Good afternoon. Thank you for inviting me here to discuss my work on developing BENDi. The focus of this work has been to develop a Bayesian Decision Support tool to aid in the management of Low Back Pain. Low back pain is one of the leading causes of disability worldwide, with an estimated 540M people living with back pain (which is increasing), and an annual cost to the UK economy of £10Bn (which is increasing) and years lived with disability is estimated to be over 1,000 per 100,000.
Pathways are complicated and a sub-optimal decision in primary care can lead to significant delays to a patient receiving care, during which time persistent pain and disability can develop. Our project aims to develop a tool which predicts which action a clinician should take to get the best outcome for an individual patient.
We proposed a structure to the clinical reasoning process, which is represented in this conceptual model. This forms the basis for the elicitation and an outline structure the Bayesian network. From this diagram, there are three main aspects that will need to be elicited: the variables in each of these categories, the relationships between them (i.e. the arrows in the diagram) and then the probabilities to populate the working model.
As such we divided the process into these four stages. The first two consisted of an individual elicitation, followed by a consensus meeting, following a modified RAND appropriateness procedure. The probability stage was conducted at an individual level only, to reduce the elicitation burden on the participants. The final stage is where we are at the moment, using some real life cases and literature based case studies to test and validate the model outputs.

We recruited 14 clinical participants from rheumatology, orthopaedics, general practice and advanced physiotherapy practitioners. They all participated in the individual elicitations remotely, and a subset of 8 convened for the consensus workshops.

I will discuss each stage in more detail, with a description of our method.
This was our online elicitation tool for stage 1. The grey box would contain available variables (used interchangeably here with “factors” in order to make the language clearer for clinical participants). This was pre-populated with 36 factors. The available factors could be dragged and dropped into the categories. The participants had the ability to add as many variables as they wished. The online elicitation resulted in 76 new suggested variables, some of which were duplications.

Variables that were consistently placed in the same category (>9 participants placed) were deemed to have reached consensus. Variables that had not reached consensus were taken forward to the workshop to be discussed by the participants. The elicitation interface was reset and the workshop participants were able to ‘vote’ again on where the variable should be placed using the interface. They were also asked to rank the variables at this stage in order to facilitate a downselection of variables for the further stages.
After deciding on the key variables to be included in the conceptual model, we next needed to elicit the structure of the model. Again we used an online individual elicitation, followed by a face to face consensus meeting.
The relationships between the variables were evaluated using a scale from 0 to 3. 0 was deemed to be “Variable x has no effect on variable y” and 3 was “Variable x always has a strong effect on variable y”. The participants were given a series of grids to populate on the online interface. Any areas of disagreement were taken forwards to the workshop for consensus building.
After these two stages, what we ended up with was a complex network.

We used a threshold score to determine the number of relationships (arrows) kept in the BN. The score was the median score following the stage 2 elicitation. The slider allowed the user to change the threshold and create a new BN. In the diagram above you can see that a threshold of 1 kept nearly all of the relationships intact across the network.
If we move the threshold up to 2.5, then we only keep the relationships that had a strong effect on another variable. A much simpler network, but a great deal of detail and nuance has been lost.

We used clinical judgement to determine a threshold which was complex enough to be clinically acceptable, minimised the elicitation burden for the subsequent stage and was simple enough to be coded and executed in a reasonable timeframe.
The final elicitation stage was to populate the conceptual model with probabilities.

The variables in the BN variables can either be binary, e.g. [True, False], labelled i.e. nominal with states without any order, e.g. [muscle, tissue, tendon], or ranked i.e. ordinal with states with increasing or decreasing order, e.g. [High, Medium, Low]. The type of each variable had to be defined for the third elicitation, as this affected the type of question asked.
Part 2

Of those who have presented with lower back pain you see 1000 patients who have cauda equina syndrome.

What percentage will have either no bladder disturbance, a reduced flow or are unable to pass urine?

Reminder: When the total is close to 100% you can click on the percentages on the right to snap that slider so the total becomes 100%

100.0%

- No issues: 93.0%
- Reduced flow: 5.1%
- Unable to pass urine: 1.9%
Of those who have presented with lower back pain you see 1000 patients who have the following risk factor attributes:

- Does the patient have an external or an internal locus of control? - **Internal**

What percentage will have a depression level of either low, medium or high?

![Bar chart showing depression levels](image)

- **Most likely value**: 
  - Low: 
  - Medium: 60% 
  - High: 30%

- **Degree of variation**: 1.00, 0.50
Pathways are complicated and a sub-optimal decision in primary care can lead to significant delays to a patient receiving care, during which time persistent pain and disability can develop. Our project aims to develop a tool which predicts which action a clinician should take to get the best outcome for an individual patient.
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