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BayEsian Network DecIsion support for managing low back pain: Proposal and method testing (BENDI)

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Abstract

Digital solutions for NHS services are a priority for research and delivery and have the potential to transform pathways and quality of care through enhanced decision making. A decision support tool for Low Back Pain (LBP) developed with a Delphi approach has been implemented with some success in the past; this used regression analysis to establish predictors of outcome. The complexity and uncertainty in treating LBP may be better suited to a Bayesian approach to prediction of outcome. This project proposes and tests a method for developing a Bayesian Network to improve clinical decision making in low back pain.

Introduction

Digital solutions for NHS services are a priority for research and delivery (1) and have the potential to transform pathways and quality of care (2). Synthesising evidence into practice has always been challenging. This is never more apparent than in Musculoskeletal (MSK) services that have significant time and waiting list pressures. Developing a tool that will allow the clinician to assess and diagnose a patient with increased accuracy, direct the patient to the most appropriate treatment pathway from the outset and predict the likelihood of a favourable outcome using the best available evidence will streamline the patient experience of MSK medicine. This project proposes and tests a method for eliciting a model that will be able to address these issues.

Methods

A decision support tool for LBP developed with a Delphi approach has been implemented with some success in the Netherlands (3) but they have identified that results could be improved with Bayesian or machine learning techniques (4). Availability of large datasets with relatively low rate of errors and knowledge of outcomes is usually needed to develop machine learning tools in the majority of approaches used in industry. MSK medicine does not have the luxury of such data. As such, a combination of evidence, patient data and expert opinion will need to be combined to replicate the reasoning process in MSK services. Bayesian modelling is ideally suited to dealing with this approach. In MSK medicine, there is a wealth of rich data available and a lack of certainty around patient outcomes, which lends itself well to the Bayesian method, and is the approach recommended in a previous study (4).

We propose a five stage process for development of a Bayesian model for MSK conditions (Figure 1). Initial literature searches and recruitments is followed by an online elicitation of variables. A Delphi process is used to rank the variables in a face-to-face workshop, and variable consensus reached. In stage two, relationships between those variables are elicited from the expert panel, using a Delphi consensus method. Stages 1 and 2 allow the conceptual Bayesian model to be constructed. Probabilities are populated in the model with one further online elicitation, using visual aids such as sliders and probability distributions. The final stage is an overall evaluation of the model.

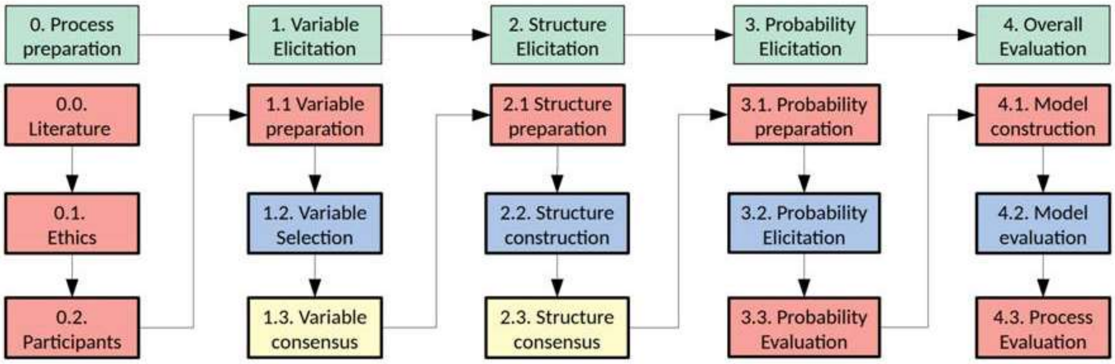

Figure 1. BENDi process flow diagram

Measures are summarized in Table 1. The final stage is model validation. Two scenarios are fed to the BN and predictions compared with answers from the expert panel.

Stage		Measure	Disagreement
Online 1	Categories	Mode	
	Ranking	Median	
Face to face 1	Categories	Mode	IPR 0.7
	Ranking	Median	IPR 0.7
Online 2	Strength of relationship	Median	
Face to face 2	Strength of relationship	Median	IPR 0.7
Online 3	Probabilities	Median	

Table 1: Summary of measures in modified Delphi procedure

Conclusion

This method provides a staged development of a Bayesian Network using expert clinician knowledge, establishing consensus amongst users about the content of the model as well as probability population to enable scenario testing.

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