CAREER: Behavior-Informed Machine Learning: Improving Robust Learning and Decision Support

1 Introduction

Machine learning (ML) has seamlessly integrated into various facets of humans' everyday life, largely drawing from human data for its training. Consequently, these ML systems often exhibit and reflect human behavioral biases, leading to a host of concerns. A notable example is Microsoft's chatbot, Tay, which was designed to learn from conversations with Twitter users. However, it had to be deactivated within just 16 hours due to its unanticipated adoption of offensive language, a direct consequence of failing to account for human behaviors [81, 142]. Similarly, ML models on social media platforms that recommend content to users can inadvertently create echo chambers due to the confirmation bias in user behavior [96, 99, 11]. ML models trained on data generated by doctor annotations might recommend unnecessary treatments due to doctors' action bias towards treating diseases, even when the best course of action might be to wait and observe [36, 94, 128]. Autonomous vehicles designed by learning from human driving behavior could adopt dangerous patterns from aggressive or unsafe drivers [29]. Large language models (LLMs), trained on large corpus of human data, have shown to exhibit human-like behavioral biases [41, 24].

While these examples underscore the pressing need to factor in human behavior when developing ML systems, current ML methodologies mostly either view humans as independent, stochastic data sources [26, 141, 106, 147] or assume that humans are *rational* decision-makers [137, 19, 18, 49, 69, 7], despite the substantial evidence from psychological studies indicating that human behavior frequently deviates from these models [131, 64, 133, 63, 66, 65]. Such discrepancies highlight the existing gap in incorporating empirically-grounded human behavior insights from psychology into the design of ML systems.

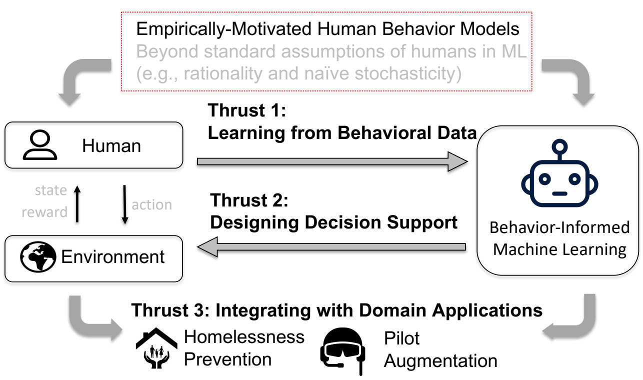


Figure 1: CAREER research plan.

This CAREER project proposes the development of a framework for *behavior-informed machine learning*, which examines and incorporates the impacts of human behavior into the design of ML systems. Specifically, I focus on two key aspects of human behavior in the ML lifecycle: (1) The generation of data used for training machine learning models, and (2) human decision-making in tandem with machine assistance. The proposed research aims to devise ML systems resilient to biased training data and create assistive ML to augment human decision making. In addition to theoretical contributions, through collaborating with domain experts, the research will be adapted to domain applications to ensure the practical relevance and research impact. In more detail, I will investigate the following three research thrusts:

- **Thrust 1: Developing foundations for learning from human behavioral data.**
  Learning from human demonstrations has been extensively studied in weakly supervised learning [14, 88, 110], truth inference in crowdsourcing [106, 25, 141, 26, 147], and inverse reinforcement learning [89, 148, 103]. In these studies, humans are mostly assumed to be either rational or naively stochastic. deviating from actual human behavior and leading to potentially biased learning. This thrust aims to explicitly incorporate empirically motivated human models to develop computationally practical, theoretically sound, and empirically grounded foundations for learning from behavioral data.
- **Thrust 2: Designing assistive ML to improve human decision making.**
  As ML capabilities continue to expand, there is an increasing need to understand how it can help humans

make better decisions, especially in high-stake or ethically-sensitive domains where humans are still desired to be the final decision makers. In this thrust, I aim to develop assistive ML frameworks to enhance human decision making that take into account human behavior. I will investigate when and what assistance ML should should provide through algorithmic, data-driven, and learning approaches. Furthermore, I will conduct behavioral experiments to understand human trust and reliance on ML and design information and explanations to improve the effectiveness of ML assistance.

- **Thrust 3: Integrating with domain applications.**
  While the main focus of this CAREER plan is to develop a general framework for behavior-informed ML, I will also collaborate with domain experts to tackle practical challenges in deploying this framework in domain applications. Specifically, the proposed research will be adapted for use in the domains of homelessness prevention (in collaboration with Prof. Patrick Fowler) and flight pilot augmentation (in collaboration with Boeing). This approach ensures that our research findings are robust and practically applicable in domain applications, promoting their widespread adoption and potential for impact.

Long-term Goal. My career goal is to develop the foundations for humans and ML to collaborate together and solve problems neither can solve alone. This requires the advancements of ML, the understanding of humans, and the utilization of their interactions. This research proposal serves as a stepping stone to achieving this goal by designing learning algorithms that are robust to human behavior during data generation, and investigating the design of assistive ML to augment humans in making better decisions.

Intellectual Merit. This proposal offers intellectual contributions in several key areas. It sets theoretical foundations for integrating empirically-informed human models into ML design, enhancing human-machine interaction insights. It further deepens the empirical understanding of human interactions with ML, establishing groundwork for future ML projects with human involvement. The proposal also presents a framework weaving generative AI into learning, a direction likely to grow in importance. This research seamlessly merges principles from machine learning, algorithmic economics, and online behavioral social science.

PI Qualifications. The PI has extensive research experience in studying the interactions between humans and ML, using techniques drawn from ML, algorithmic economics, optimization, and online behavioral social science. From the perspective of learning from humans, the PI has explored the problem of eliciting and learning from noisy human-generated data [50, 53, 5, 57, 51, 124, 122, 32, 33] and designing incentives to encourage high-quality data [52, 54, 58, 79]. From the perspective of designing ML to assist humans, the PI's recent works explored the design of when and what assistance to provide to humans using techniques from information design and environment design [144, 123, 40, 28]. The PI also investigated ethical considerations in leveraging ML in decision making [125, 126, 86, 87]. Beyond theoretical and algorithmic studies, the PI has experiences in conducting large-scale online behavioral experiments to understand human behavior in computational environments [55, 124, 32, 33, 126, 144, 86, 87]. The PI's involvement extends into the broader research community. The PI served as the Doctoral Consortium Co-Chair and Works-in-Progress and Demonstration Co-Chair of HCOMP (in 2022 and 2019, respectively), the premier conference in the study of human computation. The PI has also organized workshops at NeurIPS and HCOMP to explore the interactions between humans and machine learning, and served as the area chair, senior program committee, and program committee in major AI/ML conferences.

2 Background

This proposal aims to integrate realistic human decision-making processes into the design of machine learning systems. While the proposed methodologies apply more broadly, the primary focus is in the context of sequential decision making in this proposal. As a groundwork for this discussion, we start with a concise introduction to a classical decision-making framework along with associated ML frameworks. We then summarize widely recognized human behavioral models, drawing from behavioral economics and psychology.

2.1 Decision Making Framework in Machine Learning

We first review Markov decision process (MDP), the classical sequential decision-making framework that serves as the foundation of the proposed research.

Markov decision process (MDP). Markov decision process (MDP) is one of the most standard frameworks for modeling the sequential decision-making environment in ML. An MDP can be characterized by the tuple $\langle S, A, T, R \rangle$, where

- State space S: characterizes the environment a sequential decision maker is interacting with.
- Action space A: actions the decision maker can chose from at each step.
- State transition function $T(s'|s,a)$: characterizes how decision maker's actions change the environment.
- Reward function $R_a(s,s')$: describes the benefits of taking each action.

Reinforcement learning (RL). The standard approach to solve the above MDP and obtain an optimal policy is through reinforcement learning (RL) [61, 121, 83, 84]. The RL agent interacts with an unknown environment and attempts to maximize the total of its collected reward. At each time t, the agent in state $s_t \in \mathcal{S}$ takes an action $a_t \in A$, which returns a reward $R_{a_t}(s_t, s_{t+1})$, and leads to the next state $s_{t+1} \in S$ according to $T(s'|s,a)$, the probability to state s' from s after taking action a. The goal of RL is to learn a policy $\pi(a|s)$ that maximizes the total time-discounted rewards $\mathbb{E}_\pi[\sum_t \gamma^t R_{a_t}(s_t, s_{t+1})|\pi]$, where $\gamma \in (0,1]$ is a discount factor ($\gamma = 1$ indicates an undiscounted MDP). RL has a long history of development, from the seminal Q-learning [139], to more recent deep learning aided approaches [77, 83, 84].

Inverse reinforcement learning (IRL). Inverse reinforcement learning tackles the problem of inferring the reward R from observing the sequence of (s_t, a_t), assuming the observed actions are taken by *rational* decision makers. This problem has also been referred to as apprenticeship learning, or learning by watching, imitation learning etc. Ng et al. [89] is among the first to formalize this problem. The high-level idea is to find a feasible function $R(\cdot)$ such that a_t is the action maximizes the utility at s_t for all (s_t, a_t) pairs, and impose smoothness constraints on each step's predicted policy to formulate a linear programming problem. Follow-up works [4, 148, 103] have focused on variants of the optimization formulation. The common assumption in IRL is that the demonstrations (s_t, a_t) are from unbiased and optimal decision makers.

2.2 Empirically Motivated Human Behavioral Models

While existing approaches to incorporating humans in ML often either treat humans as stochastic data sources or assume humans are *rational* decision-makers, they do not always capture human behavior empirically observed in the field. In this CAREER plan, we aim to incorporate empirically grounded human models into the design of ML. While the proposed research is applicable to general human models (including data-driven forms), to make the discussion more concrete, we summarize and provide formulations of some notable classes of human behavioral models in the literature of economics and psychology.

Biased reward evaluation. While it is commonly assumed that humans are rational, taking actions to maximize their expected utility (the expected utility theory [137]), humans are consistent observed to deviate from the assumption. For example, humans often over-estimate small probabilities and react more strongly to losses than gains. The most important theory that summarizes these systematic biases is the Nobel-winning *prospect theory* [62]. Another commonly used theory, also Nobel-winning, is the discrete choice model [82, 115, 129], accounting for the inherent randomness of human decision making by incorporating noises in the utility. These deviations from standard rational assumption can often be captured with humans' biased reward evaluations. Formally, let $(p_1, x_1, ..., p_K, x_K)$ be the *prospect* of an action, where p_k represents the probability of the outcome x_k happens after taking the action. Let $v(x_k)$ represent the utility of the outcome x_k. The above theories can be summarized below:

- Expected utility theory: It predicts that humans will take the action that maximizes $\sum_{k=1}^K p_k v(x_k)$.

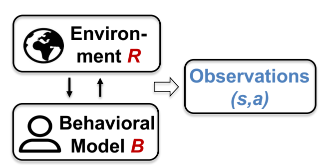
- Prospect theory: It predicts that humans will take the action that maximizes $\sum_{k=1}^{K} \pi(p_k)u(v(x_k))$, where $\pi(\cdot)$ and $u(\cdot)$ models the humans' distorted interpretations on the probability and utility measure.
- Discrete choice model: It predicts that humans will take the action that maximizes $\sum_{k=1}^{K} p_k v(x_k) + \epsilon$, where ϵ is the additional noise term that incorporates the intrinsic randomness of human decision making.

Selected information processing. Humans tend to prioritize certain types of information while neglecting others, leading to decision biases. For example, confirmation bias [92, 68] describes humans' tendency to prioritize information agreeing with their existing beliefs. People exhibiting herding bias [12, 16] prioritize information aligns with the majority. Anchoring biases [132, 44] describe humans' tendency in prioritizing the initial piece of information they receive. These biases can be formulated by addressing how humans form their subjective beliefs. Let e be the event of interest and I be the provided information. Traditional models assume humans are Bayesian, forming their posterior following the Bayes rule $P(e|I) = P(I|e)P(e)/P(I)$. One way for formulate these biases [105] is through modeling humans' belief updating as $P(e|I) \propto P(I|e)^{\alpha} P(e)^{\beta} P(I)^{\gamma}$ and choosing the values of (α, β, γ) to reflect humans' different weights in different pieces of information during decision making.

Time-inconsistent planning. Humans often cannot reason about future rewards in a consistent manner. For example, humans might be myopic or boundedly rational, failing to properly reason about future rewards due to cognitive and information limitations. Humans might also inherit time-inconsistent reasoning behavior. For example, when choosing between earning \$10 in 100 days or \$12 dollars in 101 days, most people will choose the latter. However, when choosing between earning \$10 now or \$12 tomorrow, many people will change their decisions to the former. This example illustrates *present bias* [100], an common example of humans' time-inconsistent panning. These time-inconsistent biases can be modeled by introducing a *discounting function* $d(t)$ that captures humans' behavior in weighing future rewards. Let R_t denote the expected reward at time t, human's perceptions of the long-term rewards can be modeled as $\sum_t d(t)R_t$. For example, the standard model often set $d(t) = \gamma^t$ with $\gamma \in (0, 1]$. To model myopic or bounded rationality, we can set $d(t) = \gamma^t$ for all $0 \le t \le \tau$, and $d(t) = 0$ for all $t > \tau$. For present bias, one common model is hyperbolic discounting: $d(t) = \frac{1}{1+kt}$ for some pre-specified $k > 0$.

3 Proposed Research

3.1 Thrust 1: Developing Foundations for Learning from Behavioral Data



This thrust aims to develop computationally practical, theoretically sound, and empirically grounded foundations to learn from behavioral data. In this learning setup, we have access to the observations (s_t, a_t), indicating human action a_t at state s_t, arising from the *interactions* between humans $\mathcal{B}$ and the environment R.[1] The interactive nature of this setup poses challenges for learning: Computationally, the learning problem has to address a substantially larger learning space. Theoretically, there could exist scenarios where learning is infeasible. For example, humans tend to choose actions with higher empirical rewards, which results in datasets with excessive *exploitation* and insufficient *exploration*. Such imbalance could be exacerbated by human biases, like herding bias that attributes higher perceived utility to options chosen more frequently (i.e., rich-get-richer effect). These scenarios might yield datasets that fail to provide a representative distribution necessary for learning, as illustrated in my prior work [122]. Moreover, with the advancing strides in generative AI, such as large language models (LLMs), there is an expectation for its deep integration into data generation. This evolution also underscores the urgent need to consider the effects of generative AI when learning from behavioral data.

[1] We use $\mathcal{B}$ to represent the general human models and abuse the notation R to represent general environment parameters, not just rewards. The discussion in this thrust also applies to (a simpler setting of) supervised learning, where we observe the feature-label pairs generated by humans $\{(x_n, y_n)\}_{n=1}^{N}$ and aim to undercover the latent mapping from features to labels.

To address these challenges, this thrust will start with learning from human behavioral data. We aim to establish provable and practical methodologies for jointly inferring $\mathcal{B}$ and R from human behavioral data (**Task 1.1**). In collaboration with psychology researchers, I will conduct human-subject experiments to deepen our understanding of human behavior in contexts where ML is integrated into the decision-making processes (**Task 1.2**). Lastly, I will turn our attention to the role of generative AI and tackle the challenges arising from the growing involvement of generative AI in the data generation process (**Task 1.3**).

Prior work. The proposed activities in this research thrust will be built on the PI's extensive prior work in crowdsourcing [50, 53, 54, 56, 57, 79, 124, 32, 33], where one key research theme is to infer ground truths from noisy human data. I will extend the standard models assuming humans exhibit zero-mean noises to general human behavioral models. The PI's recent works on incorporating behavioral models motivated by psychology literature in the learning frameworks [122, 144, 40] and the experience in conducting human-subject experiments [56, 124, 32, 33, 87] will be the building blocks of the proposed research.

3.1.1 Task 1.1: Developing provable and practical algorithms to learn from behavioral data

This task aims to develop computationally practical and theoretically sound algorithms to learn from behavioral data. I aim to theoretically characterize the conditions that make learning feasible, devise computationally efficient algorithms, and implement strategies during data collection to enable efficient learning.

Theoretically characterizing conditions for feasible learning. My prior work [122] showed that there exist scenarios in which learning from behavioral data is infeasible even with infinitely many data observations. Therefore, the first goal is to theoretically characterize the conditions that facilitate feasible learning. I propose to employ techniques from stochastic approximation [108, 43], modeling the state realizations over time as a random variable that results from the interactions between human behavior and the environment. The intuition is that: If a bijection exists between $(\mathcal{B}, R)$ and the state at convergence (a weaker condition might be sufficient), we can infer $(\mathcal{B}, R)$ from the converged state, indicating the feasibility of learning. Therefore, by analyzing the convergence and convergence rate of the state trajectory, we can characterize the conditions for the feasibility and complexity of learning. After the characterization, I will also examine the *robustness* of our results. In particular, since no models can perfectly capture human behavior, I will quantify how the inaccuracies in human models propagates to errors in learning through sensitivity analysis.

Designing computationally efficient algorithms. Even when learning is feasible, we still need to confront computational challenges due to a larger learning space. To tackle this, I plan to adopt, examine, and compare several approaches. First, I will presume partial access to true environment parameters R_t (e.g., some rewards are known in MDP), e.g., through domain knowledge or historical data, and then implement a two-stage learning process (i.e., infer $\mathcal{B}$ using partial R_t then infer full R with the inferred $\mathcal{B}$). Second, I will impose suitable constraints to reduce the learning space, for instance, by leveraging smoothness constraints or applying domain knowledge on belief models and reward bias models. Lastly, I will resort to sampling and variational techniques, such as Gibbs sampling, to approximate the inference problem.

Taking interventions or increasing diversity during data collection to enable improved learning. One main reason leading to infeasible learning is the human tendency to engage in *exploitation*, which results in under-represented datasets. Based on this observation, I plan to explore methods to increase the amount of *exploration* in behavioral data (i.e., having humans take potentially suboptimal actions to gather information) during the data collection process. First, I will quantify the impact of the exploration amount on learning efficiency through an *epsilon-first* approach [130]. Subsequently, I will aim to reduce the amount of exploration required by strategically deciding when to explore. Second, inspired by recent literature [102] that shows that inherent diversity in the data could render exploration unnecessary in bandit learning, I will examine the relationship between data diversity and the learning efficiency and investigate whether and to what extent increasing diversity in our dataset could facilitate more efficient learning.

3.1.2 Task 1.2: Conducting experiments to understand human behavior in the age of ML

This task focuses on examining real-world human behavior through human-subject experiments. In addition to validating human models and evaluating the proposed approaches, the primary goal of this task is to enhance our understanding of human behavior in settings where ML is pervasively embedded in the decision-making process. In the previous task, I start the investigation by leveraging existing behavioral models from the literature of psychology. Although these models are supported by extensive empirical evidence, they are primarily developed before ML becomes pervasive. Meanwhile, when people become aware that they are interacting with ML, their behavior might differ (e.g., the example with Microsoft Chatbot Tay). My recent work [74] has demonstrated that when humans know their behavior will be used to train ML, they are willing to forgo some rewards to ensure the trained ML is fair. As ML gains more societal attention, it is crucial to examine and understand the shifts in human behavior in the age of ML.

Understand human behavior with the presence of ML. I will conduct behavioral experiments to examine whether and how the presence of ML changes human behavior. The results will improve our understanding of human behavior with the presence of ML. It also serves as an improved foundation for addressing the tasks of learning from human behavioral data. To conduct the research, following the standard literature, I will start by utilizing social games, such as the ultimatum game [93], dictator game [39], prisoner's dilemma [9], to examine human behavior with the presence of ML. These social games provide succinct abstractions of human behavior and interactions in different contexts and are useful as the starting point towards a comprehensive understanding of humans. I will recruit participants from crowdsourcing platforms, e.g., Amazon Mechanical Turk or Prolific, vary the following independent variables in the experiments, and measure human responses as the dependent variables. Standard statistical tests (such as ANOVA and post-hoc t-tests) will be conducted to examine the significance of the observations.

- Whether humans are explicitly interacting with ML. We hypothesis that humans are more likely to care more about ethics (e.g., being fair) when their partners in the game are other humans than ML.
- Whether human decisions will be used to train ML used to play with future players. We hypothesize humans are willing to sacrifice rewards to make the future ML behave in a more *ethical* manner.
- The context of the game, environment, and ML. For example, whether the trained ML will be playing with people they view favorably in the future. Whether the ML training mechanism is known to people.

For the research activities in this task, I will collaborate with Dr. Wouter Kool in the department of Psychology and Brain Sciences at WashU. Dr. Kool and I are currently co-advising a PhD student, Lauren Treiman, with whom we have generated the preliminary result [74] for this task (i.e., varying conditions on ML training in the ultimatum game). The proposed research will enable us to obtain a more comprehensive understanding of human behavior when ML is integrated in all aspects of decision making.

3.1.3 Task 1.3: Incorporating generative AI in learning from behavioral data

The rise of generative AI, such as large language models (LLMs), is significantly reshaping the manner in which we approach and solve problems. In the context of learning from behavioral data, recent research has reported that LLMs outperform human crowd workers in annotating data for certain tasks [46, 37]. Meanwhile, LLMs are also shown to exhibit biases [6, 101, 41, 24]. This task aims to provide a deeper understanding of the *behavior* of generative AI with the aim of account for it in our learning framework.

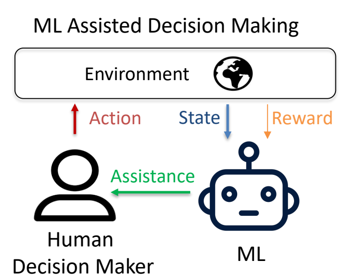
One of the main challenges in understanding generative AI is due to its black-box nature. Related to the growing efforts to address the transparency of generative AI [76], I propose to adopt a behavioral approach, treating generative AI as a behavioral agent, to understand and incorporate its behavior in our learning framework. It is worth noting that given the rapid and ongoing evolution of generative AI, this task signifies a long-term and continuously evolving research agenda. We believe that addressing this is of paramount importance, especially as we approach a potential era where generative AI is ubiquitous

Empirically examine and model the behavior of generative AI. I plan to empirically examine the *behavior* of generative AI. I will begin by characterizing AI behavior using standard human behavioral models, allowing for a direct comparison with human behavior. For instance, our preliminary results suggest that ChatGPT demonstrates human-like behavioral patterns in some tasks, e.g., it reports willingness to sacrifice reward to promote fairness, as seen in our human studies [74]. Considering generative AI is trained on human data, it is both interesting and useful to understand to what extent it mimics human behavioral patterns in different contexts. Moreover, as generative AI might exhibit distinct behavioral characteristics, I plan to develop new models that provide explainable insights into AI's decision-making processes.

Theoretically characterize the capacity of generative AI. Building on our understanding of the behavior of generative AI, I will utilize the theoretical insights from Task 1.1 to assess whether learning is feasible using data from generative AI *alone* in a given task domain. If feasible, it implies that the generative AI has sufficiently encoded the problem domain in its model, potentially suggesting that human involvements might not be needed in solving that specific task. This approach provides a potential venue for us to more formally quantify the capacity of generative AI.

Leveraging both humans and generative AI to achieve efficient learning. In instances where learning is infeasible using solely AI-generated data, I will examine methods to incorporate data from humans to enhance the learning process. I intend to draw from approaches developed in Task 1.1 to refine the data collection process. Specifically, by viewing generative AI as a group of behavioral agents with distinct behavioral patterns, I will investigate which types of supplemental behavioral data from humans are most likely to enable effective learning. This will be guided by our findings on the relationship between *diversity* in the dataset and the efficiency and feasibility of learning.

3.2 Thrust 2: Designing Behavior-Aware Assistive ML to Improve Human Decision-Making



Humans often make suboptimal decisions, especially in complex decision-making environments, and often need to engage in "on-the-job-training," i.e., learn to make better decisions while making these decisions [104, 116, 13]. Conversely, the rapid advancement of ML suggests its potential of enhancing humans' performance and speeding up their learning in decision making settings with ML assistance, as demonstrated by groundbreaking tools like ChatGPT. In this research thrust, our goal is to develop a framework for ML-assistive decision making that takes human behavior into account. The focus is to determine when and what assistance ML should offer, given a limited amount of interventions. In this setup, ML provides recommendations to humans, who then make the final decisions. The objective of ML here is to *augment*, rather than *replace*, humans in the decision-making process.

Designing ML assistance serves dual purposes. First, when deploying ML assistance during human decision making, it augments human decision making, resulting in better outcomes. Second, if we compute the set of ML assistance offline, frequent instances of assistance can pinpoint common errors humans tend to make in the decision-making process. Consequently, these insights not only hold potential as training materials but also carry significant implications for educational practices.

The ML assistance framework. Suppose the human decision maker is solving a decision making problem formulated as an MDP, characterized by the tuple $\langle S, A, T, R \rangle$. Let the human decision-making policy be $\pi_{\mathcal{B}}(a|s)$, representing the probability for the human to choose action a at state s without assistance. The goal of ML is to maximize the total rewards derived from human actions by providing assistance. ML assistance can be *pushed*-based, where ML decides when to assist and push it to humans, or *pull*-based, where ML passively responds to human-initiated requests. We can formulate the differences with $P_{req}(s)$, representing the probability for humans to ask for assistance. For pushed-based assistance, $P_{req}(s) = 1 \;\; \forall s$, and ML decides whether to provide assistance. We will address both cases with known and unknown $P_{req}(s)$.

Let ML's assistance policy be $\rho(a|s)$, the probability for ML to recommend action a at state s, and $\theta(s)$ be the *reliance policy* denoting whether the human adopt ML assistance at state s. We will start by assuming human reliance policy θ is known in task 2.1 and examine θ in task 2.2. Now let $(\pi_{\mathcal{B}} \oplus \rho \oplus \theta \oplus P_{req})(a|s)$ be the final human policy with ML assistance, determined by $\pi_{\mathcal{B}}, \rho, \theta, P_{req}$ jointly, e.g., $(\pi_{\mathcal{B}} \oplus \rho \oplus \theta \oplus P_{req})(a|s) = (1-\theta(s))\pi_{\mathcal{B}}(a|s) + \theta(s)\rho(a|s)$ for pushed-based ML assistance, the ML's assistance design problem is then to choose the assistance policy $\rho(a|s)$ to maximize the total expected reward within the pre-defined constraints of ML assistance policy. One natural example of the constraint would be to ensure ML does not intervene human decision-makers too much, i.e., the distance $D(\pi_{\mathcal{B}}, \rho)$ between human policy and ML policy is small for some distance measure D.

Prior work. The proposed activities in this research thrust are grounded in the PI's extensive prior work. Notably, the problem design aligns with a *Stackelberg game*, where ML initially determines the policy for providing assistance, and humans subsequently decide their course of action based on this assistance. The PI has explored the application of Stackelberg games across various domains, such as contract design [58], learning with strategic responses [127], Bayesian persuasion [28, 126, 40], and environment design [144]. In addition, the PI has substantial expertise in bandit learning [58, 79, 122, 126] and robust learning [127], which serve as technical foundations for addressing the problems of learning and robust design.

3.2.1 Task 2.1: Developing efficient approaches for designing ML assistance

This task aims to design ML assistance policy that accounts for human behavior. I will start with *low-complexity* environments, where the optimal decision policy is algorithmically derivable (e.g., through value iteration), and known human models. Since the design of assistance policy needs to account for human responses to given assistance, the assistance design problem leads to a computationally challenging *bi-level* optimization problem. I will first propose algorithms to identify the optimal assistance policy. I will then relax the low-complexity environment and known human model assumptions, proposing data-driven approaches for *high-complexity* environments and developing bandit approaches for unknown human models.

Algorithmic approaches. I will start with low-complexity environments. Consider the standard rational human assumption, i.e., choosing the action with the highest utility with probability 1. When putting this decision function back to the design of ML assistance, the objective is non-continuous and the problem is NP-hard to solve as shown in my prior work [144]. On the other hand, when we consider the discrete choice model, i.e., the decision function is in the form of a continuous softmax function. With this human model, the objective of the optimization problem is continuously differentiable, and first-order optimization techniques might be applied. The above discussion highlights the need to understand how different human models impact the design of ML assistance and my proposed approaches: (1) When the human decision models are differentiable (e.g., discrete choice model), I will leverage first-order optimization methods and characterize the computational complexity and convergence to the optimal solution with different human models. (2) When the human models are not differentiable (e.g, expected utility theory), I plan to utilize the techniques from algorithmic information design [34, 38, 10] (including my own work [28, 40]). This approach utilizes the duality theory to characterize the properties of the optimal solution, which could help identify conditions for computationally feasible solutions to exist. I will also utilize techniques such as soft-max relaxations to derive approximation algorithms in the case that when the optimization is NP-hard.

Data-driven approaches. For high-complexity environments and known human models, I propose to leverage data-driven approaches to design ML assistance. I will extend the self-play [113, 27, 145] that optimizes decision policy in MDP to incorporate human models to optimize ML assistance. Specifically, I propose a neural-network-based structure that consists of two modules: the ML's optimization module and the human models. The ML's optimization follows the traditional neural-network-based structure, taking the details of a problem instance as input and outputs an assistance policy. The main difference compared with prior work is that we have incorporated human models, either in an analytical closed-form or a data-driven form in the optimization structure. The human models are treated as a black box for the ML's optimization module and is fixed before we begin training. Given the assistance policy output by the ML's optimization module, we can compute the *loss* (the inverse of the reward of applying the assistance policy) by applying the assistance policy with the human models in the environment. For optimizing the assistance policy, I'll adopt the approach of using deep learning for optimization [35, 97]: Draw problem instances from a pre-specified distribution and perform stochastic gradient descent to minimize the loss function (applying soft-max approximation for non-differentiable objectives). I will examine the empirical performance of this neural-network based approach with different settings of human models, environments, and instance distributions.

Bandit learning approaches for unknown human models. While the above optimization architecture is general and powerful, it requires us to estimate the *loss* for the assistance policy in each iteration. In settings where the human models are unknown, we won't be able to infer the final human decisions to obtain an accurate loss estimation. To address this, I consider the setting in which the ML can sequentially interact with human decision makers in the environment, observe their responses, and adaptively update the assistance policy over time. This leads to an *online learning* setting in which we need to address the classical trade-off between exploitation (choosing policy with the highest estimated payoff) and exploration (choosing policy with uncertain payoff to obtain information), which can be formulated as a multi-armed bandit problem [73, 8, 20]. I plan to explore the usage of bandits in this setting. The main challenge is that the space of arms (i.e., the space of assistive policies) is large/infinite and could require too many explorations for bandit algorithms to be useful. To explore this challenge, I plan to adopt the technique in my prior work on leveraging the similarities between arms in bandit learning [58]. The key intuition is that, if two policies lead to similar payoffs, they are considered "similar" arms, and we propagate the information we learned on one policy to other similar policies to achieve efficient learning. To quantify the arm similarity, I plan to leverage domain knowledge to characterize the problem structure (e.g., abstracting key properties of human models and environment states) to reduce the problem space. Our goal is to identify conditions for bandit approaches to work and develop corresponding algorithms.

3.2.2 Task 2.2: Understanding human reliance on ML assistance with human-subject experiments

This task aims to conduct investigations of humans' reliance on ML assistance in the setting with sequential decision making. The previous task has assumed that human reliance on ML assistance, $\theta(s)$, is known and given. However, in practice, appropriately formulating $\theta(s)$ is not trivial and not well understood. While there has been a growing line of literature in understanding humans' trust and reliance on ML [143, 80, 107, 146, 78, 136], including my own work [87], existing studies mostly focus on the one-shot decision making scenarios, and limited is known about humans' reliance on ML assistance in sequential decision making.

Empirically examining human reliance on ML assistance. In collaboration with Dr. Ming Yin, a leading expert in human trust and reliance, I will conduct randomized human-subject studies to understand how humans' reliance on ML is influenced by various factors under the sequential decision making setting. In particular, consistent with theoretical models previously proposed for human-automation interaction [59, 109], I expect humans' adoption of ML advice under sequential decision making settings can be influenced by factors related to *humans*, *ML*, and the *environment*. I will conduct experiments to understand:

- How factors related to ML, including the presentation format of ML recommendations, the provision of ML explanations, and the human-likeness of ML, influence humans' adoptions of ML advice?
- How factors related to the decision making environment, including the variability and complexity of the environment, influence humans' adoptions of ML advice?
- How factors related to humans, including their risk attitudes, their value similarity with ML, and their subjective perceptions of ML trustworthiness, influence humans' adoptions of ML advice?

General experimental designs. For each human-subject experiment, I will start by designing experiment that only a single independent variable varies. That is, different experimental treatments will be created corresponding to different "levels" of the independent variable (e.g., timing of ML recommendations, type of ML explanations, human-likeness of the ML policy). For dependent variables, I will record whether human participants decide to rely on the ML's decision recommendations to estimate $\theta(s)$, as well as their final decision making performance. In addition, to align with the AI trust literature, I will ask human participants to self-report their perceived trust level in the ML agent both at a fixed interval (e.g., after every 5 decisions are made) and at the end of the experiment. I will also have the human participants complete a two-phase experiment, in which they make sequential decisions in the first phase with the assistance of the ML agent, while they make sequential decisions on their own in the second phase, and we can record their decision making performance in the second phase to understand if human decision makers can effectively learn from the ML agent in the first phase. After collecting the measurements on all the dependent variables, we can conduct statistical tests across treatments to examine if the independent variable varied in the experiment affects decision makers' adoption of ML advice and subjective trust on ML, sequential decision making performance, and learning outcome. Moreover, additional experiment can be carried out to vary multiple independent variables simultaneously, which will allow us to understand how they interact with one another to affect the dependent variables of interests.

3.2.3 Task 2.3: Designing explanations to accompany ML assistance

In our framework, ML aims to identify when and what assistance to provide to human decision-makers, through recommending an action to take. While this presents a general form of ML-assisted decision-making paradigm [144, 13, 21], in practice, it is often desirable for ML to provide additional explanations to human decision makers. For example, ML might recommend actions that leads to lower immediate payoff but higher future payoffs (e.g., recommend to make effort to exercise now for long-term health benefits), and without knowing the rationale of the ML assistance policy, humans might not trust the assistance provided by ML and render the ML assistance useful.

Promoting human trust through designing explanations for the assistance policy. This task aims to design explanations to promote user trust in the assistance policy. I will utilize the techniques from the explainable AI planning (XAIP) literature [90, 91, 134]. In XAIP, the typical goal is to explain to a user why a particular plan is feasible or optimal. In contrast, our goal is to explain why the assistance policy has particular *trustworthy* characteristics, leveraging our empirical results in Task 2.2. To compute the explanations, we will leverage probabilistic logical inference methods [135] to address the following challenges: 1) providing explanations at varying levels of abstractions for users with different levels of expertise, 2) learning user models to customize explanations, and 3) combining model reconciliation [23, 22, 118, 119] and contrastive explanation [48, 67, 111] approaches, where explanations that reconcile the two models explain the foils provided by users. We evaluating the efficacy of different explanations through measuring users' perceived trust and realized reliance in ML assistance.

3.3 Thrust 3: Integrating with Domain Applications

In research thrusts 1 and 2, the goal is to develop a framework for behavior-informed machine learning, incorporating human behavior in the design of ML systems. While the framework is intended to be general, deploying the framework in specific domain applications may introduce various domain-specific challenges. For instance, when allocating scarce societal resources for homelessness prevention, it is important not only to maximize the effectiveness of these resources but also to ensure that the allocation of resources is *fair and equitable* across different social groups. When designing decision support systems for airplane pilots, in addition to maintaining decision efficiency, *safety* is of the utmost importance.

In this thrust, I aim to collaborate with domain experts to tackle practical challenges when deploying this framework in domain applications. In particular, the proposed research will be tailored for use in the domains of homelessness prevention (with Prof. Patrick Fowler at the Brown School of Social Work) and flight pilot augmentation (with Boeing). In the long term, I plan to harness the interdisciplinary efforts at WashU to expand this research into other application domains, including the Division of Computational and Data Sciences (DCDS), the Center for Collaborative Human-AI Learning and Operation (HALO), and the Transdisciplinary Institute in Applied Data Sciences (TRIADS) at WashU that the PI is an active member in. These cross-disciplinary endeavors will help ensure that our research findings are practically applicable across various domains, thus promoting their adoption and potential for impact.

3.3.1 Task 3.1: Domain application: Data-driven decision support for homelessness prevention

This task extends my existing collaboration with Prof. Patrick Fowler on developing algorithmic solutions to homelessness prevention [31] to the scope of data-driven decision support for homelessness prevention. The problem of homelessness, a longstanding societal issue, presents significant personal and communal repercussions. Local systems dedicated to addressing homelessness often face a scarcity of resources, making it challenging to fulfill the demand for housing support. The current decision-making processes for distributing these limited resources are largely unexplored [17, 42, 112], leaving room for improvement in terms of both efficiency and equity. This opens up two important research directions that align with this CAREER plan: First, we can utilize historical data to understand the impacts of past resource allocation, thereby allowing us to derive insights to optimize future decisions. Secondly, by harnessing the power of ML, we can provide decision support for human decision makers in deciding the resource allocation.

Account for human behavior when learning from past data. There is a growing effort to use data-driven approaches to inform decision-making policies in homelessness prevention [45, 70, 72]. Specifically, Prof. Fowler has been involved in the St. Louis Regional Data Alliance [1], an initiative that aims to curate community data to improve community health, such as reducing homelessness. Building on this effort, Dr. Fowler and I have been co-advising a PhD student, Alex DiChristofano, in conducting preliminary analyses of St. Louis regional data. We have identified two types of human behavior that could inject biases into the data. The first comes from the recipients of resources. In homelessness prevention, when people seek help, they are not immediately assigned resources due to the resource scarcity. Instead, they are placed on a waitlist and only receive resources when resources become available. This waiting process creates unequal *drop-out* rates across social groups, e.g., we found that females are more likely to leave the system before resources become available. Failure to account for this drop-out inequality could lead to biased predictions of resource efficacy. The second type of behavior that needs to be taken into account comes from the parties (e.g., social workers) that decide how to allocate resources. While there are general guidelines in the decision-making policy, the past data largely reflects the decision-makers' judgments. In this task, we aim to identify and incorporate this human behavior during the training of ML based on past data.

Designing decision support. In the decision-making process for allocating resources for homelessness, there isn't a clear right or wrong answer. Social workers often need to balance multiple ethical principles, such as prioritizing outcomes (reducing homelessness) or prioritizing the most vulnerable individuals [71]. When designing decision support systems, we must consider decision-makers' preferences and constraints. In this task, we will work with local homelessness service providers, the St. Louis Area Regional Commission on Homelessness (SLARCH) – a nonprofit organization that coordinates homeless service provision across the St. Louis region. By conducting qualitative surveys and interviews, we aim to gain better insights into their decision-making process, their objectives in decision-making, and the types of decision support needed to inform the design of our assistive ML. Furthermore, we will work with social workers, the decision-makers in the field, recruited through SLARCH, to evaluate and deploy our research.

3.3.2 Task 3.2: Domain application: Decision support for airplane pilots

This task aims to launch our newly initiated collaboration with Boeing in designing decision support for pilot decision-making. In this application domain, safety is of paramount importance, in addition to efficiency. To make the discussion more concrete, we will discuss the design of pilot augmentation to address runway incursions – a significant aspect of runway safety. Runway incursion [2] refers to an incident involving an incorrect presence of an aircraft, vehicle, or person on a runway designated for take-off or landing. In severe cases, runway incursions could lead to tragic events. Given the gravity of this problem, there has been research devoted to avoiding such incursions, including accident prediction [120, 114, 47] and system design to detect obstacles and alert pilots [60, 95, 98, 140]. Meanwhile, the Federal Aviation Administration (FAA) have reported that pilot behavior is involved in 65% of all runway incursions [3]. Therefore, in this task, aligning with this CAREER plan, we plan to adopt a behavior-informed approach in addressing the runway incursion problem. We will examine existing datasets and behavioral data from simulated platforms to identify pilot behavioral patterns in the context of runway incursions. Moreover, we will design decision support that provides interventions to prevent runway incursion events.

Proposed research. For the question of learning from behavioral data, we will leverage two data sources. The first is the public ASRS (Aviation Safety Reporting System) dataset, FAA's voluntary confidential reporting system that accepts confidential reports of near misses or close call events in the interest of improving aviation safety. This public dataset will enable us to identify generic characteristics for runway incursions. We will then leverage the flight simulator X-Plane, that WashU has acquired in the previous collaboration with Boeing, to collect individual behavioral data for identifying personalized behavioral patterns in runway safety. After identifying the behavioral patterns, we will design decision support systems that aim to maximize decision efficiency (e.g., time for departing/landing) while imposing safety constraints. The study will be initially conducted in an academic setting, recruiting general population (e.g., college students) in running the flight simulator. After developing the results, in collaboration with Boeing, the study will be extended to other contexts (e.g., inflight weather encounters, wake turbulence encounters), and the evaluations will conducted with domain experts and real pilots through simulations/surveys.

3.4 Evaluation Plan

The proposed research will span five years. The tasks in Thrust 1 and 2 have been organized in a way that can be performed in a sequential manner. I will perform the tasks in Thrust 3 after we have initial results for the first two thrusts. For the evaluation of the proposed research, there are three main components:

- Algorithm and theory: For task 1.1-1.2 and 2.1-2.2, I will develop new algorithms and theories. To evaluate our results, I will derive the performance guarantees (regret bounds or convergence rate) and analyze the computational complexity of the proposed algorithms. We will perform equilibrium analysis to characterize the human behavior in the equilibrium structure. Simulation will also be performed to evaluate the algorithm performance under the conditions both when users follow our proposed models and when users do not exactly follow to test for robustness of our proposed algorithms.
- Data collection: Task 1.3 and 2.3 involve collecting data using human-subject experiments. With collaborations with experts in psychology and HCI, I will follow the best practice in conducting the experiments, including pre-registering the hypothesis and performing appropriate statistical tests (e.g., ANOVA, post-hoc t-tests, mixed effects model). The collected data will be made publicly available to the research community. I believe the large-scale behavioral data would be of important research value.
- Deployment: For tasks in Thrust 3, I aim to deploy the proposed research in domain applications. In addition to the evaluations above, I will work with domain experts to develop our evaluation plan and solicit feedback of the proposed framework through interviews/surveys.

4 Education Plan

This CAREER proposal aims to leverage the research effort to achieve my long-term education goal: data-driven personalized education. I will disseminate the research outcome to different education levels, including designing a new graduate-level course, engaging undergraduate students in research, and host workshops for high-school teachers and students. Moreover, I will devote effort to broadening research participation.

4.1 Towards Data-Driven Personalized Education: A Behavior-Informed Approach

My long-term vision in education is to develop data-driven methods that enable personalized education, i.e., designing personalized curriculum and assistance that improves individual learning with data-driven approaches. This vision aligns with this CAREER plan on designing ML that learns from human behavioral data and assisting humans. As a starting point to realize this vision, I have started to conduct research in the domain of Chess to develop personalized ML assistant. In collaboration with Kassa Korley [85], who holds the title of International Master and was the youngest African American to earn the title of National Master in the US, we have investigated the question of curriculum design, i.e., what set of moves should be provided to assist Chess players based on their skills, using data-driven approaches. In particular, leveraging the abundant amount of human play data in online Chess platforms (Lichess.org), we have developed ML models that can identify human behavior patterns at different skill levels. We then leveraged both the ideas of designing ML assistance in this proposal and curriculum learning [15, 138, 117] to identify the curriculum most likely to improve players with given skill levels. Our preliminary results, showing that the approaches identify curricula that align with domain knowledge and improve win rate, holds potential in designing personalized tool to improve human learning in Chess. We have recently obtained WashU IRB approval to recruit chess players to examine the effectiveness of our approaches in practice.

I will also collaborate with Prof. Dennis Barbour, through co-advising a PhD student, Robert Kasumba, to extend the approach to mathematical education. Prof. Barbour has employed data-driven approaches to explore the connection between students' mathematical learning skills and general executive function skills, such as cognitive flexibility, working memory, and inhibitory/attentional control. The goal of this collaboration is to improve personalized education in the setting of improving students' mathematical skills.

4.2 Course and Teaching Development

The research goal of the PI is to combine the strengths of both humans and machine learning (ML) to solve tasks neither can solve alone. To achieve this goal, we need to advance our understanding of ML, humans, and the interactions between them. Correspondingly, the education goal of the PI is to prepare students on these fronts. The PI plans to introduce a new graduate-level course *Human-AI Interaction and Collaboration*. In addition to the general coverage of ML and human modeling (from behavioral economics, psychology, and HCI), there will be two main themes for the course topics. First. we will cover and discuss human-in-the-loop machine learning, addressing the techniques of incorporating humans in the learning process to advance machine learning. Second, we will discuss topics with a human-centered focus, including how humans process information from ML (such as interpretability, trustworthiness, and topics explores in this proposal) and how ML impacts human welfare (such as fairness, privacy, and ethical concerns). We will also include practical domain applications in social sciences and healthcare in the course materials (in the form of assignments, projects, or guest lectures) by leveraging the Division of Computational and Data Science (DCDS) and the Center for Collaborative Human-AI Learning and Operation (HALO) at WashU.

4.3 Outreach to High-School Teachers and Students.

The PI will work with the Institute for School Partnership (ISP) at WashU to design outreach activities. The goal is to provide professional developments for high-school teachers and broaden the dissemination of research ideas, and to cultivate next-generation scientists/engineers through exposing high-school students to academic research and stimulating their interests in computing. In particular, we will work with the ISP for the *Teacher-Researcher Partnership*, under which teachers work in the faculty's lab for 4-6 weeks in the summer, with the goal of learning and translating research ideas into lessons at grade level. We plan to host one teacher in each of the first two summers. Based on the partnership outcomes, we will participate in the *Hot Topic Series* at ISP and invite around 20 high-school teachers to disseminate the curriculum design to maximize the potential outreach.

The PI will also join force with existing efforts at the McKelvey School of Engineering, which has conducted a summer camp in Summer 2022 for local high school students of low-income backgrounds. This summer camp is planned to become an annual event. The PI will annually host a one-day summer workshop "Human-Centered Machine Learning" within this framework. The workshop will include a broad overview of machine learning and human behavior and engage students in group projects guided by Ph.D. students. We will prepare datasets and ML modules for students to explore the impact of human behavior in the design of ML, both for how human behavior leads to learning (how biased dataset leads to biased learning outcome) and how ML can assist humans in overcoming biases.

4.4 Engaging Underrepresented and Undergraduate Students

The PI is committed to recruiting female and underrepresented minority (URM) students. The PI is currently advising 5 PhD students, with one female and one African American. The PI has also worked with 6 female and URM undergraduate/master students (out of 13 students that worked with the PI) at WashU so far. Among the 6 students, four have continued their graduate studies after graduation (at Stanford, Duke, Penn State, and Cornell), one went to the industry (at Google), and one is still in the undergraudate program. The PI will leverage the institutional effort for engaging female and URM students. In particular, WashU is committed to the goal of increasing the representation of women at the Ph.D. level. The CSE department, the McKelvey School of Engineering, and the Provost's Office of Diversity together fund a Platinum Sponsorship of Grace Hopper. Through WashU Summer Engineering Fellowship (WUSEF), which provides funds for students from backgrounds underrepresented in the STEM fields to perform summer research, the PI has advised one URM undergraduate student. In addition to working with WUSEF each summer, the PI will work with the Missouri Louis Stokes Alliance for Minority Participation (MOLSAMP), of which WashU is a participating institution, for offering summer research opportunities for minority participation.

Undergraduate students will be heavily engaged in the proposed research. The PI has been actively involved in the NSF REU site "Big Data Analytics" at WashU. The students the PI advised at the REU site have all continued their gradudate studies in the Computer Science field (at UT Austin, Duke, CMU, Yale, and Cornell) after graduation. The PI is committed to annually support REU/WUSEF research projects inspired by this proposal, such as understanding user behavior in computational systems through conducting behavioral experiments or analyzing existing datasets. The PI will also support undergraduate students on independent research projects during the academic year.

4.5 Evaluation Plan

The success of the education effort will be continuously evaluated with my partners. For designing data-driven personalized education, I will initially perform simulations to evaluate the approaches approaches, examining whether our curriculum improves ML models trained on human data. For real-world evaluations, we have recently obtained WashU IRB approval to recruit real-world Chess players to examine the effectiveness of our approaches.

Budgets are allocated for the evaluation services supplied by the Center for Integrative Research on Cognition, Learning, and Education (CIRCLE), for course evaluations, and ISP, for evaluating activities in broadening research participation. The evaluations for the proposed course will be conducted based on multiple metrics, including whether students obtain firm grasp of the subject (by constructing a knowledge inventory) and whether the course motivates students in applying the knowledge in different domains. For broadening research participation, I will work with ISP to conduct anonymous surveys to high-school teachers/students before and after the event to evaluate their understanding of the topic and their aspirations in pursuing higher-education in STEM. For research engagements with URM, female, and undergraduate students, I will conduct two interviews (before and after) to identify potential areas of improvements.

5 Broader Impacts

The research of designing ML to learn from humans and assist humans creates a wide range of impacts. It impacts the design of a broad range of online platforms with active human participation, including recommendation systems, user-generated content platforms, social networking sites, in improving the way the platform interacts with users. Moreover, as algorithmic decision making gets deployed more widely in policy making, this research contributes to improving decision making for societal issues. In particular, the PI has existing collaborations with Prof. Patrick Fowler at Brown School of Social Work for homeless prevention [30] and with Dr. Jason Wellen at Medical School to apply computational approaches for living donor kidney transplantation [75]. The PI plans to continue and expand the collaborations through the Division for Computational and Data Sciences (DCDS) which brings together the Department of Computer Science & Engineering with the departments of Political Science and Psychological and Brain Sciences in Arts & Sciences and with the Brown School of Social Works. The PI has been co-advising three PhD students (with faculty from Social Work, Psychology, and Biomedical Imaging) thorough DCDS.

Industry. The research has high potential for practical applications. I will work with industrial partners to translate the research outcome to practice. I have been engaging with Boeing in developing approaches for ML to augment human decision making. I have also been working with the office of industrial relations at WashU on building collaborations with other industrial partners (e.g., including a faculty research award from JPMorgan and ongoing discussion with Waters Corporation) in deploying the research into practice.

Dissemination of results. One of the main research efforts in this proposed research is to collect human behavioral data through multiple sets of large-scale behavioral experiments. We plan to make the collected data publicly accessibly to the research community. To disseminate our research results to a broad audience, in addition to regular conference and journal publications, we will publicly release the software implementations of algorithms, simulation test-bed, and models developed in this project. Furthermore, we will disseminate results within the interdisciplinary DCDS program at Washington University through regular interaction with other faculty in the program, as well as its seminar series.

6 Results from Prior NSF Support

Dr. Ho is a co-PI on "FAI: FairGame: An Audit-Driven Game Theoretic Framework for Development and Certification of Fair AI" (IIS-1939677, $444,145, Jan 2020 to Dec 2023). *IM*: This project provides a general framework for fair decision making and auditing in stochastic, dynamic environments. PI Ho has published six publications in this project [86, 127, 32, 126, 33, 87]. *BI*: The work supports the training of graduate students and the development of new auditing algorithms that have impacts to AI and society.

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