

Use Cases for Artificial Intelligence and Machine Learning Methods to Support Health Technology Assessment

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Ashley Pitcher, Tom Halmos, Lauren Poole, Catrina Richards,
Raja Shankar, Yuvraj Sharma, Ines Guerra

Why are we talking about this?



Background

We hear about AIML all the time; supply of data is increasing, methods are maturing, processing power is sufficient. But it isn't always clear exactly **how** or **when** we can use it in HTA.

Objective



Based on a review of past HTAs, our expertise in AI, other review papers (including the recent ISPOR task force report) and our experience in supporting clients with HTA submissions, we've categorised and summarised the ways in which AIML can be used to support HTA submissions:

- 1 Directly augmenting the evidence package
- 2 Informing HTA and reimbursement strategy
- 3 Enhancing automation

NLP approaches on IQVIA HTA Accelerator data uncovered emerging mentions of use of AIML

IQVIA HTA Accelerator database was utilized to identify AIML mentions in HTA submissions

- NLP search on the HTA database based on a list of keywords – **20 markets, 9500 launched indications**
- All English HTA records for Single/Multiple drug assessment
- Time period: Jan-2016 to Feb 2021

405 keyword matches in 32 documents; 3 publications identified to be relevant

1. Identifying treatment-related predictors in diabetes:

- As a part of evidence, the submission included an analysis of data from one of the trials
- Incorporated ML algorithms to determine predictors of adequate glycaemic control, weight gain, GI events, and hypoglycaemia occurrence in T2DM patients in the treatment and control arms of the trial

2. LASSO method in a Cox Proportional Hazards model for a Multiple Myeloma treatment

- Requested by ERG to explore the impact of different combinations of covariates on efficacy estimates (PFS, OS)
- Resubmission incorporated LASSO method for variable selection based on the clinician-identified covariates
- ERG concluded that the LASSO method was most appropriate among the range of methods presented

3. Cure-mixture model to estimate long-term survival for a lymphoma treatment

- Employed standard ML methods such as clustering using the expectation – maximisation algorithm for patient classification (long-term survivor or not) within the survival analysis
- Not accepted by ERG due to concerns about the lack of robust long-term evidence to support the cure assumption

AIML has use cases across the HTA space for clinical and economic stakeholders

Choice of target population

- For example, use value-based arguments to define a niche patient population such as:
 - High unmet need (e.g. non-responders to existing therapy)
 - High cost/high burden (large capacity to benefit from new treatment)
 - Favourable toxicity profile



Comparative effectiveness & safety

- Matched analysis using real world data, e.g. external comparators to support single arm trials or trials with the wrong comparator

Economic modelling

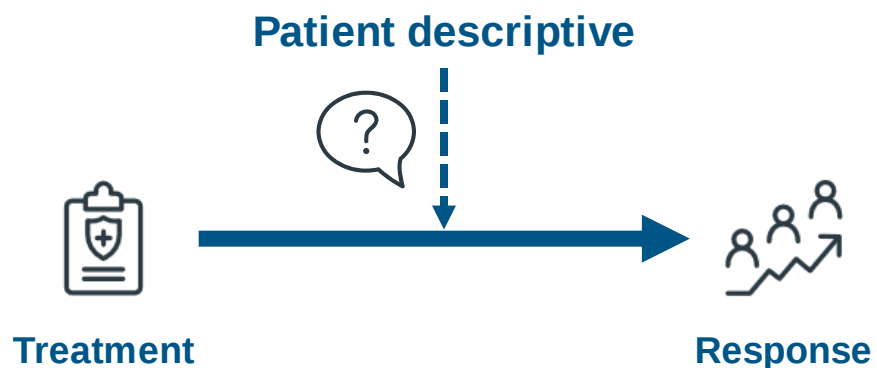
- Predict outcomes in relevant population based on local patient characteristics
- Identify variables that influence outcomes for incorporation into traditional approaches such as risk equations that help to extrapolate short term outcomes to longer term payer-relevant outcomes

AIML can provide techniques that support interpretation of non-RCT based clinical trial data

Challenge



- **Single arm trials** are a necessity in many disease areas but **cannot reliably estimate treatment effect vs. the standard of care**
- External comparators utilize RWD to provide control data, **but are open to bias**



Potential of AIML



- Doubly debiased machine learning (DDML) or G-computation are AIML based
- **They have been shown to increase statistical power and reduce bias vs. traditional methods**
- This increases confidence for therapies with single arm trials

AIML can support individualized survival estimates for patients and locally relevant populations

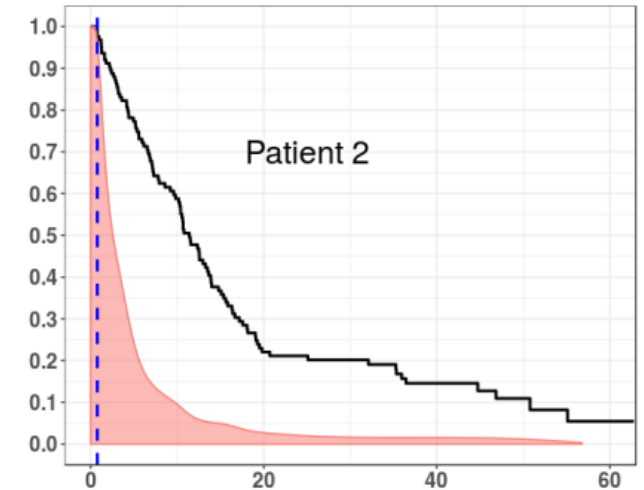
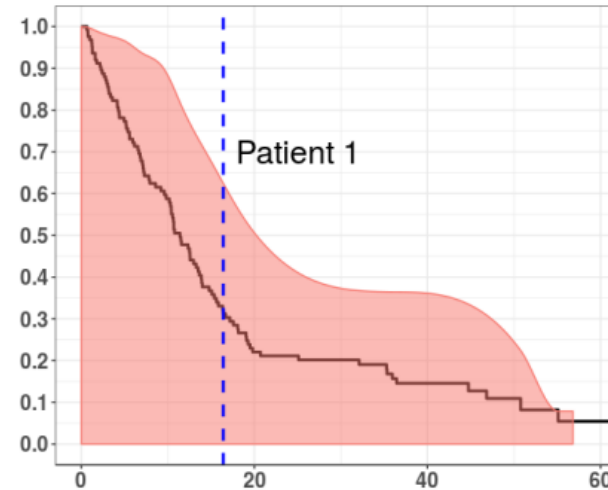
Typically Kaplan-Meier survival functions are estimated across the whole population or a handful of pre-defined subgroups

- Simple and transparent but ignores nonlinear relationships and characteristics of local population
- Real survival probability highly individualised and the population mix from the trial may not be reflective of the local population

AIML can individualise survival estimates in locally relevant populations/patients

Pros: Usually more accurate, takes into account complex relationships between variables; allows survival predictions to be more reflective of local population

Cons: Complex, less transparent (although explainable AIML methods and feature reduction methods can improve transparency)



AIML can be used to support Evidence & Market Access strategy through predictions of HTA and reimbursement decisions



Question: What is the risk of submitting early on HTA outcome vs. first move advantage?

Predictive Model Framework

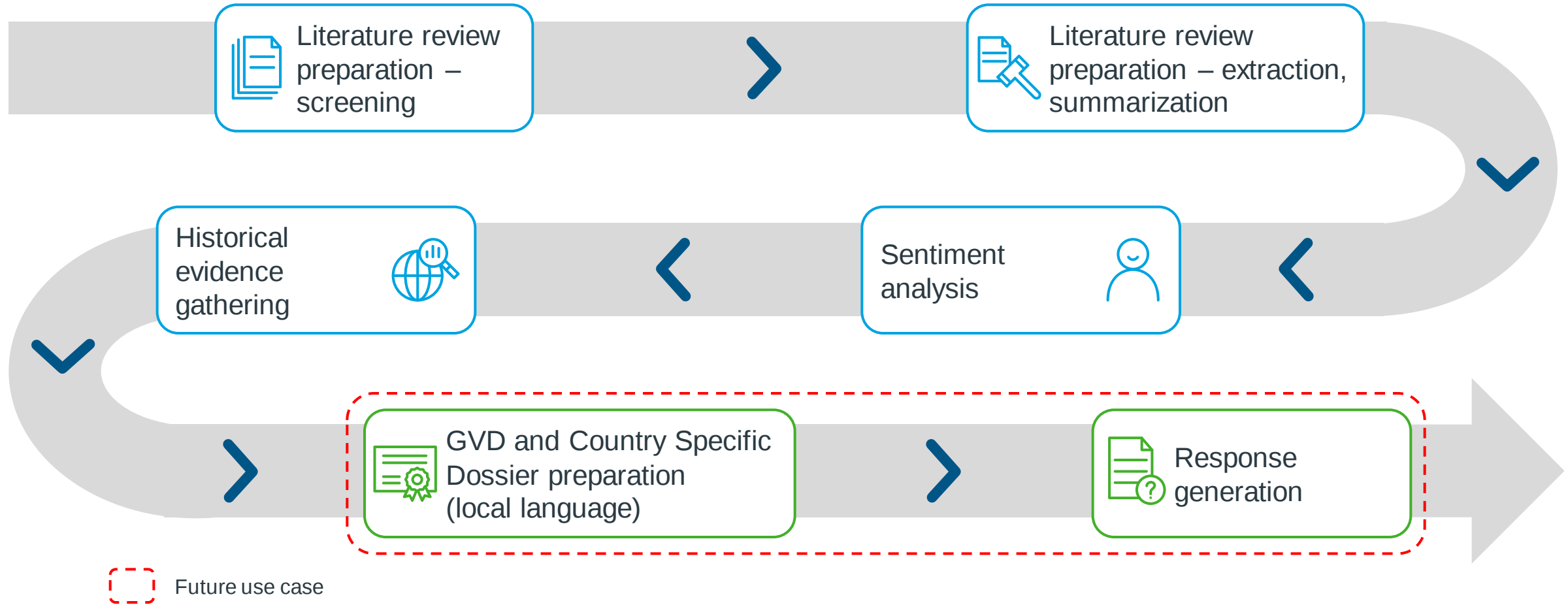
	Class 1	Class 2	Class 3
	Considerable+	Minor & Non-Q*	No/Less benefit
	ASMR III+	ASMR IV	ASMR V
	Innovative	Conditional	None
	Positive	Restricted	Negative
			

*Four-way classification for Germany also developed

	ASMR	ASMR IV	ASMR III+
Base Case	0.39	0.38	0.23
Mid Case	0.25	0.47	0.21
Best Case	0.21	0.38	0.41

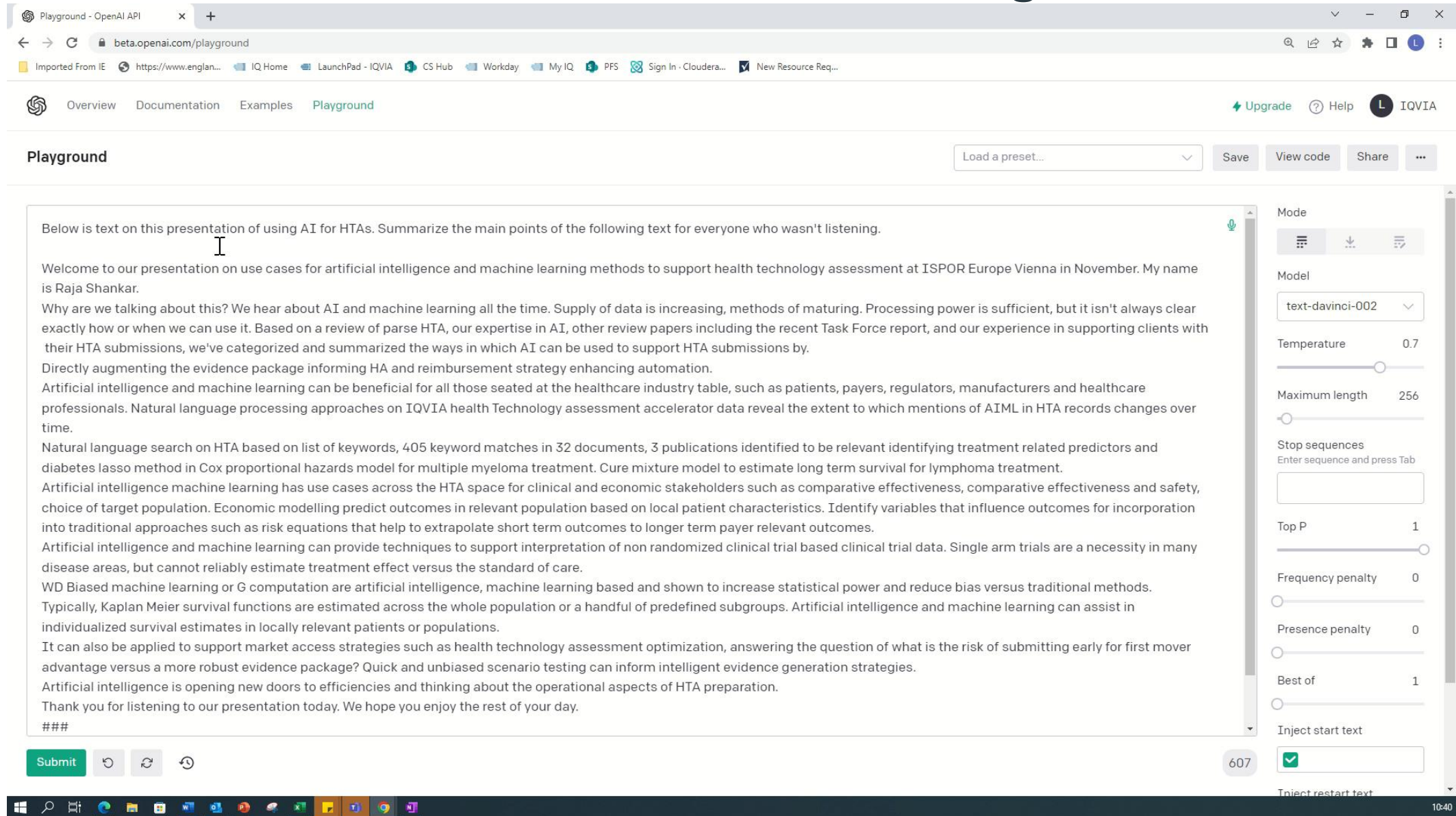
Quick and un-biased scenario testing can inform intelligent evidence generation strategies

Advancements in NLP are opening new doors to efficiencies when thinking about the operational aspects of HTA preparation



Large Language Models do not substitute analysis, but they can significantly expedite their work

To summarize for those who weren't listening...



The screenshot shows the OpenAI Playground interface in a web browser. The browser's address bar shows the URL `beta.openai.com/playground`. The page has a navigation bar with links for Overview, Documentation, Examples, and Playground. The Playground section is active, showing a text input area and a settings sidebar on the right.

Text Input:

Below is text on this presentation of using AI for HTAs. Summarize the main points of the following text for everyone who wasn't listening.

Welcome to our presentation on use cases for artificial intelligence and machine learning methods to support health technology assessment at ISPOR Europe Vienna in November. My name is Raja Shankar.

Why are we talking about this? We hear about AI and machine learning all the time. Supply of data is increasing, methods of maturing. Processing power is sufficient, but it isn't always clear exactly how or when we can use it. Based on a review of parse HTA, our expertise in AI, other review papers including the recent Task Force report, and our experience in supporting clients with their HTA submissions, we've categorized and summarized the ways in which AI can be used to support HTA submissions by.

Directly augmenting the evidence package informing HA and reimbursement strategy enhancing automation.

Artificial intelligence and machine learning can be beneficial for all those seated at the healthcare industry table, such as patients, payers, regulators, manufacturers and healthcare professionals. Natural language processing approaches on IQVIA health Technology assessment accelerator data reveal the extent to which mentions of AIML in HTA records changes over time.

Natural language search on HTA based on list of keywords, 405 keyword matches in 32 documents, 3 publications identified to be relevant identifying treatment related predictors and diabetes lasso method in Cox proportional hazards model for multiple myeloma treatment. Cure mixture model to estimate long term survival for lymphoma treatment.

Artificial intelligence machine learning has use cases across the HTA space for clinical and economic stakeholders such as comparative effectiveness, comparative effectiveness and safety, choice of target population. Economic modelling predict outcomes in relevant population based on local patient characteristics. Identify variables that influence outcomes for incorporation into traditional approaches such as risk equations that help to extrapolate short term outcomes to longer term payer relevant outcomes.

Artificial intelligence and machine learning can provide techniques to support interpretation of non randomized clinical trial based clinical trial data. Single arm trials are a necessity in many disease areas, but cannot reliably estimate treatment effect versus the standard of care.

WD Biased machine learning or G computation are artificial intelligence, machine learning based and shown to increase statistical power and reduce bias versus traditional methods. Typically, Kaplan Meier survival functions are estimated across the whole population or a handful of predefined subgroups. Artificial intelligence and machine learning can assist in individualized survival estimates in locally relevant patients or populations.

It can also be applied to support market access strategies such as health technology assessment optimization, answering the question of what is the risk of submitting early for first mover advantage versus a more robust evidence package? Quick and unbiased scenario testing can inform intelligent evidence generation strategies.

Artificial intelligence is opening new doors to efficiencies and thinking about the operational aspects of HTA preparation.

Thank you for listening to our presentation today. We hope you enjoy the rest of your day.

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Buttons: Submit, [Refresh], [Reset], [Undo]



The presentation covers the various ways that artificial intelligence can be used to support submissions for health technology assessments. The main methods are directly augmenting the evidence package, automating processes, and using AI to interpret non-randomized clinical trial data.



Thank You

