



# Explainable AI is Dead, Long Live Explainable AI!

## Hypothesis-driven Decision Support using Evaluative AI

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### ABSTRACT

In this paper, we argue for a paradigm shift from the current model of explainable artificial intelligence (XAI), which may be counter-productive to better human decision making. In early decision support systems, we assumed that we could give people recommendations and that they would consider them, and then follow them when required. However, research found that people often ignore recommendations because they do not trust them; or perhaps even worse, people follow them blindly, even when the recommendations are wrong. Explainable artificial intelligence mitigates this by helping people to understand how and why models give certain recommendations. However, recent research shows that people do not always engage with explainability tools enough to help improve decision making. The assumption that people will engage with recommendations and explanations has proven to be unfounded. We argue this is because we have failed to account for two things. First, recommendations (and their explanations) take control from human decision makers, limiting their agency. Second, giving recommendations and explanations does not align with the cognitive processes employed by people making decisions. This position paper proposes a new conceptual framework called **Evaluative AI** for explainable decision support. This is a machine-in-the-loop paradigm in which decision support tools provide evidence for and against decisions made by people, rather than provide recommendations to accept or reject. We argue that this mitigates issues of over- and under-reliance on decision support tools, and better leverages human expertise in decision making.

### CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**; • **Human-centered computing** → **HCI theory, concepts and models**.

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### 1 INTRODUCTION

Imagine you have two friends, Bluster and Prudence<sup>1</sup>. Whenever you have a difficult decision to make, you can approach them for help. Both have shown excellent judgement on complex decisions in the past. Bluster always tells you what they think is the right decision, even when they are not confident, and then tells you why they think that. But Bluster does not consider what you think. Would that be helpful? If your decision and reasons were the same as Bluster's, it would give you confidence. If not, Bluster could change your mind to an answer that you were happier with or that resulted in better outcomes. Prudence, in contrast, hardly ever gives their opinion, especially when not confident. Prudence instead asks you what you are proposing and then provides feedback: evidence for and against your proposed decision. If you propose alternatives, Prudence provides feedback on these, giving feedback until you reach a decision. But Prudence never gives you an answer. Would this be helpful? Prudence helps you to form a decision, and provides feedback on your own options, rather than justifying their own opinion. This would help you to question your decisions, and would give you control over which options you receive feedback for.

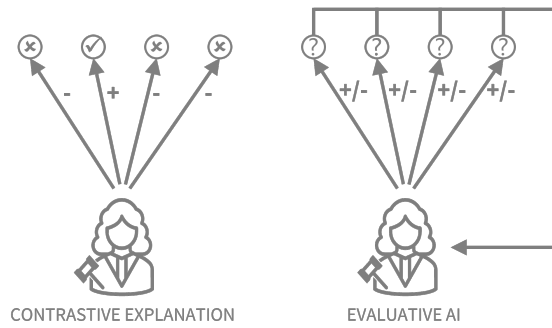
Reader, which would you prefer? An informal survey conducted by the author during a recent talk showed that just three out of over 100 people preferred Bluster; the remaining 100+ people preferring Prudence. Prudence helps us find strengths and weaknesses in our thinking and gives us control over which options we discuss with them. The ability to assess the strengths and weaknesses of judgements and decisions is key to expert decision making [18, 20].

Despite this preference, the current model of (explainable) AI-assisted decision support gives us Bluster instead of Prudence, right? AI decision aids are designed to tell the user what they think the best answer is (e.g. a recommendation), and explain why that is considered the best answer. This is a 'recommend and defend'<sup>2</sup> approach. If the user disagrees or does not find the reasons convincing, the machine offers little else. A counterfactual explanation [27] allows us to ask why another option is *not* the best answer; but does not provide us with reasons the alternative may well be the *right* answer or a good answer. 'Recommend and defend' approaches, which we call **recommendation-driven** decision support, do little to help us critique its answers or our own ideas.

The Bluster model of recommendation-driven decision support leads to two problems. First, AI tools are not correct all of the time, so we should be sceptical at least some of the time. However, people find it difficult to correctly calibrate their trust in a decision aid [10, 13, 21, 37]. Research shows that people tend to either *under-rely* on

<sup>1</sup>Thanks to Piers Howe for these names.

<sup>2</sup>Sean Koon introduced this nice term to me.



**Figure 1: Contrastive explanation vs. Evaluative AI.** Contrastive paradigms are ‘recommend and defend’ approaches. They provide evidence that supports the recommendation and refutes all others. Evaluative AI proposes not necessarily giving recommendations from machines, but instead providing evidence for/against each option.

tools, meaning they have no effect on decision making, or they *over-rely* on tools [1, 6, 37], likely because providing recommendations makes them *fixate* on that recommendation. Both under- and over-reliance have negative consequences [29]. Second, Bluster reduces our locus of control [36], because we cannot control which options we received feedback for.

This paper argues for a paradigm shift: that the decision aids (DAs) should be less like Bluster, and more like Prudence, which we call **hypothesis-driven** decision support. We propose a new conceptual framework for decision support, with two key properties not present in the current paradigm. First, evaluative AI tools do not provide recommendations. They mitigate fixation by either allowing the decision maker to determine which options are best or helping them to narrow down to a manageable set of options [34]. Second, instead of justifying AI recommendations, DAs generate and present evidence to support or refute human judgements, and explain trade-offs between any set of options, not just the machine recommendation. This helps with trust calibration because the machine does not give recommendations, as well as over/under-reliance because there is no recommendation to follow. We argue that the reason this Prudence-like approach is more effective for decision support because it **aligns with the cognitive decision-making process that people use when making judgements and decisions** [11, 17, 30]. We call this paradigm **evaluative AI**.

Figure 1 shows the difference between evaluative AI and perhaps the most common form of explainability: contrastive explanation. Contrastive explanation is like Bluster — it gives us an answer and justifies it, telling us why it is correct and why other options are not. Evaluative AI is like Prudence — it helps us critique our own ideas. This provides a better feedback loop — if the evidence helps us eliminate our preferred hypothesis, we start to explore others.

Evaluative AI is not intended to be used in all scenarios. It is more suitable for medium- and high-stakes decisions when the decision maker is ultimately accountable, and low frequency decision making where the decision maker has time to explore options.

We conclude that for decision making, the recommendation-driven paradigm of explainable AI is ‘dead’ (for some situations),

but that the evaluative AI paradigm is still a form of explainable AI, and many of the current paradigm will play a part in this new conceptualisation; so, long live explainable AI!

Section 2 reviews related work on cognitive decision making, what makes a good decisions, and the main modes of explainable AI. Section 3 evaluates how current decision support models align with human decision making processes, with a focus on explainable and interpretable AI. Section 4 presents evaluative AI, a new conceptual framework for human-centred decision making, and argues that this framework aligns better the cognitive processes humans use for decision making. It also presents a high-level research agenda for evaluative AI. Section 5 concludes the paper.

## 2 AI-ASSISTED DECISION SUPPORT

### 2.1 Decision making and decision support

Before we consider what makes good decision support, we consider what good decision making is. A definition of ‘decision making’ is surprisingly elusive. Often, definitions consider three steps [12]: (1) an assessment of the situation, such as what options are available; (2) making judgements and trade-off about options; and (3) selecting an option or committing to a course of action. Hoffman and Yates [12] argue that this ‘final-point notion’, in which there is a point that decision “made” is a (sometimes useful) simplification of the decision-making process. However, as a model, it misses some important aspects of decision support; importantly: that decision making is a process, not a point in time.

Table 1 outlines 10 *cardinal decision issues*, defined by Yates and Potworowski [45]. These include issues such as deriving options and making judgements, but also factors such as exploring consequences of actions, and who will be part of deciding. The issues in italics are the aspects that we believe to be of most importance to AI-assisted decision support. While the first three and the final issue can be supported, these are less relevant for AI research.

We define a **decision aid** (DA) as any system that supports the process of deciding. But what is a *good* DA? In Table 2, we propose six criteria for good decision support. The first five are based on the 10 cardinal issues from Table 1 [12, 45]. The criteria that are omitted can certainly be supported by a DA, but these criteria are decisions in their own right, and therefore the six criteria apply to each. The sixth criteria is *understandable*, which simply means that a good DA helps people understand how and why it works, and where it fails. This is a common criteria for AI-based DAs [9], and is important to calibrate trust & reliance, and to find mistakes.

Note two things about the criteria in Table 2. First, a DA helps a decision maker. It does not necessarily provide the answers for any of the criteria. Second, it goes beyond recommendations and judgements, which are typically the focus in XAI; largely because these are considered to be some of the harder problems.

### 2.2 Cognitive processes for decision making

Hoffman et al. [11] argue that, when a person tried to understand a system output, they engage in the cognitive process known as **abductive reasoning**. Abductive reasoning is the process of forming hypotheses and judging their likelihood for the purpose of explaining observations or facts [30]. This abductive process is engaged as soon as people start interacting with a system, irrelevant of any

**Table 1: The 10 ‘cardinal decision issues’ outlined by Yates and Potworowski [45]. The issues in *italics* represent those that are of most interest to explainable AI.**

Cardinal issue	Definition
Need	Why do we need to make a decision at all?
Mode	Who will decide and how will they do it?
Investment	What kinds of amounts of resources will be invested in the process?
<i>Options</i>	What are the different actions we could take to solve the need?
<i>Possibilities</i>	What outcomes could happen if for each action, if it were taken?
<i>Judgement</i>	Which of the outcomes would happen if we took the action?
<i>Value</i>	How much would any stakeholder care if this outcome happened?
<i>Trade-offs</i>	How do we trade-off the outcomes to settle on an action?
<i>Acceptability</i>	How can we get other stakeholders to accept our decision?
Implementation	Now we have decided, how can we action it?

**Table 2: Criteria for good decision support, based on the 10 ‘cardinal decision issues’ [45]**

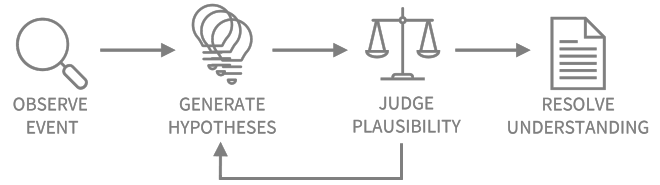
Criteria	Definition
Options	Help to identify options, as well as help to narrow down the list of feasible or realistic options
Possibilities	Help to to identify possible outcomes for each of the identified options
Judgement	Help to judge which outcomes are most likely
Value	Help to identify the positive and negative impacts on stakeholders for each of the identified options
Trade-offs	Help to make trade-offs on the above criteria for each options
Understandable	Help to understand how and why the tools works as it does, and when it fails

particular explainability or interpretability tools. As such, Hoffman et al. argue that abductive reasoning is a suitable foundational model for conceptualising explainable AI.

Peirce [30] defines the process of **abductive reasoning** as five step process, outlined in Figure 2<sup>3</sup>:

- (1) *Observe an event or phenomenon*: A person observes an event, usually one that is surprising and does not fit their current

<sup>3</sup>The final step of *extending* the explanation is omitted because it simply repeats the process when new events are observed.



**Figure 2: A model of abductive reasoning. When someone observes an event, they generate hypotheses of the cause, and then judge the plausibility of (some) hypotheses; potentially iterating to generate more hypotheses as new evidence emerges. Eventually, the understanding is resolved.**

mental model. This leads to them to start searching for explanatory hypotheses.

- (2) *Generate hypotheses*: The person generates potential reasons for why they would have observed the event or phenomenon. The reasons are *hypotheses*.
- (3) *Judge the plausibility of the hypotheses*: The person searches for evidence that may support or undermine different hypotheses, perhaps ruling out some or making some more likely. Some hypotheses are ruled out, while others are judged as more likely. This process may lead to new hypotheses.
- (4) *Resolve understanding*: A particular hypothesis fits the new observation and previous experience of the decision maker, so is adopted as the most likely cause of the observation. This may be a tentative resolution.
- (5) *Extend*: Revise and extend the process when new evidence is observed or considered.

This philosophical model of decision making is supported by research from cognitive science. Klein et al. [17] present a theory of sensemaking known as the *Data/Frame Theory*, built from studies with expert decision makers. The *frame*, a generalisation of a hypothesis, is a model of how something works, while the *data* contains observations made and inferences that combine the observations and the frame. The data is used to adjust the frame (similar to judging plausibility) and the frame is used to determine what new data to find, what outcomes to evaluate, and how these relate. Klein et al. show that people make decisions by first using their intuition to narrow down to a set of likely options (the frames), and then going through each option one-by-one, searching for evidence (data) to make judgements. *Good* decision makers search for evidence that both supports and refutes a hypothesis. Klein et al. [17] argue that abductive reasoning plays a central role in this process. We build the evaluative AI framework around the Data/Frame model.

Hoffman et al. [11] argue that abductive reasoning is a suitable foundation for conceptualising explainable AI. In this paper, we argue for a similar – yet orthogonal – view; specifically, explainable AI for **decision making**. In decision making, the **decision maker is involved in two (related) reasoning processes**. First, the decision maker is trying to make a judgement/decision about the world (e.g. a diagnosis). The observed event is something that needs explaining, such as a medical symptom, the hypotheses are the potential causes of that observation, such as a disease, and the judgement is about the likelihood of a particular hypotheses being true given the evidence. Second, the decision maker is also

making a judgement about the DA (e.g. whether its reasoning is sound, as proposed by Hoffman et al. [11]). The observed event is an output  $o$  of an AI system  $f$  given an input  $i$ . The hypotheses characterise which combinations of inputs  $i$  and computations (parts of  $f$ ) caused this output to occur. The process of judgement is to determine why the system produced the output that it did. Table 3 outlines this for a medical diagnosis scenario. Decision makers need to ‘invert’ the explainable AI process to align with the decision-making process. Hoffman et al. argue that machines reasoning in an abductive manner align better with this process. The argument in this paper is similar, but rather than necessarily giving abductive explanations, we argue that DAs should be designed to explicitly support abductive reasoning.

**Table 3: How Explainable AI and Evaluative AI align against the human abductive reasoning process.**

Human Reasoning	Explainable AI	Evaluative AI
Event to explain	AI diagnosis	Medical symptoms
Hypotheses	AI reasoning	Medical conditions
Evidence	Models, Explainability	Evidence for/against hypotheses
Judgement	Causes between inputs & AI diagnosis	Likelihood of medical conditions

### 2.3 Explainable AI and decision making

The initial assumption of AI-assisted DAs was that people would follow recommendations when required, leading to better decisions. However, issues such as warranted and unwarranted distrust [13] mean that AI systems are often deployed and then largely ignored [9, 37]. Explainable/interpretable AI aims to mitigate these by helping people to understand why decisions are made. However, recent research has shown that the recommendation-driven explainable/interpretable AI has little effect on decision making [1, 6–8, 28, 32], although this is not always the case [22, 23, 41]. The two primary issues are *over-reliance* and *under-reliance*. Over-reliance means decision makers accept a machine recommendations even when it is wrong, caused by unwarranted trust [13]. This is often attributed to *automation bias*, where the machine is “must be right” because it is a machine. Under-reliance means decision makers reject a machine recommendation even when it is correct, caused by unwarranted distrust [13]. This is often attributed to *algorithmic aversion*, where machine outputs are rejected but would be accepted had they come from a human. In either case, a poor decision can often be attributed to *fixation* [17] – searching for evidence to support one hypothesis without considering others.

Some experimental studies [2, 5, 42] indicate that most participants do not cognitively engage with explainability tools. Participants who do seem to believe that they understand explanatory information, leading to over-confidence [2], even when presented with explanations that contain no useful information [5]. We have seen this in currently unpublished observational studies. In a study

where expert board gamers used an AI-based recommendation system, we saw that many players did not truly engage with recommendations or explanatory information either. When they did, we saw some behavioural changes, but not enough to see a statistically significant improvement in decision making.

Similarly, in experiments on a general task with general participants, Bućinca et al. [1] and Gajos and Mamykina [6] show that explainability did not mitigate over-reliance, and in some cases it increased over-reliance. They assert that this is because participants did not pay attention to explainability information. They propose three *cognitive forcing* strategies to mitigate over-reliance, such as forcing people to give a decision before seeing a recommendation. Their results showed that cognitive forcing slightly mitigated over-reliance, compared to feature-based and uncertainty judgements, particularly disregarding incorrect AI recommendations, but with no statistically significant differences in task performance. Interestingly, despite cognitive forcing functions being more effective, they were least preferred by participants. Bućinca et al. [1] attribute this to the phenomenon of people not wanting to exert mental energy [19]. This indicates that Evaluative AI could prove useful by not fixating people on particular recommendations, but allowing people to assess whether evidence supports their hypotheses, rather than trying to understand the DA’s reasoning.

These studies show that the recommendation-driven XAI does little to mitigate over- and under-reliance. This has lead to several authors to argue that XAI research should return to the foundation of cognitive and social processes involved in decision making [7, 8, 15, 42, 44]. Some authors [1, 6, 42] have attributed the cause of ignoring explanatory information to the ‘failure’ of system 1 processing in dual process theory [14]. In brief, the theory is that system 1 thinking (fast, heuristic, and biased) ‘interferes’ with system 2 thinking (slow and more accurate). The conclusion that is often, but not always drawn, is that DAs should aim to support system 2 thinking and prevent system 1 ‘interference’.

However, **we caution against the idea of prioritising system 2 thinking over system 1 thinking**, for three reasons. First, research in **Naturalistic Decision Making** (NDM) demonstrates that ‘system 1’ thinking, which they call **intuition**, is a powerful source of problem solving that often produces better and/or faster decisions than system 2 [16]. For example, Coderre et al. [3] found that intuition significantly outperformed hypothetico-deductive reasoning in gastroenterology clinical diagnoses. Klein [18] show that experts make decisions by first using their intuitive problem solving ability to generate likely options, and then using both intuition and slower structured thinking to assess which options will work. As such, any technique that aims to ‘override’ intuitive thinking risks losing the benefits of expertise and prior knowledge. Second, there is now sufficient research questioning whether the system 1 vs system 2 distinction is so clear [25, 35]. For example, many experiments showing biases system 1 thinking, such as base-rate fallacies, could be partly attributed to the experiment design [35], which may not reflect many environments where real decisions are made. Finally, we need further research using expert decisions makers, rather than just general participants, as well as studies where poor decisions have real consequences. The effect of system 1 thinking may differ between contexts such as the experience of the decision maker and the stakes of the decision.

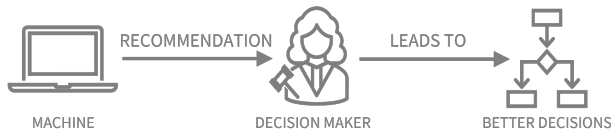
In short, we argue against simply treating intuition as ‘bad’. DAs should exploit the strengths of intuition and expertise, as well as structured thinking.

### 3 (EXPLAINABLE) AI AS DECISION SUPPORT

This section provides a narrative of how we have arrived at the current status quo. We evaluate the four dominant paradigms of decision support against the criteria of decision support identified in Table 2. The four paradigms we discuss are: (1) recommendations; (2) recommendations with explanatory information; (3) interpretable models; and (4) cognitive forcing.

#### 3.1 Giving recommendations with no explanatory information

The idea of decision support using AI came from the use of AI as automation. Given situations in which an AI model provides more accurate judgements/decisions than human decision makers, a simple model of AI-assisted DAs is to give recommendations, which decision makers can then take into account. Recommendations can be ranked lists of options such as in many recommender systems, but the typical model is to propose just the one recommendation that the AI model determines is the most likely or ‘best’. The assumption here is that for situations in which DAs can handle many more factors simultaneously, it can provide insight when the assumptions of the underlying modelling theory hold. This model is depicted below in Figure 3.



**Figure 3: A model of giving recommendations for decision support. This assumes that decision makers will carefully consider recommendations. However, empirical evidence suggests this is not the case.**

The primary issue with this model was that, even if the DA gives better judgements/decisions than the human, people tend to ignore this due to unwarranted distrust [9, 10, 13, 26, 37, 39] or accept wrong decisions due to unwarranted trust [1, 6, 29]. The inability to scrutinise why decisions are made mean that the only information to rely upon to judge the correctness is: (1) extrinsic information such as accuracy measures; and (2) the decision makers’ own expertise and knowledge. Given the former does not change from decision to decision, it is unsurprising that experts rely on their own expertise and novices over-rely on the tool [37].

Comparing this to the properties that comprise good decision support outlined in Table 2, we can see why this approach is largely ineffective. Giving only recommendations:

- (1) **does not** help to provide new options or to filter out unlikely options;
- (2) **does not** consider possibilities or judgements beyond one option;
- (3) **does not** help determine stakeholder values;

- (4) **does not** support making trade-offs; and
- (5) **does not** provide understanding of the machine decision.

Can this still be useful? Of course! If a recommendation matches or is similar to our own judgement, it gives us confidence in our own decision, although this confidence may be misplaced. Further, if a recommendation is not similar to our own judgement, it may decrease our confidence and make us reconsider, potentially helping us to make a better decision. However, in either case, we receive no further support to help with the decision.

#### 3.2 Giving recommendations with explanatory information

One solution to mis-calibrated trust is to provide explanatory information. This means giving justifications for decisions, providing evidence to support the decisions, and making models simple and easy to understand (see more on this in Section 3.3). A model of interaction between decision maker and DA is shown in Figure 4.

Comparing this to the properties that comprise good decision support outlined in Table 2, we can see the criteria that the default model of XAI bring are that it:

- (1) **does not** help to provide new options or to filter out unlikely options;
- (2) **partially** considers possibilities or judgements beyond one option: contrastive explanations argue why other options are NOT recommended;
- (3) **does not** help determine stakeholder values;
- (4) **partially** supports making trade-offs; and
- (5) **does** provide understanding of the machine decision.

So, explainability provides understanding. Contrastive explanations [27] partially support trade-offs when they answer ‘Why *A* instead of *B*?’, where *A* is the output and *B* a *foil*. However, this still defends the recommendation. Can this be useful? Of course! If we agree with the recommendation, we can check that we agree for similar reasons; and if we disagree, we can check the reasons why, potentially helping us to improve our initial decision.

#### 3.3 Giving recommendations with an interpretable model

The third paradigm is to give recommendations using an ‘interpretable’ model. Rudin [33] argues that for high-stakes decisions, people should avoid using black-box models altogether, and instead should use interpretable models. Interpretable models use a small set of features with a low complexity of interaction between them.

The model of interaction with an interpretable model is same as for recommendations with explanatory information, outlined in Figure 4. The assumption is that because the model is interpretable, it contains most of the explanatory information that is required. However, interpretable models are not designed with *decision support* in mind. The model’s options, possibilities, and trade-offs would have to be calculated by the decision maker. Assistance to calculate these is a combination of interpretability and explainability, so overlaps with the previous section. Effectively, the purpose of interpretable models is complementary to the criteria in Table 2.



**Figure 4: A model of explainable AI for decision support. This assumes that the problem of distrust can be mitigated by giving reasons or explanations for decisions. However, empirical evidence suggests people do not pay careful attention to the reasons/explanations.**

Comparing this to the properties that comprise good decision support outlined in Table 2, we can see the criteria that the interpretability brings are that it:

- (1) **does not** help to provide new options or to filter out unlikely options;
- (2) **does not** consider possibilities or judgements beyond one option;
- (3) **does not** help determine stakeholder values;
- (4) **does not** support making trade-offs; and
- (5) **does** provide understanding of the machine decision.

### 3.4 Cognitive forcing

The final paradigm is cognitive forcing. The assumption of cognitive forcing is that forcing people to engage with the decision cognitively can mitigate over-reliance. Gajos and Mamykina [6] and Bućinca et al. [1] implement this idea using three approaches, as outlined in Section 2.3. The commonality between these three approaches is that decisions are initially withheld from the decision maker, but explanatory information is provided, forcing the decision maker to engage with the explanatory information. This model is depicted below in Figure 5. Withholding recommendations ‘forces’ the decision maker to cognitively engage with the decision and therefore, to consider different options and make trade-offs. Giving explanatory information from the start may help the decision maker to focus on useful information.

Comparing this to the properties that comprise good decision support outlined in Table 2, we can see the criteria that cognitive forcing brings are that it:

- (1) **partially** helps to provide new options or to filter out unlikely options by forcing the decision maker to do so;
- (2) **does not** consider possibilities or judgements beyond one option;
- (3) **does not** help determine stakeholder values;
- (4) **partially** supports making trade-offs; and
- (5) **does** provide understanding of the machine decision.

While this is an improvement beyond the default XAI approaches, weaknesses remain. First, this approach is still an instance of our friend Bluster, rather than our friend Prudence – it is just that Bluster pauses before stating their opinion. Second, it does not provide helpful decision-making information for options other than the recommendation.

Next, we propose a model that builds on the strength of cognitive forcing, but on a **foundation of the cognitive science of decision making**.

## 4 EVALUATIVE AI: A CONCEPTUAL FRAMEWORK OF EXPLAINABLE DECISION SUPPORT

In this section, we present a new conceptual framework of hypothesis-driven explainable decision support called **evaluative AI**. The two primary design criteria for this are:

- (1) Support the properties of good decision making outlined in Section 2.3. That is, support the decision maker’s **cognitive decision making process**.
- (2) Provide better **internal locus of control** [36] to the decision maker about which options to explore and when.

To do this, we propose that the vision of evaluative AI is to:

**Support the decision maker to access the information they want and need to evaluate a hypothesis, when they want it.**

### 4.1 Conceptual framework

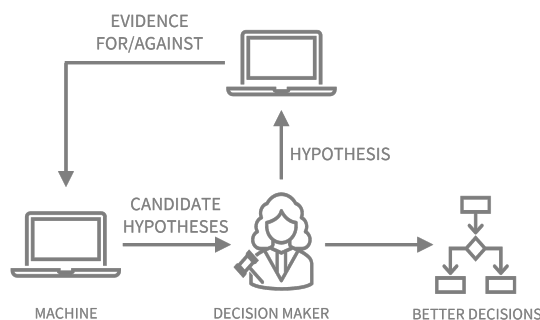
The conceptual framework for evaluative AI is shown in Figure 6. Evaluative AI does not (necessarily) provide recommendations, but instead offers support to filter out unlikely options, generate new hypotheses, or both. The decision maker then analyses a hypothesis, asking the DA to provide evidence for and against the hypothesis. Evidence could also be presented contrastively: what is the evidence for/against a particular hypothesis rather than some other hypothesis. Importantly, the decision maker to maintains **control** over which hypotheses to explore.

**4.1.1 Options.** Existing explainable AI approaches tend to provide one or sometimes two options to consider. The evaluative AI paradigm argues that the presentation of options should be context-specific. For example, given a probabilistic classifier, a evaluative AI system could highlight options that are within a certain probability of the most likely, perhaps withholding the probabilities themselves. Alternatively, it could use uncertainty estimates, which are known to help decision making [40], and from that, determine which options to filter. Approaches such as this help to reduce fixation because there is no single recommendation. Cognitive forcing takes a similar approach, but current cognitive forcing techniques are recommendation-driven [1, 6].

**4.1.2 Judgement support.** All five paradigms support judgements. The evaluative AI framework puts the human at the centre of the judgement process. In this framework, the judgement is made by the human decision maker with support from the DA, which gives feedback (evidence for/against) of proposed hypotheses. This is



**Figure 5: A model of cognitive forcing.** By withholding recommendations (for perhaps a short period) and giving an ‘explanation’, it forces people to engage, limiting over-reliance. However, it is still a ‘recommend and defend’ approach.



**Figure 6: A model of Evaluative AI, which aligns with decision making processes, keeping the decision maker in control and asking users to rely on evidence instead of recommendations.**

**supporting judgement**, rather than **giving judgement**. The difference is who owns control over which hypotheses to explore. In a recommendation-driven approach, both the human and machine provide a judgement. In the evaluative AI paradigm, the human provides judgement and the machine provides feedback.

**4.1.3 Trade-off support.** Contrastive explanations trade-off outcomes. However, they explain only why non-recommended options are ‘incorrect’. This is a ‘persuasive’ approach — it justifies why the machine’s decision is correct. The evaluative AI framework instead:

- (1) explains trade-offs between any two sets of options; and
- (2) provides evidence both for *and* against each option, irrelevant of the judged likelihood of that option.

Good decision makers assess an option by looking for evidence that supports it, but also evidence that refutes it. For example, in a study with anaesthesiology residents, Rudolph [34] showed that participants who fixated on an initial option did poorly, but that participants who kept an open mind on all options do not perform much better. Instead, those who jump to an initial conclusion and test it, looking for *negative evidence*, make the best decisions. Recommendation-driven approaches typically do not provide evidence against the recommendation, nor evidence supporting other options. Evaluative AI supports both, rather than aiming to persuade that the machine is correct.

Supporting trade-offs has gained interest in recent years under the name **option awareness** — the analysis and understanding of various options and their relative trade-offs [31]. Pfaff et al. [31] show that using visual analytics to allow decision makers to explore options increases their option awareness, resulting in more accurate and faster decisions. More recently, Drury et al. [4] proposed a framework in which machines consider their own option awareness

to support human decision makers. However, research into machine-assisted option awareness is still in its infancy.

## 4.2 Example: Diagnosis

Consider an example of a DA for diagnosing skin cancers, such as the ISIC 2018 lesion diagnosis challenge<sup>4</sup>. There are seven possible disease categories: (1) melanoma; (2) melanocytic nevus; (3) basal cell carcinoma; (4) actinic keratosis; (5) benign keratosis; (6) dermatofibroma; and (7) vascular lesion. Given a dermoscopic image of a lesion along with some meta information, such as where the lesion is found, the task is to diagnose the most likely category.

Figure 7 shows a simple prototype interface for such a system. In this case, there are seven hypotheses/diagnoses. The DA filters out those that are unlikely, leaving just three: melanoma, basal cell carcinoma (BCC), or actinic keratosis (AK)<sup>5</sup>, highlighted with bold text. By highlighting only likely hypothesis instead of just one, this could help to mitigate fixation on just one option. Hypotheses can be explored. In Figure 7, the location of the lesion, its colour, scarring, and that it sometimes bleeds, is strong support for a BCC diagnosis. However, the asymmetric shape, itchiness, and recent colour change are evidence against BCC. Other forms of evidence could be provided to the decision maker, such as finding similar instances using case-based reasoning [38, 44]. It is up to the decision maker to make the final decision, integrating their expert knowledge and the information from the DA.

## 4.3 Summary

Comparing model to the properties that comprise good decision support outlined in Table 2, we can see the criteria that evaluative AI brings are that it:

- (1) **does** help to provide new options or to filter out unlikely options by forcing the decision maker to do so;
- (2) **does** help to identify possibilities and support judgement for options;
- (3) **does not** help determine stakeholder values;
- (4) **does** support making trade-offs; and
- (5) **does** provide understanding of the machine decision.

Table 4 compares the five approaches to explainable DAs. Evaluative AI explicitly aims to provide support for options, judgement, understanding, and trade-offs. The difference between cognitive forcing and evaluative AI is two-fold:

- (1) **Cognitive processes:** Evaluative AI is built on the Data/Frame model of sensemaking [17], so supports the decision maker’s cognitive process by allowing them to explore hypotheses,

<sup>4</sup>See <https://challenge.isic-archive.com/landing/2018/47/>.

<sup>5</sup>It is unlikely that these three would be the case as AK is quite different from BCC and melanoma, but this makes for a good illustrative example.

Figure 7: A simple prototype of a diagnostic interface using evaluative AI

Table 4: A summary of the decision support provided by different paradigms.  $1/n$  means that this only provides information to confirm the recommended option(s);  $\checkmark/\times$  means partial support for other options. Evaluative AI explicitly provides support to explore options and perform trade-offs. XAI and cognitive forcing allow this if they support contrastive explanation. In evaluative AI, it should be default.

Decision support	Support provided					
	Options	Possibilities	Judgement	Value	Trade-offs	Understandable
Recommendation	$\times$	$1/n$	$1/n$	$\times$	$\times$	$\times$
XAI	$\times$	$1/n$	$1/n$	$\times$	$\checkmark/\times$	$\checkmark$
Interpretability	$\times$	$\times$	$\times$	$\times$	$\times$	$\checkmark$
Cognitive forcing	$\checkmark/\times$	$1/n$	$1/n$	$\times$	$\checkmark/\times$	$\checkmark$
Evaluative AI	$\checkmark$	$\checkmark$	$\checkmark$	$\times$	$\checkmark$	$\checkmark$

rather than providing only the information to the justifies a machine recommendation.

- (2) **Control**: Evaluative AI explicitly hands control of which hypotheses are investigated and prioritised to the decision maker, resulting a **machine-in-the-loop** paradigm [7, 8], rather than a human-in-the-loop paradigm.

For this reason, we assert that evaluative AI obtains the benefits of cognitive forcing, while giving **control** to the decision maker to explore the strengths and weaknesses of any option, rather than just the strengths recommendations and the weaknesses of alternatives.

#### 4.4 Long live explainable AI!

This article proposes a paradigm shift from recommendation-driven decision support to hypothesis-driven decision support. Does this imply that explainable AI is dead? We do not believe so.

First, there are applications of XAI beyond decision support, such as verification, regulation, scientific discovery, generating insights about underlying data, etc. Further, there are applications where recommendation-driven approaches may be the best way to improve decisions, such as making decisions at scale.

Second, for a machine to judge decisions, we will need an underlying decision-making model, meaning that recommendation approaches such as machine learning, planning, and optimisation will be required, along with XAI techniques.

Third, evaluative AI is explainable AI. The cognitive and social aspects of good explainability apply to evaluative AI: [26]: (1) explanations are contrastive; (2) explanations are selected; (3) explanations are interactive; and (4) explanations are causal.

Fourth, from the earlier example, it is clear that many existing tools will play a part in evaluative AI: contrastive explanation [27], Weights of Evidence (WoE) [24], feature importance, case-based reasoning techniques [38], etc., all generate evidence. New models of XAI are needed, but existing work lays a solid foundation.

#### 4.5 Challenges and Limitations

There are clear potential limitations with this approach. First, if people tend to dismiss recommendations and any explainability information, why would they pay attention to evidence? The evaluative AI framework makes the same assumptions as earlier work: that people care at all about what a machine has to say. A very real



risk is that decision makers will not engage with a tool that supports cognitive reasoning either. However, one argument against this is that this evaluative AI provides decision makers with better **control** [36, 43], and follows a process that they will **naturally follow**, rather than recommendation-driven approaches, which somewhat disrupt the decision-making process.

Second, it is difficult to imagine evaluative AI solutions will result in lower cognitive load. A strength of the recommendation-driven approaches is that they reduce the information that a decision maker needs to consider to just the most relevant. Evaluative AI will likely result in designs that force more engagement with the decision, but less preferred by decision makers [1]. However, following a model of abductive reasoning can still reduce information compared to having no decision support; e.g. presenting only the most likely hypotheses; prioritising access to the most important information, etc. Striking this balance is a challenge.

## 4.6 An incomplete research agenda

In this section, we present an incomplete research agenda based around the evaluative AI framework.

**4.6.1 Observing events.** The first step is observing an event. While it is difficult to control the attention a decision maker pays to information, we can support this in several ways:

- (1) **Design interfaces to make it clear what has happened, what data is being used**, etc. [11]. This includes allowing people to explore relevant attributes of a system.
- (2) **Highlight anomalous behaviour/events**, as these are typically the events that people require to make decisions or to understand [26].

**4.6.2 Generating options.** The ability for the machine to put forward options can help decision makers in two ways. First, it can present options that decision makers did not consider. Second, it can speed up decision making in time-sensitive environments by filtering out some options and/or allowing options to be assessed more systematically.

Generating options can be supported in several ways beyond providing 1-2 recommendations or a ranking:

- (1) **Provide probabilities over options:** This can help the decision maker to narrow down likely options, but is perhaps subject to over-fixation (on the most likely option) in the same way that recommendations are.
- (2) **Provide a set of likely options:** This can help to narrow down the set of hypothesis without giving a recommendation, as in the example in Section 4.2, reducing fixation.
- (3) **Provide uncertainty measures:** The DA provides its uncertainty about its filtered options (a decision of set of decisions) to encourage healthy scepticism [46].
- (4) **Intervention:** The DA does not initially narrow down options, but allows the decision maker to explore and select their answer, and then intervenes if it disagrees above some threshold, prompting the decision maker to consider the DA's most likely responses.
- (5) **Relate inputs and hypotheses:** The decision maker selects the inputs they believe are important and the tool shows which hypotheses are supported or denied by that evidence.

**4.6.3 Judging plausibility.** Judging the plausibility of outcomes can be supported several ways by a DA:

- (1) **Explainable/interpretable AI:** Provide reasoning steps that link the evidence to the hypothesis, such as rules, decision steps, or explanations.
- (2) **Provide evidence weights:** Show how different inputs positively and negatively contribute to a hypothesis.
- (3) **Provide epistemic uncertainty:** Show uncertainty in the form of e.g. an uncertainty measure using entropy.
- (4) **Provide aleatoric uncertainty:** Show a measure of uncertainty of the evidence itself.
- (5) **Evidence selection:** Allowing the decision maker to change evidence (inputs) and ask the DA to re-evaluate.
- (6) **Argumentation:** The decision maker identifies evidence that supports (refutes) a hypothesis, and the DA highlights: (a) other evidence that strongly refutes (supports) that hypothesis; and (b) other hypotheses that are strongly supported (refuted) by that evidence.

**4.6.4 Resolution and re-evaluation.** For any DA, it is important that justification for that decision is recorded. Allowing the decision maker to record: (a) the outcome; (b) evidence for/against that outcomes; and (c) alternatives that were not chosen and why; is important for both decision resolution and also re-evaluation. Note that recording evidence must include evidence that is used by the human decision maker but not available to the DA. Further research is required to determine how to support decision makers when re-evaluating a decision to come up to speed quickly and effectively.

## 5 CONCLUSION

Our friends Bluster and Prudence can both be useful in supporting our decisions, but Prudence puts us in control and is better at helping us weigh up different options. Bluster can be useful; for example, in low stakes decisions or if time is limited; but overall, Bluster does not support our cognitive process as well as Prudence. This paper calls for AI-assisted DAs to follow the lead of Prudence, and it presents a new conceptual framework of machine-in-the-loop DAs. We call this conceptual framework evaluative AI.

However, evaluative AI is not a panacea for DAs. Our friend Prudence makes us do more work, which people prefer to avoid [19], so we may find that participants prefer less work, but with worse results Bućinca et al. [1]. This is a side effect of having people cognitively engage with decisions; however, one that we may need to accept if we want to truly improve AI-assisted decision support.

We conclude by repeating that the current paradigm of explainable AI as justified recommendations is 'dead'. But the new paradigm that includes hypothesis-driven explainability could take the throne, so long live explainable AI!

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