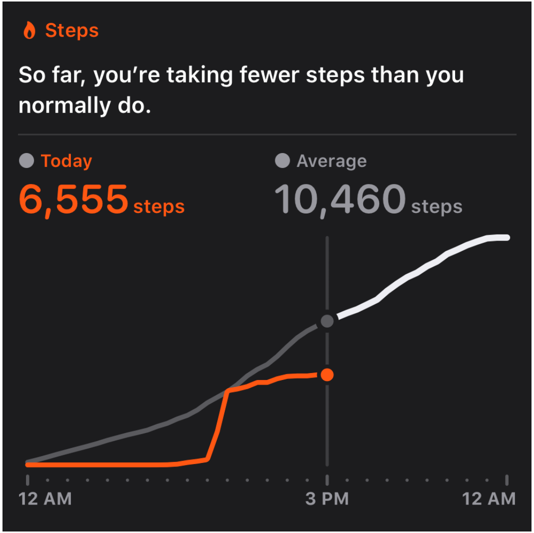
Frustrations of reductive systems



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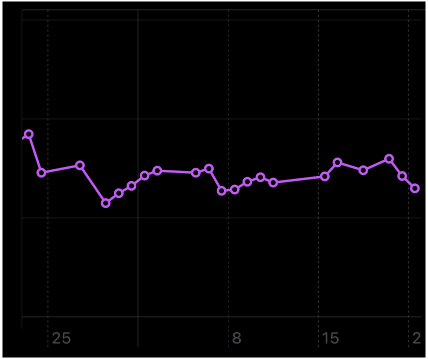

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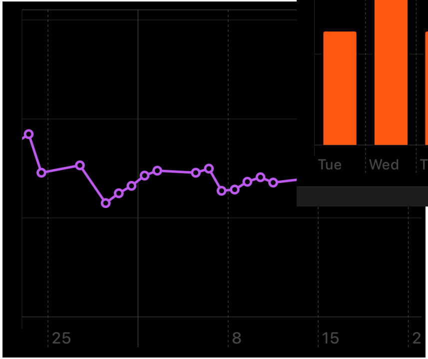

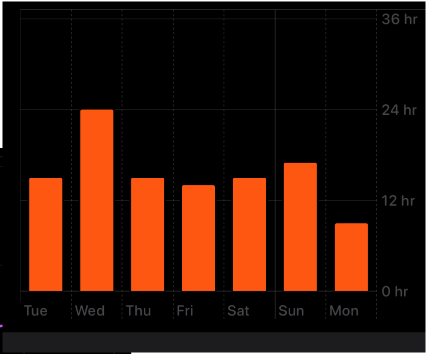

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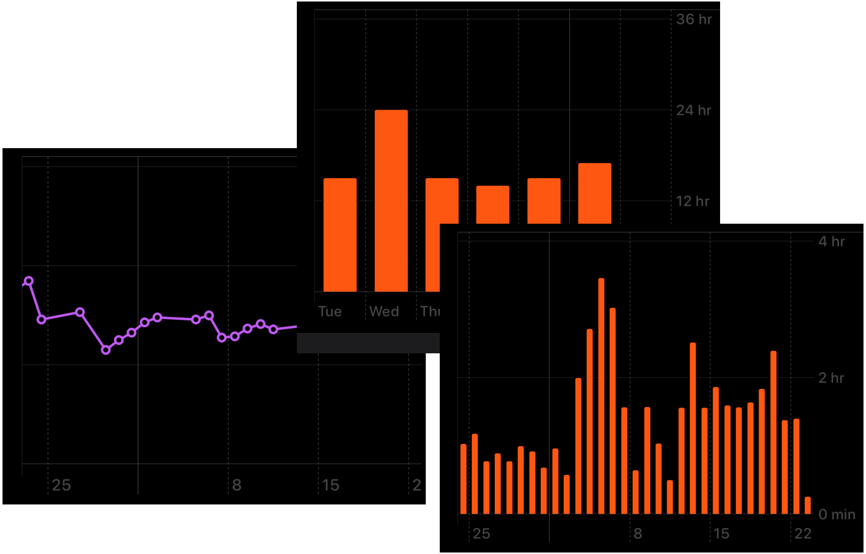

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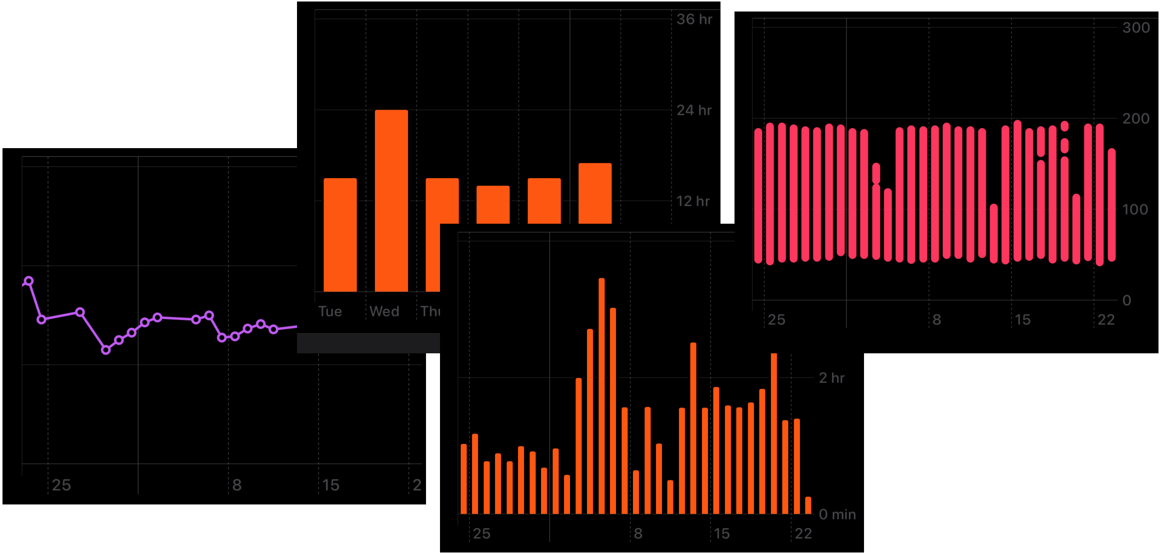

Emotion Regulation for Frustrating Driving Contexts

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ABSTRACT
Driving is a challenging task because of the physical, attentional, and emotional demands. When drivers become frustrated by events their negative emotional state can escalate dangerously. This study examines behavioral and attitudinal effects of cognitively reframing frustrating events. Participants (N = 36) were asked to navigate a challenging driving course that included frustrating events such as long lights and being cut-off. Drivers were randomly assigned to three conditions. After encountering a frustrating event, drivers in a *reappraisal-down* condition heard voice prompts that reappraised the event in an effort to deflate negative reactions. Drivers in the second group, *reappraisal-up,* heard voice prompts that brought attention to the negative actions of vehicles and pedestrians. Drivers in a *silent* condition drove without hearing any voice

if their emotional state is known [9], near-term solutions should use available knowledge of the road to anticipate driver frustrations.

Emotion Regulation

The field of psychology provides a significant body of work to aid in addressing negative emotions and promoting healthier states. The process model of emotion regulation [3, 5] posits that emotions may be regulated at one of five points during the time course of emotion: selection of the situation; modification of the situation; deployment of attention; change of cognitions; and modulation of the response. If we aim to improve frustration during everyday circumstances, not all of these stages are feasible points for an intervention.

Considering the selection of the situation, drivers can

Emotion Regu

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Using Time and Space Efficiently in Driverless Cars: Findings of a Co-Design Study

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ABSTRACT
The alternative use of travel time is one of the widely discussed benefits of driverless cars. We therefore

Design Study. In *2019 CHI Conference on Human Factors in Computing Systems Proceedings (CHI 2019), May 4–9, 2019, Glasgow, Scotland, UK.* ACM, New York, NY, USA. Paper 405, **11** pages. https://doi.org/10.1145/3290607.3300635 1234567890


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Unremarkable AI: Fitting Intelligent Decision Support into Critical, Clinical Decision-Making Processes

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ABSTRACT

Clinical decision support tools (DST) promise improved healthcare outcomes by offering data-driven insights. While effective in lab settings, almost all DSTs have failed in practice. Empirical research diagnosed poor contextual fit as the cause. This paper describes the design and field evaluation of a radically new form of DST. It automatically generates slides for clinicians' decision meetings with subtly embedded machine prognostics. This design took inspiration from the notion of *Unremarkable Computing*, that by augmenting the users' routines technology/AI can have significant importance for the users yet remain unobtrusive. Our field evaluation suggests clinicians are more likely to encounter and embrace such a DST. Drawing on their responses, we discuss the importance and intricacies of finding the right level of unremarkableness in DST design, and share lessons learned in prototyping critical AI systems as a situated experience.

CCS CONCEPTS

• **Human-centered computing** → *User centered design*;

KEYWORDS

Decision Support Systems, Healthcare, User Experience

1 INTRODUCTION

The idea of leveraging machine intelligence in healthcare in the form of decision support tools (DSTs) has fascinated healthcare and AI researchers for decades. These tools often promise insights on patient diagnosis, treatment options, and likely prognosis. With the adoption of electronic medical records and the explosive technical advances in machine learning (ML) in recent years, now seems a perfect time for DSTs to impact healthcare practice.

Interestingly, almost all these tools have failed when migrating from research labs to clinical practice in the past 30 years [5, 8, 9]. In a review of deployed DSTs, healthcare researchers ranked the lack of HCI considerations as the most likely reason for failure [12, 23]. This includes a lack of consideration for clinicians' workflow and the collaborative nature of clinical work. The interaction design of most clinical decision support tools instead assumes that individual clinicians will recognize when they need help, walk up and use a system that is separate from the electronic health record, and that they want and will trust the system's output.

We are collaborating with biomedical researchers on the design of a DST supporting the decision to implant an artificial heart. The artificial heart, VAD (ventricular assist

Unremarkable AI: Fitting Intelligent Decision Support into Critical, Clinical Decision-Making Processes

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ABSTRACT

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critical AI systems

CCS CONCEPTS

• **Human-centere**

KEYWORDS

Decision Support S

1 INTRODUCTION

The idea of leveraging machine intelligence in healthcare

Will You Accept an Imperfect AI? Exploring Designs for Adjusting End-user Expectations of AI Systems

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The Scheduling Assistant can correctly detect meeting requests about 50% of the time.

The Scheduling Assistant examines each sentence separately and looks for meeting related phrases to

Adjust how aggressive you would want the Scheduling Assistant to be in detecting meetings in your emails:


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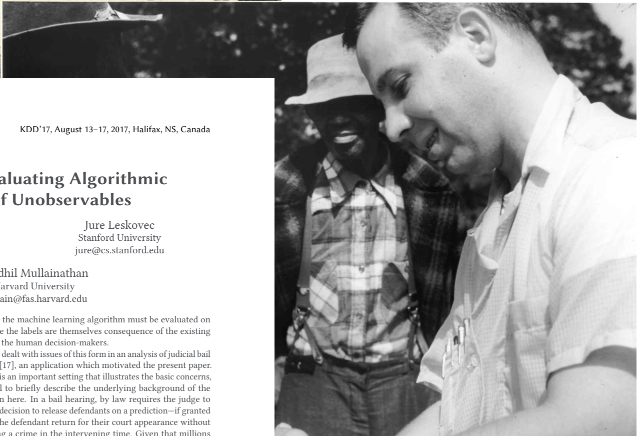

The Selective Labels Problem: Evaluating Algorithmic Predictions in the Presence of Unobservables

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ABSTRACT

Evaluating whether machines improve on human performance is one of the central questions of machine learning. However, there are many domains where the data is *selectively labeled* in the sense that the observed outcomes are themselves a consequence of the existing choices of the human decision-makers. For instance, in the context of judicial bail decisions, we observe the outcome of whether a defendant fails to return for their court appearance only if the human judge decides to release the defendant on bail. This selective labeling makes it harder to evaluate predictive models

where the the machine learning algorithm must be evaluated on data where the labels are themselves consequence of the existing choices of the human decision-makers.

We first dealt with issues of this form in an analysis of judicial bail decisions [17], an application which motivated the present paper. Since this is an important setting that illustrates the basic concerns, it is useful to briefly describe the underlying background of the application here. In a bail hearing, by law requires the judge to base their decision to release defendants on a prediction—if granted bail, will the defendant return for their court appearance without

The Selective Labels Problem: Evaluating Algorithmic Predictions in the Presence (

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ABSTRACT

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Human Perceptions of Fairness in Algorithmic Decision Making: A Case Study of Criminal Risk Prediction

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ABSTRACT

ACM Reference Format:


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TOWARDS “THIN DESCRIPTION”

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> *[Thin description is] about how we all travel …through the thicket of time and space*

– Jackson Jr 2013

TOWARDS "THIN DESCRIPTION"

> *[Thin description is] about how we all travel …through the thicket of time and space*

– Jackson Jr 2013

> *[Thinness is] a methodological counterpoint to the hubris that animates so much tech development.*

– Benjamin 2019

We pass through so many systems, and ecologies, and environments, just like all the life of the forests scientists nearly destroyed

We pass through so many systems, and ecologies, and environments, just like all the life of the forests scientists nearly destroyed

It would be impossible, and hubris, to try to capture and quantify all of that