CAREER: Behavior-Informed Machine Learning: Achieving Robust Learning and Enhancing Decision Support

1 Introduction

Machine learning (ML) is becoming increasingly pervasive, seamlessly integrating itself into various aspects of everyday human life. Central to this evolution is ML's ability to *learn from humans*. By learning from human demonstrations or training on human-annotated data, machines have been empowered to mimic, and even surpass, human capabilities across a range of domains [51, 132, 107, 17, 126]. Furthermore, as ML technology continues to advance, it offers immense potential to *augment human decision-making* [28, 14, 98, 26], ultimately fostering more informed choices and improved outcomes. While this two-way interaction between humans and ML holds transformative potential, accounting for the role of humans in the design of ML systems also introduces challenges, due to inherent human imperfect or even biased decision-making.

From the perspective of learning from humans, the inherent imperfection of human decisions hinders ML development by introducing biases into the training data. These biases become especially concerning in times calling for responsible ML technologies. Recent examples have shown that ML systems built with biased data can produce negative, discriminatory outcomes harmful to the society [20, 27, 137, 103, 48]. Additionally, from the viewpoint of developing ML systems to augment human decision-making, it is vital to understand and incorporate knowledge about human behavior to prevent humans from succumbing to biases [98, 26, 18]. While the imperfections of human behavior have been extensively studied in the field of psychology [62, 12, 92, 121, 68, 8, 122, 67, 70, 69, 29], research on the incorporation of human behavior and biases in the development of ML is still relatively underexplored.

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 machine learning systems. Specifically, we will 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 capable of enhancing human decision-making for improved outcomes. In addition to theoretical contributions, the research, through collaboration with domain experts, will be adapted to domain applications such as homelessness prevention and pilot augmentation. This ensures that the research findings will have practical relevance in domain applications, promoting their widespread adoption and impact. In more detail, we will investigate the following three research thrusts:

- **Thrust 1: Developing foundations for learning from human behavioral data.**
  Designing ML to learn from human supervisions and demonstrations has been extensively studied within weakly supervised learning [15, 88, 105], truth inference in crowdsourcing [34, 99, 31, 64, 131, 32, 138, 30], and inverse reinforcement learning [89, 139, 97]. In these studies, it is typically assumed that humans are either independent, stochastic data sources, or that humans are fully rational and make (near-)optimal decisions. These assumptions enable the use of inference techniques to uncover the ground truth from human demonstrations. However, empirical evidence suggests that human behavior consistently deviates from these assumptions, and failing to account for the deviation could lead to suboptimal learning. This thrust aims to develop computationally practical, theoretically sound, and empirically grounded foundations for learning from behavioral data, explicitly accounting for human behavior in data generation.
- **Thrust 2: Designing assistive ML to improve human decision making.**
  While humans are known to make imperfect decisions, ML is beginning to achieve superhuman performance in some domains. Consequently, it is becoming more important than ever to explore whether and how ML can be leveraged to assist humans in making better decisions. In this thrust, we aim to develop assistive ML frameworks to enhance human decision making that take into account human biases and

preferences. In particular, we will investigate approaches to determine when and what assistance ML should should provide through algorithmic, data-driven, and learning approaches. Furthermore, we will conduct behavioral experiments to account for human trust and reliance on ML advice that will in turn impact the design of the assistive ML framework.

- **Thrust 3: Integrating with domain applications.**
  While the main focus of this CAREER plan is to develop a general framework for behavior-informed ML, we 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 (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 machine learning, the understanding of humans, and the utilization of their interactions. This research proposal serves as the stepping stone to achieving this goal by developing behavioral-informed machine learning, designing learning algorithms that are robust to human behavior during data generation, and investigating how to design machine learning algorithms to assist humans in making better decisions.

Intellectual Merit. This proposed research will contribute to the empirical understanding of human behavior when interacting with ML and provide theoretical foundations for studying the human-machine interactions. The results of the proposal will provide insights on developing human-centered machine learning algorithms and in combining humans and machines to solve problems neither can solve alone. This research is interdisciplinary in nature, combining ideas and techniques 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 machine learning, 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 [52, 55, 5, 59, 53, 115, 113, 39, 40] and designing incentives to encourage high-quality data [54, 56, 60, 80]. From the perspective of designing ML to assisting 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 [134, 114, 45, 36] and investigating ethical considerations in leveraging ML in decision making [116, 118, 86, 87]. In addition to the theoretical and algorithmic studies, the PI has experiences in conducting large-scale online behavioral experiments to understand human behavior in computational environments [57, 115, 39, 40, 118, 134, 86, 87]. The PI is active in the research communities. 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 incorporate realistic human decision making into the design of machine learning, focusing on two aspects of the ML lifecycle: learning from humans and aiding humans in decision-making. Below we begin with a brief introduction to the classical decision making frameworks in ML, followed by a summary of well-known human behavioral models motivated from behavioral economics and psychology.

2.1 Decision Making Framework in Machine Learning

We first review the decision-making framework that serves as the foundation of the proposed work. Note that in this line of literature, the decision maker is assumed to the rational, and the goal of ML development is to either solve the optimal policy or infer the environment from (near-)optimal demonstrations.

Markov decision process (MDP) and reinforcement learning (RL). Markov decision process (MDP) is one of the most standard frameworks for modeling the sequential decision-making environment. 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.

The standard approach to solve the above MDP and obtain an optimal policy is through reinforcement learning (RL) [65, 112, 83, 84]. In the standard setup, 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 a transition probability kernel $T(s'|s,a)$, encoding 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 [129], to more recent deep learning aided approaches [77, 83, 84].

Inverse reinforcement learning (IRL). Inverse reinforcement learning tackles a challenging task of inferring the reward R from observing the sequence of (s_t, a_t)s. 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. They characterize the set of reward functions that would produce the same optimal policy as observed. 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. Then the authors imposed smoothness constraints on each step's predicted policy to formulate a linear programming problem to solve. Follow-up works [4, 139, 97] have focused on variants of the optimization formulation. The common assumption in IRL is that the demonstrations (s_t, a_t)s are from unbiased and optimal decision makers.

2.2 Empirically Motivated Human Behavioral Models

Existing approaches in modeling humans in ML frameworks mostly fall into two categories: (1) modeling humans as independent, stochastic data sources [34, 99, 31, 64, 131, 32, 138, 30], or (2) assuming humans are *rational* decision makers aiming to take actions that maximize their expected utility [127, 24, 23, 50, 71, 7]. While these models provide elegant and simple formulations, 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. To make the discussion more concrete, below we summarize some well-known human behavioral models in the literature of behavioral economics and psychology.

Time-inconsistent planning. Humans often cannot reason about future rewards in a consistent manner. For example, humans are rational and might not be able to reason future rewards due to cognitive and information limitations. Humans might also inherit time-inconsistent reasoning behavior. For example, when choosing between earning 10 dollars 100 days from now or 12 dollars 101 days from now, most people will choose the second option. However, when being asked to choose between earning 10 dollars now or 12 dollars tomorrow, many people will change their decisions and choose 10 dollars now. This example illustrates *present bias* [96], describing humans' tendency to give stronger weights on immediate costs and benefits rather than balancing them against costs and benefits in the future. These biases in time-inconsistent reasoning 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 $\sum_t d(t) R_t$. This notion characterizes many behavioral models related to time-inconsistent planning, with some illustrative examples below:

- Standard model: $d(t) = \gamma^t$
- Bounded rationality: $d(t) = \gamma^t$ for all $0 \le t \le \tau$, and $d(t) = 0$ for all $t > \tau$.
- Present bias: One common model is hyperbolic discounting: $d(t) = \frac{1}{1+kt}$ for some pre-specified $k > 0$.

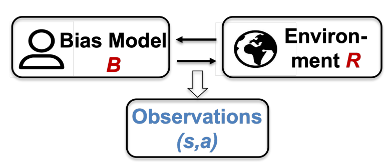
Biased reward evaluation. While it is commonly assumed that humans are rational, taking actions to maximize their expected utility (the expected utility theory [127]), humans are consistent observed to deviate from the assumption. For example, humans often over-estimate small probabilities and react more strongly to losses than gains. The most important theory that summarizes these systematic biases is the Nobel-winning *prospect theory* by Kahneman and Tversky [66]. Another commonly used theory, also Nobel-winning, is the discrete choice model [82, 109, 120], which accounts 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.

3 Proposed Research

The proposed research aims to explore the human-machine partnership by focusing on integrating human behavior in the design of machine learning. We plan to develop theoretically sound and empirically grounded foundations for behavior-informed machine learning that both learns from humans and assists them. Moreover, through collaboration with domain experts, we will tackle the practical challenges associated with deploying behavior-informed ML in domain applications.

3.1 Thrust 1: Developing Foundations for Learning from Behavioral Data



This thrust aims to develop computationally practical, theoretically sound, and empirically grounded foundations that that infer the latent environment parameters (e.g., MDP rewards or feature-label mappings) and human models from human behavioral data. Take RL for example, when humans are rational decision makers, they follow a policy π that maximizes $\mathbb{E}[\sum_t \gamma^t R_{a_t}(s_t, s_{t+1}) | \pi]$. Conditional on this assumption, the standard learning framework (e.g., inverse reinforcement learning) aims to infer the underlying rewards R or recover the optimal policy π from observing the realized state-action pairs $\{(s_t, a_t)\}$.[1] However, humans often do not make decisions according to the optimal policy. Instead, they might follow some behavior models $\mathcal{B}$, e.g., $\mathcal{B}$ could include time-inconsistent planning $\mathcal{B}_T(t)$ and biased reward evaluation $\mathcal{B}_{R,a}(s, s')$, as reviewed in Section 2.2. Their goal is to maximize the *biased* expected rewards: $\mathbb{E}[\sum_t \mathcal{B}_T(t) \mathcal{B}_{R,a_t}(s_t, s_{t+1}) | \pi]$. The aim of the algorithms that learns from behavioral data is to infer $\mathcal{B}_T, \mathcal{B}_R, R$ with only observing potentially biased (s_t, a_t)s.

In this learning setup, the observations (s_t, a_t) are produced from the *interactions* between humans $\mathcal{B}$

[1] 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.

and the environment R.[2] This interactive nature raises a few challenges: Computationally, we have to grapple with a significantly larger space for the learning problem. Moreover, there can be scenarios where learning might prove unfeasible. For instance, if human decision-makers always choose actions with the highest empirical rewards, this could result in a dataset generated with *pure exploitation*, where humans overlook potentially high-utility actions that initially provide low rewards due to chance. This might lead to a dataset that fails to offer a representative distribution necessary for enabling learning. In fact, my previous work [113] has demonstrated that in certain stylized human models, learning can be impossible even with an infinite number of data observations. To tackle these challenges, this thrust will develop computationally efficient algorithms for jointly inferring $\mathcal{B}$ and R from behavioral data (**Task 1.1**). We will also construct theoretical foundations that characterize the feasibility of learning (**Task 1.2**). Lastly, in close collaboration with psychology researchers, we plan to conduct human-subject experiments to further our understanding of human behavior in the context of pervasive ML integration in everyday decision-making (**Task 1.3**).

Prior work. The proposed activities in this research thrust will be built on the PI's extensive prior work in crowdsourcing [52, 55, 56, 58, 59, 80, 115, 39, 40], where one key research theme is to infer ground truths from noisy human data. We will extend the standard models that assume humans exhibit some 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 [113, 134, 45] and the experience in conducting human-subject experiments [58, 115, 39, 40, 87] will be the building blocks of the proposed research.

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

Our first task is to develop computationally practical algorithms to learn from human behavioral data. The proposed algorithms will be evaluated with both theoretical analysis (for a smaller set of general conditions) and simulations (for a wider range of conditions) to examine their accuracy (of estimating environment/behavioral parameters) and computational efficiency under different settings of human models $\mathcal{B}$ and environments R. Below we briefly describe our proposed approaches.

Two-stage learning. We will start with an easier setting: assume partial access to true environment parameters R_t (e.g., assuming some rewards are known in MDP), obtained through domain knowledge or historical information. With this assumption, we can leverage supervised learning techniques to first infer $\mathcal{B}$, utilizing provided R_t and observed $\{(s_t, a_T)\}$, and then infer R, by utilizing inferred $\mathcal{B}$ and $\{(s_t, a_t)\}$. This two-stage learning could significantly reduce the problem space and induce efficient learning.

Imposing constraints. The requirement of "ground truth" rewards is strong in practice. We will also investigate methods of learning $R, \mathcal{B}$ without accessing any of the true R_t. To address the computational issue, we will investigate methods of imposing proper constraints. For example, by leveraging the idea of my prior work in dealing with bandits with infinite search space [56], if we impose a mild condition that for two *similar* states s_t and $s_{t'}$, their rewards are also *similar*, we would be able to significantly reduce the search space and improve learning. In addition to this approach, we will also explore imposing constraints on the belief models and reward bias models, e.g., based on domain knowledge, to reduce the search space.

Sampling-based inference approach: Consider the Bayesian inference framework[19, 33, 123, 79]. Let θ be the parameters that represent $\mathcal{B}$, and $\mathcal{H}_t$ be the information set up to time t, we can formulate the inference problem by imposing a certain prior and Bayesian structure between R, θ and (s, a). We can then solve the inference problem: $\arg\max_{R,\theta} \log \mathbb{P}(\{(s_n, a_n)\})_{n=1}^{t} | R, \theta)$. The inference is often computationally heavy due to continuous and large parameter space. We will resort to sampling and variational approaches to solve this problem. For instance, we can adopt Gibbs sampling. More specifically, according to Bayes' theorem, the conditional distribution of s_n, a_n satisfies $\mathbb{P}(s_n, a_n | R, \theta, \mathcal{H}_t) \propto \frac{\mathbb{P}(R,\theta|\mathcal{H}_{t+1})}{\mathbb{P}(R,\theta|\mathcal{H}_t)}$. Leveraging this, we generate samples via tracking the posterior distribution of the parameters $\mathbb{P}(R, \theta | \mathcal{H}_t)$, and compare the losses.

[2] For convenience, we use the notation R in a broad sense to represent general environment parameters, not just rewards.

3.1.2 Task 1.2: Developing theories for learning from behavioral data

When humans are interacting with the environment, learning could become challenging or even infeasible. My prior work [113] has proved that with certain human models, we cannot uncover the underlying latent parameters (environment and human parameters) even with infinitely many data points. This observation calls for a rigorous theoretical understanding of the complexity of human models and how it impacts learning. In this task, we will first aim to quantify the complexity of human behavioral models. This understanding is useful on its own: we are starting to shift from traditional theory-base developments to data-driven developments for human models [6, 21, 95], and theoretical notions of models complexity enables us to explore the generalizability of human models. Moreover, we will examine the feasibility of learning on behavioral data generated according to the interaction between the behavioral model and the decision making environment.

Characterize the complexity of human models. We will first characterize the theoretical complexity of human models. The first natural attempt would be to adopt the notion of VC dimension [124]. However, VC dimension is a measure that considers the worst-case data distribution. Since human behavior often follows some basic characteristics (e.g., more likely to choose a decision when the decision payoff is higher), it is natural to consider a distribution-dependent approach. In this task, we will first identify some sets of reasonable axioms of human behavior (e.g., decisions are monotonic to associated rewards) and constrain our discussion in distributions that satisfy these axioms. We will then apply distribution-dependent notions, such as the *Rademacher complexity* [13, 72], to perform the analysis. This notion has two nice properties: (1) it is a distribution-dependent measure, and (2) it can be estimated with empirical data. We will analyze the Rademacher complexity with different sets of axioms for human behavior and empirically estimate the complexity using the empirical dataset. Moreover, we will utilize standard cross-validation method to examine its generalization and see whether the theories characterize empirical observations well.

Investigate the feasibility of learning. With the knowledge of the complexity of human models, we will investigate how it impacts learning from behavioral data. We plan to adopt the techniques from stochastic approximation [101, 47]. The idea is to formulate the realizations of states as a random variable based on the interaction of the behavioral model and the environment. By analyzing the convergence and convergence rate of the state trajectory, we can characterize conditions for the feasibility and the complexity of learning. As an illustrating example, my prior work [113] has adopted this approach for a simpler setting with two specific human models and with a bandit learning environment. The *state* is modeled as the empirical rewards obtained by each action. Humans are assumed to choose the next action based on the state (realized rewards) and their behavioral patterns. For one behavioral model, we show that the state converges to a fixed point for any given initial state and leverage the convergence rate to prove the upper bound of learning efficiency. For another behavior model, we show that the state converges to a random variable with non-zero variance and prove that learning is infeasible with information theoretical arguments. In this task, we aim to obtain more general results beyond specific human models and in general environments.

3.1.3 Task 1.3: Conducting experiments to understand human behavior in the ML age

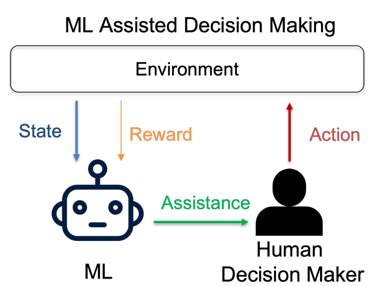
In the previous tasks, we start our investigation by leveraging existing behavioral models from the literature of psychology (e.g., see Section 2.2). While these models are backed by extensive empirical evidence, they were mostly developed before ML became so pervasive and widely acknowledged by the general population. Meanwhile, when people become aware that they are interacting with ML, their behavior might differ from scenarios without ML involvement. My recent work [75] has demonstrated this phenomena. We show that when people know that their behavior will be used to train ML, they are willing to forgo rewards to ensure that the trained ML exhibits fairer behavior. As ML continues to gain more societal attention, it is important to examine and understand the shifts in human behavior when ML is integrated into our daily lives.

Proposed research. We 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, we will start by utilizing social games, such as the ultimatum game [90], dictator game [44], prisoner's dilemma [10], 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. We will recruit participants from crowdsourcing platforms, e.g., Amazon Mechanical Turk or Prolific. In particular, we plan to vary the following independent variables in our experiment design and measure human responses as the dependent variables. Standard statistical tests (such as ANOVA and postdoc 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, we 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 [75] 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.

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



In this research thrust, our objective is to develop an algorithmic framework for ML-assistive decision making that takes into account human behavior. In this framework, ML provides recommendations to humans, who then make the final decisions. Here, the goal of machine learning is to *augment*, instead of *replacing*, humans in decision making.

In **task 2.1,** we will focus on designing ML assistance in *low-complexity* environments where deriving the optimal decision policy is feasible using standard analytical approaches (e.g., value iteration). However, unlike conventional methods of solving the optimal decision policy, the optimization of the ML assistance must consider the behavior of human decision maker, leading to a more complex optimization problem. To tackle this, we will first assume known human models and propose efficient algorithms to identify the optimal assistance policy. Next in **task 2.2**, we plan to extend our work by relaxing both the low-complexity environment and the known human model assumptions. Specifically, we will investigate how to optimize ML assistance in *high-complexity* environments, where traditional approaches do not scale, and data-driven methods are needed to determine the optimal policy. We aim to explore how to incorporate models of human behavior into optimizing ML assistance within a data-driven architecture. In situations where human models are not known a priori, we will design online learning algorithms that learn human models simultaneously. Finally, in **task 2.3**, we will conduct human-subject experiments to understand the conditions for humans to adopt the ML recommendations, extending our results to more practical setups.

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 [60], learning with strategic responses [119], Bayesian persuasion [36, 118, 45], and environment design [134]. In addition, the PI has substantial expertise in bandit learning [60, 80, 113, 118] and robust learning [119], which serve as technical foundations for addressing the problems of learning and robust design.

3.2.1 Task 2.1: Developing efficient algorithms for designing ML assistance

There have been recent works in leveraging ML to help humans make decisions [134, 14, 28], which only address settings with specific human models and settings. In this task, we aim to relax these assumptions and provide a general framework for designing ML assistance. Note that while solving the optimal policy in MDP is often feasible in low-complexity environments, my prior work [134] has proven that optimizing ML assistance while incorporating humans decisions is NP-hard in general. In this task, we will focus on low-complexity environments and assuming known human models. We aim to identify conditions that efficient algorithms are feasible, and propose the corresponding algorithms. We will investigate the relaxation of the assumptions of low-complexity environments and known human models in the next task.

Formulation of ML assistance framework. We will establish a general framework that integrates models of human behavior (as reviewed in Section 2.2) into the standard decision-making frameworks in ML (as discussed in Section 2.1). We will then formalize the problem of designing ML assistance, where the objective of ML is to determine when and what assistance to provide to human decision makers, under varying levels of assumptions. In our setting, both an ML agent and a human agent operate within the same sequential decision-making environment, formulated as an MDP. The human agent aims to maximize their own payoff through a series of actions, whereas the ML agent's payoffs are derived from the actions of the human agent. In our setting, the ML agent first determines the policy for providing assistance, and then the human agent makes decisions with the assistance provided by the ML agent.

Let the human decision-making policy be $\pi_{\mathcal{B}}(a|s)$, representing the probability for human to choose action a at state s. The goal of ML is to maximize the total rewards derived from human actions by providing assistance. Let ML's assistance policy be $\rho(a|s)$, denoting the intervention ML makes at state s [3], and $\theta(s)$ be the *reliance policy* whether human adopt ML assistance at state s. We will start by assuming human reliance policy θ is known and given in task 2.1 and 2.2. We will examine θ in task 2.3. Now let $(\pi_{\mathcal{B}} \oplus \rho \oplus \theta)(a|s)$ be the final executed policy with ML assistance, e.g., $(\pi_{\mathcal{B}} \oplus \rho \oplus \theta)(a|s) = (1-\theta(s))\pi_{\mathcal{B}}(a|s) + \theta(s)\rho(a|s)$, 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 close for some distance measure D.

Proposed approaches. With the optimization formulation in place, in this task, we explore approaches to solve the problem of designing ML assistance. Depending on the properties of human models, we can categorize the design problem into settings with differentiable and non-differentiable objectives. To illustrate the difference, consider the standard assumption that humans are rational, i.e., the decision maker puts all the probability mass on the action that maximizes the payoff. When putting this decision function back to the optimization problem, the objective is non-continuous and the optimization is NP-hard to solve. 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. In fact, the PI's recent work [134] has demonstrated that it is indeed possible to derive computationally efficient algorithms with this particular human model. The above discussion highlights the need to understand how different human models impact the design of ML assistance. In this task we will address the following research questions:

- *Designing ML assistance with differentiable human models*: When the human decision model follows the discrete choice model or other models that lead to stochastic decision making, the optimization objective can usually be written as a continuous differentiable function. This enables the first-order optimization methods, such as gradient descent [102], to be applied. In this type of problems, we plan to characterize

[3] When $\rho(a|s) = \pi_{\mathcal{B}}(a|s)$ for all a, it means there is no ML assistance in state s.

the computational complexity and convergence to the optimal solution with different human models. The key element is to quantify the *smoothness* of human models, i.e., how much human behavior changes with a small change of provided information. My prior work on the convergence rate of secure convex optimization [117] will serve as the technical foundation for this problem.

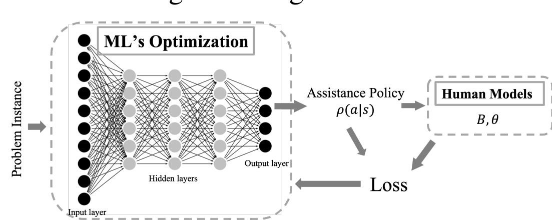
- *Designing ML assistance with non-differentiable human models*: When the human models are not differentiable (e.g, when the decision model follows the expected utility theory), the objective of the optimization problem will be non-differentiable, and standard first-order methods cannot be applied. In this type of problems, we plan to utilize the techniques from recent research efforts in algorithmic information design [41, 43, 11] (including the PI's own works [36, 45]) to characterize the solution and the computational complexity. On a high-level, this line of approach often involves utilizing the duality theory to characterize the properties of the optimal solution and could help identify conditions for computationally feasible solutions to exist. We will also utilize techniques such as soft-max relaxations to derive approximation algorithms in the case that when the optimization is NP-hard.

3.2.2 Task 2.2: Designing ML assistance with data-driven and learning approaches

In the above task, we focus on low-complexity environments and have assumed full knowledge of human models. While these assumptions could be approximately satisfied in simple domains and when we have access to an abundant amount of human behavior data, it is generally a strong assumption that might not hold in practice. In this task, we aim to move towards relaxing the above assumptions and take data-driven and learning approaches to optimize the ML assistance.

Background and challenges. To design ML assistance in high-complexity environments, one potential approach is to extend the idea of data-driven approaches of self-play [107, 35, 135], which learns the optimal decision policy of MDP through simulations. However, it is not trivial to incorporate human models in our setup to implement this approach. Moreover, when the human models are not know a priori, the problem becomes even more challenging as it is hard to estimate the policy performance using simulations. In this case, we will consider settings when the ML can interact with humans to obtain information over time and adaptively update policy based on what ML has learned. This naturally leads to the trade-off between exploration, taking potentially suboptimal actions to obtain information, and exploitation, taking optimal actions based on the available information, that need to be addressed.

Develop a neural-network-based optimization structure that encodes human models. We first explore how to leverage data-driven approaches to design ML assistance, assuming human models are known. In particular, we propose to extend the data-driven approach of self-play of optimizing decision policy in MDP to incorporate human decision models to optimize ML assistance. Specifically, we propose a neural-network-based structure that consists of two modules: the ML's optimization module and the human models. The ML's optimization module follows the traditional neural-network-based structure. It takes the details of the problem instances as input and outputs an assistance policy. The main difference compared with prior works is that we have incorporated human models, either in an analytical closed-form or a data-driven form (e.g., another ML model trained on human data) 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, we can follow the standard approach of using deep learning for optimization [42, 93]: draw problem instances from a pre-specified distribution and perform stochastic gradient descent to minimize the loss function (applying soft-max approximation when the objective is not differentiable). We will examine the empirical performance of this neural-network based approach with different settings of human models, environments, instance distributions.

Design bandit algorithms 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, we 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 [74, 9, 25]. We 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, we plan to adopt the technique in the PI's work on leveraging the similarities between arms in bandit learning [60]. 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, we 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.

3.2.3 Task 2.3: Understanding human reliance on ML assistance with human-subject experiments

In the previous tasks, to simplify the discussion, we have 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 has been developed recently to understand humans' trust and reliance on ML [133, 81, 100, 136, 78, 125], including my own work [87], most existing studies focus on the one-shot decision making scenarios. Limited is known about how humans trust and rely on ML assistance in *sequential decision making settings*. In this task, we aim to conduct investigations of humans' trust and reliance on ML recommendations in the setting with sequential decision making.

Proposed research. In collaboration with Dr. Ming Yin, a leading expert in human trust and reliance on AI at Purdue University, we will conduct randomized human-subject studies to understand how human decision makers' reliance on ML are influenced by various factors under the sequential decision making setting. In particular, consistent with theoretical models previously proposed for human-automation interaction [61, 104], we expect humans' adoption of ML advice under sequential decision making settings can be influenced by factors related to *humans*, *ML*, and the *environment*. We 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. We plan to conduct randomized human subject experiments. For each human-subject experiment, we 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, we will record whether human subjects 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, we will ask human subjects 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. We can also have the human subjects 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.

3.3 Thrust 3: Integrating with Domain Applications

In research thrusts 1 and 2, our 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, we 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, we 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 our existing collaboration with Prof. Patrick Fowler on developing algorithmic solutions to homelessness prevention [38] 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 [22, 46, 106], 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. 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 type comes from the recipients of resources. In homelessness prevention, when people seek help, they usually are not immediately assigned resources due to the resource scarcity. Instead, they are placed on a waitlist and only receive resources when they become available. This waiting process creates unequal *drop-out* rates across social groups. For example, 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 [73]. 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. As a starting point, we will design 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 substantial research devoted to avoiding such incursions, including accident prediction [111, 108, 49] and system design to detect obstacles and alert pilots [63, 91, 94, 130]. These approaches have mostly taken a traditional approach, aiming to detect the incursion events and provide warnings to pilots. 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 the objectives of this CAREER plan, we plan to adopt a behaviorally 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 enables 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 that can be used for identifying personalized behavioral patterns in runway safety. After identifying the behavioral patterns, we will address the research question of designing 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 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. We 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: We 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: The collected data of the behavioral experiments will be made publicly available to the research community. We believe the large-scale behavioral data would be of important research value.
- Deployment: We aim to deploy the proposed research in domain applications. In addition to the evaluations above, we will work with domain experts to develop our evaluation plan and solicit feedback of the proposed framework through interviews/surveys.

4 Education Plan

The PI aims to broaden research participation and develop education plans that integrate with the proposed research throughout the duration of the CAREER project. To maximize the impacts of the proposed activities, the PI will collaborate with several existing programs at WashU.

4.1 Broadening Research Participation

This project will invest efforts in broadening the participation in computing, including developing activities to expose high-school students in research, actively recruiting female and underrepresented minority students, and engaging undergraduate research participation.

Outreach to high-school students. The PI will partner with the Institute for School Partnership (ISP) at WashU to design outreach activities for high-school students and teachers. The goal is to cultivate next-generation scientists/engineers through exposing high-school students to academic research and stimulating their interests in computing. We also plan to involve high-school teachers in the design and dissemination of the curriculum to maximize the outreach and impacts. Budgets are allocated for ISP for these activities (letter of collaboration attached). In particular, the McKelvey School of Engineering at WashU has conducted a summer camp in Summer 2022 for local high school students of low-income backgrounds. This program is planned to become an annual summer workshop. The PI plans to develop a one-day summer workshop "Human-Centered Machine Learning" within this framework. The workshop will include a broad overview of machine learning (ML) and human behavior and engage students in group projects guided by Ph.D. students. We will prepare data sets and ML modules for students to explore different system designs (grounded by research activities in this proposal) for ML to assist human decision-making and investigate the benefits and pitfalls of each design. In the first two summers, we will work with ISP and recruit a local high-school teacher during the summer to help develop the workshop. The teacher will get exposed to on-going research in the field and work with the PI in identifying topics that will better motivate and engage high-school students. In the third summer, we will host a workshop with around 25 high-school teachers to disseminate the curriculum design to maximize the potential outreach and obtain feedback. We will then host the workshop in year 4 and 5 by recruiting around 20 high-school students with the help from ISP.

Evaluation plan: The ISP will provide consultations for evaluations. In particular, we will 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.

Engagements of female and underrepresented minority students. The PI is committed to recruiting female and underrepresented minority (URM) students to join the research. Out of five Ph.D. students that the PI is advising, one is female and another one is African American. For the undergraduate/Master students, the PI has worked with six female and URM students (out of thirteen students that worked with the PI). Except for one still in the undergraduate program, four of them have continued their graduate studies after graduation (at Stanford, Duke, Penn State, and Cornell), and one of them has been going to the industry (at Google). The PI will also leverage the institutional effort for engaging female and URM students. In particular, Washington University is actively committed to the goal of increasing the representation of women at the Ph.D. level. For example, the CSE department, the McKelvey School of Engineering, and the Provost's Office of Diversity together fund a Platinum Sponsorship of Grace Hopper. The PI has advised one URM undergraduate student through WashU Summer Engineering Fellowship (WUSEF), which provides funds for students from backgrounds underrepresented in the STEM fields to perform summer research. In addition to working with WUSEF each summer, the PI will also 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 research 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.

4.2 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 in these fronts. To achieve this education goal, the PI has been regularly teaching two courses: *Introduction to Machine Learning* and *Human-in-the-Loop Computation*. As part of this CAREER project, the PI plans to heavily revise the second course into a new 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. The course materials will be made available online to enable self-study or to be used in other institutions.

Evaluation plan. The PI will work with the Center for Integrative Research on Cognition, Learning, and Education (CIRCLE) at WashU to develop evaluation plan for the proposed course. We have allocated budgets for the evaluation service. The evaluations 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.

4.3 Long-term Vision: Towards Personalized Education

My long-term vision in education is to develop data-driven methods that enable personalized education. This vision aligns with my research plan on designing ML that learns from behavioral data and assist human decision maker. As a starting point to realize this long-term vision, we have started to conduct research in the domain of Chess and aimed to develop personalized ML assistant that can improve human skills in Chess. In collaboration with Kassa Korley [85], who holds the title of International Master and the youngest African American to earn the title of National Master in the US, we have examined the question of curriculum design, i.e., what moves should be provided to 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 mimic human plays at different skill levels. We then leveraged both the idea of designing ML assistance in this proposal and curriculum learning [16, 128, 110] to design curriculum. Our preliminary results, showing that the approaches can identify curriculums that align with domain knowledge and improve human win rate, holds potential in designing personalized tool to improve human learning in Chess. In addition to further our understanding on designing assistive ML for Chess learning, we plan to work with Prof. Dennis Barbour, who have been taking data-driven approaches in exploring the connection between students' mathematical learning skills and general executive function skills such as cognitive flexibility, working memory, inhibitory/attentional control. The goal is to improve personalized education in the setup of improve mathematical skills.

5 Broader Impacts

This research has a direct impact on the design of a broad range of platforms with active human participation, including recommendation systems, user-generated content platforms, systems, social networking sites. In addition, as algorithmic decision making gets deployed more widely in policy making, this research also 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 to study the allocation of scarce resources for homeless prevention [37] and with Dr. Jason Wellen at Medical School to apply computational approaches for living donor kidney transplantation [76]. 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. to address societal issues. Moreover, the PI is a founding member of the Center for Collaborative Human-AI Learning and Operation (HALO) at WashU, which provides additional collaboration opportunities with the medical school at Washington University on healthcare problems.

Dissemination of results. One of the main research effort in this proposed research is to collect human behavioral data through multiple sets of large-scale behavioral experiments. We plan to make the collected 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 the co-PI on the grant ("FAI: FairGame: An Audit-Driven Game Theoretic Framework for Development and Certification of Fair AI", IIS-1939677, $444,145, Jan 2020 to Dec 2023). *Intellectual Merit*: This project provides a general game theoretical framework for fair decision making and auditing in stochastic, dynamic environments. PI Ho has published six publications in this project [86, 119, 39, 118, 40, 87]. *Broader Impacts*: The work is supporting the training of graduate students and the development of new auditing algorithms that have impacts to AI and society.

References

[1] St. louis regional data alliance. commnuity information exchange. URL `https://stldata.org/project-community-information-exchange/`.

[2] Runway incursions. URL `https://www.faa.gov/airports/runway_safety/resources/runway_incursions`.

[3] Runway incursion totals for fy 2014, 2014. URL `http://www.faa.gov/airports/runway_safety/statistics/regional/?fy=2014`.

[4] Pieter Abbeel and Andrew Y Ng. Apprenticeship learning via inverse reinforcement learning. In *Proceedings of the twenty-first international conference on Machine learning*, page 1. ACM, 2004.

[5] Jacob Abernethy, Yiling Chen, Chien-Ju Ho, and Bo Waggoner. Low-cost learning via active data procurement. In *16th ACM Conf. on Economics and Computation (EC)*, 2015.

[6] Mayank Agrawal, Joshua C Peterson, and Thomas L Griffiths. Using machine learning to guide cognitive modeling: A case study in moral reasoning. *arXiv preprint arXiv:1902.06744*, 2019.

[7] Tal Alon, Magdalen Dobson, Ariel Procaccia, Inbal Talgam-Cohen, and Jamie Tucker-Foltz. Multiagent evaluation mechanisms. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 2020.

[8] Hal R Arkes and Catherine Blumer. The psychology of sunk cost. *Organizational behavior and human decision processes*, 35(1):124–140, 1985.

[9] Peter Auer, Nicolò Cesa-Bianchi, and Paul Fischer. Finite-time analysis of the multiarmed bandit problem. *Machine Learning*, 47(2-3):235–256, 2002. Preliminary version in *15th ICML*, 1998.

[10] Robert Axelrod. Effective choice in the prisoner's dilemma. *Journal of conflict resolution*, 24(1): 3–25, 1980.

[11] Ashwinkumar Badanidiyuru, Kshipra Bhawalkar, and Haifeng Xu. Targeting and signaling in ad auctions. In *Proceedings of the Twenty-Ninth Annual ACM-SIAM Symposium on Discrete Algorithms*, pages 2545–2563. SIAM, 2018.

[12] Natã M Barbosa and Monchu Chen. Rehumanized crowdsourcing: A labeling framework addressing bias and ethics in machine learning. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, page 543. ACM, 2019.

[13] Peter L Bartlett and Shahar Mendelson. Rademacher and gaussian complexities: Risk bounds and structural results. *Journal of Machine Learning Research*, 3(Nov):463–482, 2002.

[14] Hamsa Bastani, Osbert Bastani, and Wichinpong Park Sinchaisri. Improving human decision-making with machine learning. *arXiv preprint arXiv:2108.08454*, 2021.

[15] Shai Ben-David, Dávid Pál, and Shai Shalev-Shwartz. Agnostic online learning. In *COLT*, volume 3, page 1, 2009.

[16] Yoshua Bengio, JÃ©rÃ´me Louradour, Ronan Collobert, and Jason Weston. Curriculum learning. In *Proceedings of the 26th annual international conference on machine learning*, page 41â48, 2009.

[17] Christopher Berner, Greg Brockman, Brooke Chan, Vicki Cheung, Przemysław Dębiak, Christy Dennison, David Farhi, Quirin Fischer, Shariq Hashme, Chris Hesse, et al. Dota 2 with large scale deep reinforcement learning. *arXiv preprint arXiv:1912.06680*, 2019.

[18] Astrid Bertrand, Rafik Belloum, James R Eagan, and Winston Maxwell. How cognitive biases affect xai-assisted decision-making: A systematic review. In *Proceedings of the 2022 AAAI/ACM conference on AI, ethics, and society*, pages 78–91, 2022.

[19] David M Blei, Alp Kucukelbir, and Jon D McAuliffe. Variational inference: A review for statisticians. *Journal of the American Statistical Association*, (just-accepted), 2017.

[20] Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In *Advances in neural information processing systems*, pages 4349–4357, 2016.

[21] David D Bourgin, Joshua C Peterson, Daniel Reichman, Stuart J Russell, and Thomas L Griffiths. Cognitive model priors for predicting human decisions. In *International conference on machine learning*, pages 5133–5141. PMLR, 2019.

[22] Molly Brown, Camilla Cummings, Jennifer Lyons, Andrés Carrión, and Dennis P Watson. Reliability and validity of the vulnerability index-service prioritization decision assistance tool (vi-spdat) in real-world implementation. *Journal of Social Distress and the Homeless*, 27(2):110–117, 2018.

[23] Michael Brückner and Tobias Scheffer. Stackelberg games for adversarial prediction problems. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 547–555, 2011.

[24] Michael Brückner, Christian Kanzow, and Tobias Scheffer. Static prediction games for adversarial learning problems. *Journal of Machine Learning Research*, 13(Sep):2617–2654, 2012.

[25] Sébastien Bubeck and Nicolo Cesa-Bianchi. Regret Analysis of Stochastic and Nonstochastic Multi-armed Bandit Problems. *Foundations and Trends in Machine Learning*, 5(1):1–122, 2012.

[26] Zana Buçinca, Maja Barbara Malaya, and Krzysztof Z Gajos. To trust or to think: cognitive forcing functions can reduce overreliance on ai in ai-assisted decision-making. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1):1–21, 2021.

[27] Aylin Caliskan, Joanna J Bryson, and Arvind Narayanan. Semantics derived automatically from language corpora contain human-like biases. *Science*, 356(6334):183–186, 2017.

[28] Frederick Callaway, Yash Raj Jain, Bas van Opheusden, Priyam Das, Gabriela Iwama, Sayan Gul, Paul M Krueger, Frederic Becker, Thomas L Griffiths, and Falk Lieder. Leveraging artificial intelligence to improve peopleâs planning strategies. *Proceedings of the National Academy of Sciences*, 119(12):e2117432119, 2022.

[29] Ziv Carmon and Dan Ariely. Focusing on the forgone: How value can appear so different to buyers and sellers. *Journal of consumer research*, 27(3):360–370, 2000.

[30] Yiling Chen, Chara Podimata, Ariel D. Procaccia, and Nisarg Shah. Strategyproof linear regression in high dimensions. In *Proceedings of the 2018 ACM Conference on Economics and Computation (EC)*, 2018.

[31] Sharath R. Cholleti, Sally A. Goldman, Avrim Blum, David G. Politte, and Steven Don. Veritas: Combining expert opinions without labeled data. In *Proceedings 20th IEEE international Conference on Tools with Artificial intelligence (ICTAI)*, 2008.

[32] A. P. Dawid and A. M. Skene. Maximum likeihood estimation of observer error-rates using the EM algorithm. *Applied Statistics*, 28:20–28, 1979.

[33] Alexander Philip Dawid and Allan M Skene. Maximum likelihood estimation of observer error-rates using the em algorithm. *Applied statistics*, pages 20–28, 1979.

[34] Arthur P. Dempster, Nan M. Laird, and Donald B. Rubin. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society: Series B*, 39:1–38, 1977.

[35] Anthony DiGiovanni and Ethan C Zell. Survey of self-play in reinforcement learning. *arXiv preprint arXiv:2107.02850*, 2021.

[36] Bolin Ding, Yiding Feng, Chien-Ju Ho, Wei Tang, and Haifeng Xu. Competitive information design for pandora's box. In *Proceedings of the 2023 Annual ACM-SIAM Symposium on Discrete Algorithms (SODA)*, pages 353–381. SIAM, 2023.

[37] Zehao Dong, Sanmay Das, Patrick Fowler, and Chien-Ju Ho. Efficient nonmyopic online allocation of scarce resources. In *Proceedings of the 20th International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS)*, 2021.

[38] Zehao Dong, Sanmay Das, Patrick Fowler, and Chien-Ju Ho. Efficient nonmyopic online allocation of scarce reusable resources. In *AAMAS Conference proceedings*, 2021.

[39] Xiaoni Duan, Chien-Ju Ho, and Ming Yin. Does exposure to diverse perspectives mitigate biases in crowdwork? an explorative study. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, pages 155–158, 2020.

[40] Xiaoni Duan, Chien-Ju Ho, and Ming Yin. The influences of task design on crowdsourced judgement: A case study of recidivism risk evaluation. In *Proceedings of the ACM Web Conference 2022*, pages 1685–1696, 2022.

[41] Shaddin Dughmi and Haifeng Xu. Algorithmic bayesian persuasion. *SIAM Journal on Computing*, 2019.

[42] Paul Dütting, Zhe Feng, Harikrishna Narasimhan, David Parkes, and Sai Srivatsa Ravindranath. Optimal auctions through deep learning. In *International Conference on Machine Learning*, pages 1706–1715. PMLR, 2019.

[43] Yuval Emek, Michal Feldman, Iftah Gamzu, Renato PaesLeme, and Moshe Tennenholtz. Signaling schemes for revenue maximization. *ACM Transactions on Economics and Computation (TEAC)*, 2 (2):1–19, 2014.

[44] Christoph Engel. Dictator games: A meta study. *Experimental economics*, 14:583–610, 2011.

[45] Yiding Feng, Chien-Ju Ho, and Wei Tang. Rationality-robust information design: Bayesian persuasion under quantal response. *arXiv preprint arXiv:2207.08253*, 2022.

[46] Patrick J Fowler, Peter S Hovmand, Katherine E Marcal, and Sanmay Das. Solving homelessness from a complex systems perspective: insights for prevention responses. *Annual review of public health*, 40:465–486, 2019.

[47] Noufel Frikha, Stéphane Menozzi, et al. Concentration bounds for stochastic approximations. *Electronic Communications in Probability*, 17, 2012.

[48] Mitchell L Gordon, Michelle S Lam, Joon Sung Park, Kayur Patel, Jeff Hancock, Tatsunori Hashimoto, and Michael S Bernstein. Jury learning: Integrating dissenting voices into machine learning models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, pages 1–19, 2022.

[49] Jean-Baptiste Gotteland, Nicolas Durand, Jean-Marc Alliot, and Erwan Page. Aircraft ground traffic optimization. In *ATM 2001, 4th USA/Europe Air Traffic Management Research and Development Seminar*, pages pp–xxxx, 2001.

[50] Moritz Hardt, Nimrod Megiddo, Christos Papadimitriou, and Mary Wootters. Strategic classification. In *Proceedings of the 2016 ACM conference on innovations in theoretical computer science*, pages 111–122, 2016.

[51] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In *Proceedings of the IEEE international conference on computer vision*, pages 1026–1034, 2015.

[52] Chien-Ju Ho and Jennifer Wortman Vaughan. Online task assignment in crowdsourcing markets. In *26th AAAI Conference on Artificial Intelligence (AAAI)*, 2012.

[53] Chien-Ju Ho and Ming Yin. Working in pairs: Understanding the effects of worker interactions in crowdwork. *arXiv preprint arXiv:1810.09634*, 2018.

[54] Chien-Ju Ho, Yu Zhang, Jennifer Wortman Vaughan, and Mihaela van der Schaar. Towards social norm design for crowdsourcing markets. In *4th Human Computation Workshop (HCOMP)*, 2012.

[55] Chien-Ju Ho, Shahin Jabbari, and Jennifer Wortman Vaughan. Adaptive task assignment for crowdsourced classification. In *30th Intl. Conf. on Machine Learning (ICML)*, 2013.

[56] Chien-Ju Ho, Aleksandrs Slivkins, and Jennifer Wortman Vaughan. Adaptive contract design for crowdsourcing markets: Bandit algorithms for repeated principal-agent problems. In *15th ACM Conf. on Electronic Commerce (EC)*, 2014.

[57] Chien-Ju Ho, Aleksandrs Slivkins, Siddharth Suri, and Jennifer Wortman Vaughan. Incentivizing high quality crowdwork. In *Proceedings of the 24th International Conference on World Wide Web*, pages 419–429, 2015.

[58] Chien-Ju Ho, Aleksanrs Slivkins, Siddharth Suri, and Jennifer Wortman Vaughan. Incentivizing high quality crowdwork. In *24th Intl. World Wide Web Conf. (WWW)*, 2015.

[59] Chien-Ju Ho, Rafael Frongillo, and Yiling Chen. Eliciting categorical data for optimal aggregation. In *30th Advances in Neural Information Processing Systems (NIPS)*, 2016.

[60] Chien-Ju Ho, Aleksandrs Slivkins, and Jennifer Wortman Vaughan. Adaptive contract design for crowdsourcing markets: Bandit algorithms for repeated principal-agent problems. *Journal of Artificial Intelligence Research*, 55:317 – 359, 2016.

[61] Kevin Anthony Hoff and Masooda Bashir. Trust in automation: Integrating empirical evidence on factors that influence trust. *Human factors*, 57(3):407–434, 2015.

[62] Christoph Hube, Besnik Fetahu, and Ujwal Gadiraju. Understanding and mitigating worker biases in the crowdsourced collection of subjective judgments. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, page 407. ACM, 2019.

[63] Yasuo Ishihara and Steve Johnson. Aircraft systems and methods for managing runway awareness and advisory system (raas) callouts, February 12 2019. US Patent 10,204,523.

[64] Rong Jin and Zoubin Ghahramani. Learning with multiple labels. In *Advances in Neural Information Processing Systems (NIPS)*, 2003.

[65] Leslie Pack Kaelbling, Michael L Littman, and Andrew W Moore. Reinforcement learning: A survey. *Journal of artificial intelligence research*, 4:237–285, 1996.

[66] Daniel Kahneman and Amos Tversky. Prospect theory: An analysis of decisions under risk. *Econometrica*, pages 263–291, 1979.

[67] Daniel Kahneman and Amos Tversky. Prospect theory: An analysis of decision under risk. In *Handbook of the fundamentals of financial decision making: Part I*, pages 99–127. World Scientific, 2013.

[68] Daniel Kahneman, Stewart Paul Slovic, Paul Slovic, and Amos Tversky. *Judgment under uncertainty: Heuristics and biases*. Cambridge university press, 1982.

[69] Daniel Kahneman, Jack L Knetsch, and Richard H Thaler. The endowment effect, loss aversion, and status quo bias. *The Journal of Economic Perspectives*, 5(1):193–206, 1991.

[70] Niklas Karlsson, George Loewenstein, and Duane Seppi. The ostrich effect: Selective attention to information. *Journal of Risk and uncertainty*, 38:95–115, 2009.

[71] Jon Kleinberg and Manish Raghavan. How do classifiers induce agents to invest effort strategically? In *Proceedings of the 2019 ACM Conference on Economics and Computation*, pages 825–844, 2019.

[72] Vladimir Koltchinskii and Dmitriy Panchenko. Rademacher processes and bounding the risk of function learning. In *High dimensional probability II*, pages 443–457. Springer, 2000.

[73] Amanda Kube, Sanmay Das, Patrick J Fowler, and Yevgeniy Vorobeychik. Just resource allocation? how algorithmic predictions and human notions of justice interact. In *Proceedings of the 23rd ACM Conference on Economics and Computation*, pages 1184–1242, 2022.

[74] Tze Leung Lai and Herbert Robbins. Asymptotically efficient adaptive allocations rules. *Advances in Applied Mathematics*, 6:4–22, 1985.

[75] Wouter Kool Lauren Treiman, Chien-Ju Ho. Humans forgo reward to instill fairness into ai. Working paper, 2023.

[76] Zhuoshu Li, Kelsey Lieberman, William Macke, Sofia Carrillo, Chien-Ju Ho, Jason Wellen, and Sanmay Das. Incorporating compatible pairs in kidney exchange: A dynamic weighted matching model. In *Proceedings of the 2019 ACM Conference on Economics and Computation (EC)*, 2019.

[77] Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. *arXiv preprint arXiv:1509.02971*, 2015.

[78] Han Liu, Vivian Lai, and Chenhao Tan. Understanding the effect of out-of-distribution examples and interactive explanations on human-ai decision making. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2):1–45, 2021.

[79] Qiang Liu, Jian Peng, and Alexander Ihler. Variational inference for crowdsourcing. In *26th Advances in Neural Information Processing Systems (NIPS)*, 2012.

[80] Yang Liu and Chien-Ju Ho. Incentivizing high quality user contributions: New arm generation in bandit learning. In *32nd AAAI Conference on Artificial Intelligence (AAAI)*, 2018.

[81] Zhuoran Lu and Ming Yin. Human reliance on machine learning models when performance feedback is limited: Heuristics and risks. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pages 1–16, 2021.

[82] Daniel McFadden. Econometric models of probabilistic choice. *Structural analysis of discrete data with econometric applications*, 198272, 1981.

[83] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*, 2013.

[84] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature*, 518(7540):529, 2015.

[85] Saumik Narayanan, Kassa Korley, Chien-Ju Ho, and Siddhartha Sen. Improving the strength of human-like models in chess. In *Human in the Loop Learning (HiLL) Workshop at NeurIPS*, 2022.

[86] Saumik Narayanan, Guanghui Yu, Wei Tang, Chien-Ju Ho, and Ming Yin. How does predictive information affect human ethical preferences? In *ACM Conference on AI, Ethics, and Society*, 2022.

[87] Saumik Narayanan, Guanghui Yu, Chien-Ju Ho, and Ming Yin. How does value similarity affect human reliance in ai-assisted ethical decision making? In *ACM Conference on AI, Ethics, and Society*, 2023.

[88] Nagarajan Natarajan, Inderjit S Dhillon, Pradeep K Ravikumar, and Ambuj Tewari. Learning with noisy labels. *Advances in neural information processing systems*, 26, 2013.

[89] Andrew Y Ng, Stuart J Russell, et al. Algorithms for inverse reinforcement learning. In *International Conference on Machine Learning*, 2000.

[90] Martin A Nowak, Karen M Page, and Karl Sigmund. Fairness versus reason in the ultimatum game. *Science*, 289(5485):1773–1775, 2000.

[91] Shutai Okamura, Takeshi Hatakeyama, Takahiro Yamaguchi, and Tsutomu Uenoyama. Radar detection system and radar detection method, January 19 2021. US Patent 10,895,638.

[92] Jahna Otterbacher, Pınar Barlas, Styliani Kleanthous, and Kyriakos Kyriakou. How do we talk about other people? group (un) fairness in natural language image descriptions. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, pages 106–114, 2019.

[93] Neehar Peri, Michael Curry, Samuel Dooley, and John Dickerson. Preferencenet: Encoding human preferences in auction design with deep learning. *Advances in Neural Information Processing Systems*, 34:17532–17542, 2021.

[94] Joseph T Pesik and David Matty. Determination of collision risks between a taxiing aircraft and objects external to the taxiing aircraft, February 4 2020. US Patent 10,553,123.

[95] Joshua C Peterson, David D Bourgin, Mayank Agrawal, Daniel Reichman, and Thomas L Griffiths. Using large-scale experiments and machine learning to discover theories of human decision-making. *Science*, 372(6547):1209–1214, 2021.

[96] Matthew Rabin and Ted O'Donoghue. Doing It Now or Later. *American Economic Review*, 1999.

[97] Deepak Ramachandran and Eyal Amir. Bayesian inverse reinforcement learning. In *IJCAI*, volume 7, pages 2586–2591, 2007.

[98] Charvi Rastogi, Yunfeng Zhang, Dennis Wei, Kush R Varshney, Amit Dhurandhar, and Richard Tomsett. Deciding fast and slow: The role of cognitive biases in ai-assisted decision-making. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW1):1–22, 2022.

[99] Vikas Raykar, Shipeng Yu, Linda Zhao, Gerardo Valadez, Charles Florin, Luca Bogoni, and Linda Moy. Learning from crowds. *Journal of Machine Learning Research*, 11:1297–1322, 2010.

[100] Amy Rechkemmer and Ming Yin. When confidence meets accuracy: Exploring the effects of multiple performance indicators on trust in machine learning models. In *CHI Conference on Human Factors in Computing Systems*, pages 1–14, 2022.

[101] Herbert Robbins and Sutton Monro. A stochastic approximation method. *The annals of mathematical statistics*, pages 400–407, 1951.

[102] Sebastian Ruder. An overview of gradient descent optimization algorithms. *arXiv preprint arXiv:1609.04747*, 2016.

[103] Maarten Sap, Dallas Card, Saadia Gabriel, Yejin Choi, and Noah A Smith. The risk of racial bias in hate speech detection. In *Proceedings of the 57th annual meeting of the association for computational linguistics*, pages 1668–1678, 2019.

[104] Kristin E Schaefer, Jessie YC Chen, James L Szalma, and Peter A Hancock. A meta-analysis of factors influencing the development of trust in automation: Implications for understanding autonomy in future systems. *Human factors*, 58(3):377–400, 2016.

[105] Clayton Scott. A rate of convergence for mixture proportion estimation, with application to learning from noisy labels. In *Artificial Intelligence and Statistics*, pages 838–846. PMLR, 2015.

[106] Marybeth Shinn, Andrew L Greer, Jay Bainbridge, Jonathan Kwon, and Sara Zuiderveen. Efficient targeting of homelessness prevention services for families. *American journal of public health*, 103 (S2):S324–S330, 2013.

[107] David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, et al. A general reinforcement learning algorithm that masters chess, shogi, and go through self-play. *Science*, 362(6419):1140–1144, 2018.

[108] Abneesh Singla, Srinivas D Gonabal, Pradeep Huncha, Vedavyas Rallabandi, Jaibir Singh, Sunil Kumar KS, et al. System and method for monitoring compliance with air traffic control instructions, August 25 2020. US Patent 10,755,583.

[109] Kenneth A Small. A discrete choice model for ordered alternatives. *Econometrica: Journal of the Econometric Society*, pages 409–424, 1987.

[110] Petru Soviany, Radu Tudor Ionescu, Paolo Rota, and Nicu Sebe. Curriculum learning: A survey. *International Journal of Computer Vision*, 130(6):1526–1565, 2022.

[111] Zhe Sun, Cheng Zhang, Pingbo Tang, Yuhao Wang, and Yongming Liu. Bayesian network modeling of airport runway incursion occurring processes for predictive accident control. In *Advances in Informatics and Computing in Civil and Construction Engineering: Proceedings of the 35th CIB W78 2018 Conference: IT in Design, Construction, and Management*, pages 669–676. Springer, 2019.

[112] Richard S. Sutton and Andrew G. Barto. *Reinforcement Learning: An Introduction*. The MIT Press, second edition, 2018.

[113] Wei Tang and Chien-Ju Ho. Bandit learning with biased human feedback. In *Proceedings of the 18th International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS)*, pages 1324–1332, 2019.

[114] Wei Tang and Chien-Ju Ho. On the bayesian rational assumption in information design. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, volume 9, pages 120–130, 2021.

[115] Wei Tang, Ming Yin, and Chien-Ju Ho. Leveraging peer communication to enhance crowdsourcing. In *The World Wide Web Conference*, pages 1794–1805. ACM, 2019.

[116] Wei Tang, Chien-Ju Ho, and Yang Liu. Differentially private contextual dynamic pricing. In *Proceedings of the 19th International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS)*, 2020.

[117] Wei Tang, Chien-Ju Ho, and Yang Liu. Optimal query complexity of secure stochastic convex optimization. In *34th Conference on Neural Information Processing Systems (NeurIPS)*, 2020.

[118] Wei Tang, Chien-Ju Ho, and Yang Liu. Bandit learning with delayed impact of actions. *Advances in Neural Information Processing Systems*, 34:26804–26817, 2021.

[119] Wei Tang, Chien-Ju Ho, and Yang Liu. Linear models are robust optimal under strategic behavior. In *International Conference on Artificial Intelligence and Statistics*, pages 2584–2592. PMLR, 2021.

[120] Kenneth E Train. *Discrete choice methods with simulation*. Cambridge university press, 2009.

[121] Amos Tversky and Daniel Kahneman. Belief in the law of small numbers. *Psychological bulletin*, 76 (2):105, 1971.

[122] Amos Tversky and Daniel Kahneman. The framing of decisions and the psychology of choice. *science*, 211(4481):453–458, 1981.

[123] Dimitris G Tzikas, Aristidis C Likas, and Nikolaos P Galatsanos. The variational approximation for bayesian inference. *IEEE Signal Processing Magazine*, 25(6):131–146, 2008.

[124] V. N. Vapnik and A. Ya. Chervonenkis. On the uniform convergence of relative frequencies of events to their probabilities. *Theory of Probability and its Applications*, 16(2):264–280, 1971.

[125] Oleksandra Vereschak, Gilles Bailly, and Baptiste Caramiaux. How to evaluate trust in ai-assisted decision making? a survey of empirical methodologies. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2):1–39, 2021.

[126] Oriol Vinyals, Igor Babuschkin, Wojciech M Czarnecki, Michaël Mathieu, Andrew Dudzik, Junyoung Chung, David H Choi, Richard Powell, Timo Ewalds, Petko Georgiev, et al. Grandmaster level in starcraft ii using multi-agent reinforcement learning. *Nature*, 575(7782):350–354, 2019.

[127] John von Neumann and Oscar Morgenstern. *Theory of Games and Economic Behavior*. Princeton University Press, 1944.

[128] Xin Wang, Yudong Chen, and Wenwu Zhu. A survey on curriculum learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(9):4555–4576, 2021.

[129] Christopher J.C.H. Watkins and Peter Dayan. Q-learning. *Machine learning*, 8(3-4):279–292, 1992.

[130] Christabel Wayllace, Sunwoo Ha, Yuchen Han, Jiaming Hu, Shayan Monadjemi, William Yeoh, and Alvitta Ottley. Dragon-v: detection and recognition of airplane goals with navigational visualization. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 13642–13643, 2020.

[131] Jacob Whitehill, Ting fan Wu, Jacob Bergsma, Javier R. Movellan, and Paul L. Ruvolo. Whose vote should count more: Optimal integration of labels from labelers of unknown expertise. In *Advances in Neural Information Processing Systems (NIPS)*, 2009.

[132] Wayne Xiong, Lingfeng Wu, Fil Alleva, Jasha Droppo, Xuedong Huang, and Andreas Stolcke. The microsoft 2017 conversational speech recognition system. In *2018 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pages 5934–5938. IEEE, 2018.

[133] Ming Yin, Jennifer Wortman Vaughan, and Hanna Wallach. Understanding the effect of accuracy on trust in machine learning models. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, page 279. ACM, 2019.

[134] Guanghui Yu and Chien-Ju Ho. Environment design for biased decision makers. In *Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI)*, 2022.

[135] Kaiqing Zhang, Zhuoran Yang, and Tamer Başar. Multi-agent reinforcement learning: A selective overview of theories and algorithms. *Handbook of reinforcement learning and control*, pages 321–384, 2021.

[136] Yunfeng Zhang, Q Vera Liao, and Rachel KE Bellamy. Effect of confidence and explanation on accuracy and trust calibration in ai-assisted decision making. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, pages 295–305, 2020.

[137] Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. Men also like shopping: Reducing gender bias amplification using corpus-level constraints. *arXiv preprint arXiv:1707.09457*, 2017.

[138] Yudian Zheng, Guoliang Li, Yuanbing Li, Caihua Shan, and Reynold Cheng. Truth inference in crowdsourcing: Is the problem solved? *Proceedings of the VLDB Endowment*, 10(5):541–552, 2017.

[139] Brian D Ziebart, Andrew Maas, J Andrew Bagnell, and Anind K Dey. Maximum entropy inverse reinforcement learning. 2008.