performance within delphi groups. In preparation. Draft at https://tinyurl.com/bard-publications.

Blalock Jr, H. M. (2018). *Causal inferences in nonexperimental research.* UNC Press Books.

Boehm, B. W. (1988). A spiral model of software development and enhancement. *Computer, 5*, 61–72.

Boerlage, B. (1983). *Link Strength in Bayesian Networks.* Master’s thesis University of British Columbia Vancouver, BC, Canada, Canada.

Bolger, F., Nyberg, E., Belton, I., Thakur, S., Crawford, M., Oshini Alvandi, A., Hamlin, I., J., R., Sissons, A., Pearson, R., LÅka, C., Vasilichi, A., Nicholson, A., & Wright, G. (2019). Improving the production and evaluation of structural models using a Delphi process. Under review, Decision Support Systems. Draft at https://tinyurl.com/bard-publications.

Boneh, T. (2010). *Ontology and Bayesian decision networks for supporting the meteorological forecasting process.* Ph.D. thesis Monash University.

Bramley, N. R., Dayan, P., Griffiths, T. L., & Lagnado, D. A. (2017). Formalizing neurath’s ship: Approximate algorithms for online causal learning. *Psychological review, 124*, 301–338. doi:10.1037/rev0000061.

Brooke, J. et al. (1996). Sus-a quick and dirty usability scale. *Usability evaluation in industry, 189*, 4–7.

Charness, G., & Sutter, M. (2012). Groups make better self-interested decisions. *Journal of Economic Perspectives, 26*, 157–76.
Chee, Y. E., Wilkinson, L., Nicholson, A. E., Quintana-Ascencio, P. F., Fauth, J. E., Hall, D., Ponzio, K. J., & Rumpff, L. (2016). Modelling spatial and temporal changes with GIS and spatial and dynamic Bayesian networks. *Environmental Modelling & Software, 82*, 108–120. doi:10.1016/j.envsoft.2016.04.012

Choi, K.-H., Joo, S., Cho, S. I., & Park, J.-H. (2007). Locating intersections for autonomous vehicles: A Bayesian network approach. *ETRI journal, 29*, 249–251.

Chris, E. (1987). Explanation of probabilistic inference for decision support systems. In *Proceedings of the AAAI-87 Workshop on Uncertainty in Artificial Intelligence* (pp. 394–403). Seattle, Washington.

Clapper, J. (2015). *Intelligence Community Directive (ICD) 203, Analytic Standards*. United States Office of the Director of National Intelligence. URL: https://www.dni.gov/files/documents/ICD/ICD%20203%20Analytic%20Standards.pdf

Cruz, N., Desai, S. C., Dewitt, S., Hahn, U., Lagnado, D., Liefgreen, A., Phillips, K., Pilditch, T., & Tesic, M. (2019). Widening access to Bayesian problem solving. In preparation. Draft at https://osf.io/28w9e/?view_only=ae302eba64547d4bab9ae66b774191a

Dwyer, T., Marriott, K., & Wybrow, M. (2009). Topology preserving constrained graph layout. In I. G. Tollis, & M. Patrignani (Eds.), *Graph Drawing* (pp. 230–241). Berlin, Heidelberg: Springer Berlin Heidelberg.

Etminani, K., Naghibzadeh, M., & Peña, J. M. (2013). DemocraticOP: A Democratic way of aggregating Bayesian network parameters. *International Journal of Approximate Reasoning, 54*, 602–614.

Fenton, N., & Neil, M. (2000). The “Jury Fallacy” and the use of Bayesian networks to present probabilistic legal arguments.

Fenton, N., & Neil, M. (2014). Decision support software for probabilistic risk assessment using Bayesian networks. *Ieee Software, 31*, 21–26. doi:10.1109/Ms.2014.32

Fenton, N., Neil, M., & Lagnado, D. A. (2013). A general structure for legal arguments about evidence using Bayesian networks. *Cognitive science, 37*, 61–102.

Flores, M., Nicholson, A., Brunskill, A., Korb, K., & Mascaro, S. (2011). Incorporating expert knowledge when learning Bayesian network structure: A medical case study. *Artificial Intelligence in Medicine, 53*, 181–204.

van der Gaag, L. C., Renooij, S., Schijf, H. J., Elbers, A. R., & Loeffen, W. L. (2012). Experiences with eliciting probabilities from multiple experts. In *International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems* (pp. 151–160). Springer.

van der Gaag, L. C., Renooij, S., Witteman, C. L. M., Aleman, B. M. P., & Taal, B. G. (1999). How to elicit many probabilities. In *Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence UAI’99* (pp. 647–654). San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.

Gigerenzer, G., & Hoffrage, U. (1995). How to improve Bayesian reasoning without instruction: frequency formats. *Psychological review, 102*, 684.

Gopnik, A., Sobel, D. M., Schulz, L. E., & Glymour, C. (2001). Causal learning mechanisms in very young children: Two-, three-, and four-year-olds infer causal relations from patterns of variation and covariation. *Developmental psychology, 37*, 620.

Gordon, T., & Pease, A. (2006). Rt delphi: An efficient, “round-less” almost real time delphi method. *Technological Forecasting and Social Change, 73*, 321–333.
Hahn, U. (2014). The Bayesian boom: good thing or bad? *Frontiers in psychology*, 5, 765.

Hahn, U., & Harris, A. J. (2014). What does it mean to be biased: Motivated reasoning and rationality. In B. H. Ross (Ed.), *Psychology of Learning and Motivation* chapter 2. (pp. 41–102). Academic Press volume 61. doi:[10.1016/B978-0-12-800283-4.00002-2](https://doi.org/10.1016/B978-0-12-800283-4.00002-2).

Hahn, U., & Oaksford, M. (2006). A Bayesian approach to informal argument fallacies. *Synthese*, 152, 207–236.

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

Healy, P. J., & Moore, D. A. (2007). Bayesian overconfidence. *Available at SSRN 1001820*.

Hemming, V., Burgman, M., Hanea, A., McBride, M., & Wintle, B. (2018a). A practical guide to structured expert elicitation using the idea protocol. *Methods in Ecology and Evolution*, 9, 169–180.

Hemming, V., Walshe, T., Hanea, A., Fidler, F., & Burgman, M. (2018b). Eliciting improved quantitative judgements using the idea protocol: A case study in natural resource management. *PLoS One*, 13, e0198468.

Jarvstad, A., & Hahn, U. (2011). Source reliability and the conjunction fallacy. *Cognitive Science*, 35, 682–711.

Jitnah, N., Zukerman, I., McConachy, R., & George, S. (2000). Towards the generation of rebuttals in a Bayesian argumentation system. In *Proceedings of the first international conference on Natural language generation-Volume 14* (pp. 39–46). Association for Computational Linguistics.

Kahneman, D., Slovic, P., & Tversky, A. (1982). *Judgment Under Uncertainty: Heuristics and Biases*. Cambridge University Press.

Keppens, J. (2011). On extracting arguments from Bayesian network representations of evidential reasoning. In *Proceedings of the 13th International Conference on Artificial Intelligence and Law ICAIL ’11* (pp. 141–150). New York, NY, USA: ACM.

Korb, K., McConachy, R., & Zukerman, I. (1997). A cognitive model of argumentation. In *Proceedings of the 19th Annual Conference of the Cognitive Science Society* (pp. 400–405).

Korb, K. B. (2004). Bayesian informal logic and fallacy. *Informal Logic*, 24, 41–70.

Korb, K. B., Alvandi, A. O., Thakur, S., Nyberg, E. P., Ozmen, M., Li, Y., Pearson, R., & Nicholson, A. E. (2019). A collaborative system for Bayesian reasoning: an experimental study. Under review, Frontiers in Psychology. Draft at [https://tinyurl.com/bard-publications](https://tinyurl.com/bard-publications).

Korb, K. B., Geard, N., & Dorin, A. (2013). A Bayesian approach to the validation of agent-based models. In *Ontology, Epistemology, and Teleology for Modeling and Simulation* (pp. 255–269). Springer.

Korb, K. B., & Nicholson, A. E. (2011). *Bayesian Artificial Intelligence*. Chapman & Hall/CRC Computer Science & Data Analysis, 2nd ed. Boca Raton, FL: CRC Press.

Korb, K. B., & Nyberg, E. P. (2016). Analysing arguments using causal Bayesian networks. *url: https://bayesianwatch.wordpress.com/2016/03/30/aaucbn/Accessed 11 Aug 2018*, .

Korb, K. B., Nyberg, E. P., & Hope, L. (2011). A new causal power theory. In P. M. Illari, F. Russo, & J. Williamson (Eds.), *Causality in the Sciences* (pp. 628–652). Oxford University Press.
Kugler, T., Kausel, E. E., & Kocher, M. G. (2012). Are groups more rational than individuals? A review of interactive decision making in groups. *Wiley Interdisciplinary Reviews: Cognitive Science, 3*, 471–482.

Kushnir, T., Gopnik, A., Lucas, C., & Schulz, L. (2010). Inferring hidden causal structure. *Cognitive science, 34*, 148–160.

Lagnado, D. A., Fenton, N., & Neil, M. (2013). Legal idioms: a framework for evidential reasoning. *Argument & Computation, 4*, 46–63.

Lagnado, D. A., & Gerstenberg, T. (2017). Causation in legal and moral reasoning. *Oxford handbook of causal reasoning*, (pp. 565–602).

Lagnado, D. A., & Sloman, S. (2004). The advantage of timely intervention. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 30*, 856.

Lagnado, D. A., & Sloman, S. A. (2006). Time as a guide to cause. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 32*, 451.

Laskey, K. B., & Mahoney, S. M. (1997). Network fragments: Representing knowledge for constructing probabilistic models. In *Proceedings of the Thirteenth conference on Uncertainty in artificial intelligence* (pp. 334–341). Morgan Kaufmann Publishers Inc.

Laskey, K. B., & Mahoney, S. M. (2000). Network engineering for agile belief network models. *IEEE Transactions on knowledge and data engineering, 12*, 487–498.

Lichtenstein, S., Fischhoff, B., & Phillips, L. (1982). Calibrations of probabilities: The state of the art to 1980. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under uncertainty: Heuristics and biases* (pp. 306–334). Cambridge University Press.

Liefgreen, A., TeÅi, M., & Lagnado, D. (2018). Explaining away: significance of priors, diagnostic reasoning, and structural complexity. In T. Roger, M. Rau, X. Zhu, & W. Kalish (Eds.), *Proceedings of the 40th Annual Conference of the Cognitive Science Society* (pp. 2044–2049). Austin, TX: Cognitive Science Society.

Linstone, H., & Turoff, M. (1975). *The Delphi Method: Techniques and Applications*. London: Addison-Wesley.

Malcolm, D. G., Roseboom, C. E., Clark, C. E., & Fazar, W. (1959). Application of a technique for research and development program evaluation. *Operations Research, 7*, 646–649.

Mascaro, S., Nicholson, A. E., & Korb, K. B. (2014). Anomaly detection in vessel tracks using Bayesian networks. *International Journal of Approximate Reasoning, 55*, 84–98. doi:10.1016/j.ijar.2013.03.012. Applications of Bayesian Networks.

Misirli, A. T., & Bener, A. B. (2014). Bayesian networks for evidence-based decision-making in software engineering. *IEEE Transactions on Software Engineering, 40*, 533–554.

Mumford, M. D., Blair, C., Dailey, L., Leritz, L. E., & Osburn, H. K. (2006). Errors in creative thought? Cognitive biases in a complex processing activity. *The Journal of Creative Behavior, 40*, 75–109.

Newell, B. R., Lagnado, D. A., & Shanks, D. R. (2015). *Straight choices: the psychology of judgment and decision*. (2nd ed.). Psychology Press.
Nicholson, A., Woodberry, O., Mascaro, S., Korb, K., Moorrees, A., & Lucas, A. (2011). ABC-BN: A tool for building, maintaining and using Bayesian networks in an environmental management application. In *Proceedings of the 8th Bayesian Modelling Applications Workshop* (pp. 331–335). Volume 818.

Nicholson, A. E., Mascaro, S., Thakur, S., Korb, K. B., & Ashman, R. (2016). Delphi Elicitation for Strategic Risk Assessment. Technical Report TR-2016 Bayesian Intelligence Pty Ltd.Https://bayesian-intelligence.com/publications/TR2016_1_Delphi_Elicitation.pdf.

Novak, J. (2010). *Learning, creating, and using knowledge: Concept maps as facilitative tools in schools and corporations.* (2nd ed.). Routledge.

O’Donnell, R. T., Allison, L., & Korb, K. B. (2006). Learning hybrid Bayesian networks by MML. In S. A., & K. B. (Eds.), *AI2006: Advances in Artificial Intelligence* (pp. 192–203). Springer, Berlin, Heidelberg.

Packer, D. J. (2009). Avoiding groupthink: Whereas weakly identified members remain silent, strongly identified members dissent about collective problems. *Psychological Science, 20*, 546–548.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: networks of plausible inference*. Morgan Kaufmann, San Mateo, California.

Pearl, J., & Mackenzie, D. (2018). *The book of why: the new science of cause and effect*. Basic Books.

Pilditch, T., Hahn, U., & Lagnado, D. (2018). Integrating dependent evidence: nave reasoning in the face of complexity. In T. Roger, M. Rau, X. Zhu, & W. Kalish (Eds.), *Proceedings of the 40th Annual Conference of the Cognitive Science Society* (pp. 884–889). Austin, TX: Cognitive Science Society. URL: osf.io/kxf98

Pilditch, T. D., Fenton, N., & Lagnado, D. (2019). The zero-sum fallacy in evidence evaluation. *Psychological science, 30*, 250–260. doi:10.1177/0956797618818484

Pitchforth, J., & Mengersen, K. (2013). A proposed validation framework for expert elicited bayesian networks. *Expert Systems with Applications, 40*, 162 – 167. URL: http://www.sciencedirect.com/science/article/pii/S0957417412008810 doi:https://doi.org/10.1016/j.eswa.2012.07.026.

Pollino, C., Woodberry, O., Nicholson, A. E., Korb, K. B., & Hart, B. T. (2007). Parameterisation of a Bayesian network for use in an ecological risk management case study. *Environmental Modelling and Software, 22*, 1140–1152.

Rowe, G., & Wright, G. (1999). The delphi technique as a forecasting tool: issues and analysis. *International journal of forecasting, 15*, 353–375.

Rowe, G., Wright, G., & Bolger, F. (1991). Delphi: a reevaluation of research and theory. *Technological forecasting and social change, 39*, 235–251.

Salerno, J. M., Bottoms, B. L., & Peter-Hagene, L. C. (2017). Individual versus group decision making: Jurors reliance on central and peripheral information to evaluate expert testimony. *PloS one, 12*, e0183580.

Sember, P., & Zukerman, I. (1989). Strategies for generating micro explanations for Bayesian belief networks. In *Proceedings of the Fifth Workshop on Uncertainty and Artificial Intelligence* (pp. 295–302). Windsor, Ontario.
Serwylo, P. (2015). *Intelligently Generating Possible Scenarios for Emergency Management during Mass Gatherings*. Ph.D. thesis Monash University.

Sesen, M. B., Nicholson, A. E., Banares-Alcantara, R., Kadir, T., & Brady, M. (2013). Bayesian networks for clinical decision support in lung cancer care. *PloS one, 8*, e82349. doi:10.1371/journal.pone.0082349

Simon, H. (1954). Spurious correlation: A causal interpretation. *Journal of the American Statistical Association, 49*, 467–479.

Sloman, S. A., & Lagnado, D. (2015). Causality in thought. *Annual Review of Psychology, 66*, 223–247.

Soll, J., & Klayman, J. (2004). Overconfidence in interval estimates. *Journal of Experimental Psychology Learning Memory and Cognition, 30*, 299–314.

Speirs-Bridge, A., Fidler, F., McBride, M., Flander, L., Cumming, G., & Burgman, M. (2010). Reducing overconfidence in the interval judgments of experts. *Risk Analysis, 30*, 512–523.

Spirtes, P., Glymour, C. N., Scheines, R., Heckerman, D., Meek, C., Cooper, G., & Richardson, T. (2000). *Causation, prediction, and search*. MIT press.

Stacey, K., Sonenberg, E., Nicholson, A., Boneh, T., & Steinle, V. (2003). A teaching model exploiting cognitive conflict driven by a Bayesian network. In P. Brusilovsky, A. Corbett, & F. de Rosis (Eds.), *User Modeling 2003* (pp. 352–362). Berlin, Heidelberg: Springer Berlin Heidelberg.

Stettinger, M., Felfernig, A., Leitner, G., & Reiterer, S. (2015). Counteracting anchoring effects in group decision making. In *International Conference on User Modeling, Adaptation, and Personalization* (pp. 118–130). Springer.

Straus, S. G., Parker, A. M., & Bruce, J. B. (2011). The group matters: A review of processes and outcomes in intelligence analysis. *Group Dynamics: Theory, Research, and Practice, 15*, 128.

Suermontd, H. J. (1992). *Explanation in Bayesian Belief Networks*. Ph.D. thesis Stanford University Palo Alto, California.

Tversky, A., & Kahneman, D. (1982). Evidential impact of base rates. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment Under Uncertainty: Heuristics and Biases* (pp. 153–160). Cambridge University Press.

Villejoubert, G., & Mandel, D. R. (2002). The inverse fallacy: An account of deviations from Bayes’s theorem and the additivity principle. *Memory & Cognition, 30*, 171–178. doi:10.3758/BF03195278

Vreeswijk, G. A. W. (2005). Argumentation in Bayesian belief networks. In I. Rahwan, P. Moraïtis, & C. Reed (Eds.), *Argumentation in Multi-Agent Systems* (pp. 111–129). Berlin, Heidelberg: Springer Berlin Heidelberg.

Welsh, M. B., & Navarro, D. J. (2012). Seeing is believing: Priors, trust, and base rate neglect. *Organizational Behavior and Human Decision Processes, 119*, 1–14.

Wright, S. (1934). The method of path coefficients. *The annals of mathematical statistics, 5*, 161–215.

Zukerman, I., Herrmann, M., Azad, M., Nyberg, E. P., Mascaro, S., & Nicholson, A. E. (2019). *Automated explanation of Bayesian network reasoning to support structured analysis*. Technical Report TR-2019-1 Bayesian Intelligence Pty Ltd. https://bayesian-intelligence.com/publications/TR2019_1_Automated_Explanation.pdf.
Zukerman, I., McConachy, R., & Korb, K. B. (1998). Bayesian reasoning in an abductive mechanism for argument generation and analysis. In *AAAI98 – Proceedings of the 15th National Conference on Artificial Intelligence* (pp. 833–838). Madison, Wisconsin.

Zukerman, I., McConachy, R., Korb, K. B., & Pickett, D. (1999). Exploratory interaction with a Bayesian argumentation system. In *IJCAI-99 – Proceedings of the 16th International Joint Conference on Artificial Intelligence* (pp. 1294–1299). Stockholm, Sweden.