and healthcare workers. Lack of training in health economics was cited as the major challenge to supply of HTA evidence.
**Conclusions.** There is a need to institute a formal, systematic and transparent processes of determining value of health technologies.

**Conclusions.** Early cost-effectiveness models are a valuable tool to inform further product development and evidence requirements, but characterization of uncertainty and transparency in modelling assumptions are key.

# OP29 Lifecycle Assessment Of Machine Learning-Derived Early Warning System. An Early Economic Evaluation Of An Intraoperative Hypotension Prediction Index

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**Introduction.** An iterative, life-cycle approach to the evaluation of healthcare technologies requires that clinical and economic evidence is collected since the initial stages of diffusion. Nevertheless, early cost-effectiveness models are challenging mainly due to the difficulties in estimating model parameters and faithfully characterizing parameter uncertainty. This is especially true with AI-based diagnostics, where attribution of effects on costs and patient-relevant outcomes is more challenging. Empirical applications of early-models are useful to identify the main challenges of iterative modelling and provide recommendations on best-practices. Here, we reported on a case study on a machine learning-derived hypotension predictive index (HPI), that predicts the onset of intraoperative hypotension and trigger corrective measures.
**Methods.** A hybrid decision-tree/Markov model was developed comparing an HPI-based intervention protocol to standard-of-care intervention protocol during gynecological procedures. A short-term component of the model was populated using data from individual patients collected at one hospital in Italy. An historical control group was also defined using propensity score matching. Long-term costs and consequences of HPI were modelled using secondary data. A probabilistic version of the headroom approach was used to determine the maximum achievable price of HPI based on available evidence. Value of Information analysis was also conducted to identify the parameters that contribute the most to the overall uncertainty, and to identify optimal future study designs. Extensive deterministic and probabilistic sensitivity analyses were conducted to characterize the uncertainty over the cost-effectiveness of HPI.
**Results.** The preliminary results of the analysis suggest that HPI has potential to improve patients' outcomes and generate efficiency gains by reducing hypotension events and permanent complications, such as acute kidney injury. The link between reduction in hypotension and the rate of complications, or the long-term effects on healthcare costs and patients' quality of life are the parameters that contribute the most to model uncertainty.

# OP30 Model for ASsessing The Value Of AI In Medical Imaging (MAS-AI)

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**Introduction.** Artificial intelligence (AI) is seen as one of the major disrupting forces in the future healthcare system. However, assessment of the value of these new technologies is still unclear and no agreed international HTA-based guideline exists. Therefore, a Model for ASsessing the value of AI (MAS-AI) in medical imaging was developed by a multidisciplinary group of experts and patient representatives.
**Methods.** The MAS-AI guideline is based on four steps. First a literature review of existing guides, evaluations, and assessments of the value of AI in the field of medical imaging (5,890 studies were assessed with 86 studies included in the scoping review). Next, interviews with leading researchers in AI in Denmark. The third step was two workshops where decision-makers, patient organizations and researchers discussed crucial topics when evaluating AI. Between workshops, the multidisciplinary team revised the model according to comments from workshop-participants. Last step is a validation workshop in Canada.
**Results.** The MAS-AI guideline has three parts. There are two steps covering nine domains and then advises for the evaluation process. Step 1 contains a description of patients, how the AI-model was developed, and initial ethical and legal considerations. Finishing the four domains in Step 1 is a prerequisite for moving to step 2. In step 2, a multidisciplinary assessment of outcomes of the AI-application is done for the five remaining domains: safety, clinical aspects, economics, organizational aspects and patient aspects. The last part, is five advices to facilitate a good evaluation process.
**Conclusions.** We have developed an HTA based framework to support the prospective phase while introducing novel AI technologies into healthcare in medical imaging. MAS-AI can assist HTA organizations (and companies) in selecting the relevant domains and outcome measures in the assessment of AI applications. It is important to ensure uniform and valid decisions regarding the adoption of AI technology with a structured process and tool. MAS-AI can help support these decisions and provide greater transparency for all parties involved.

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