The Impact of Social Information on Private Use of Algorithmic Decision Support

Keywords: human-AI interaction, social signaling, teams, decision-making, experiments

Extended Abstract

Introduction

Algorithmic decision support (ADS) is ubiquitous and takes many forms – customer relationship management tools that provide sales forecasting functionality, grammar correction extensions we install on our browsers, and medical diagnostic aids, to name a few. In many contexts, users of these tools interact with and receive signals (explicit and implicit) from other people who may or may not be users themselves; these signals can impact the willingness to use such tools, and a user's effectiveness at doing so.

For example, consider a team of two employees, instructed by their manager to forecast two distinct quantities for use in a report: the employees could generate their forecasts from manual analysis, or outsource their forecasting tasks to an algorithm. It is reasonable to hypothesize that users may underutilize ADS out of concerns that they may be perceived as less competent [1], or overutilize ADS as a scapegoat to which the blame for poor decisions can be assigned [2]. Beyond individual-level factors affecting technology use, social information processing theory suggests that each employee's decision to utilize the ADS may not be independent of the other's, as demonstrated by Gallivan et al in the context of employees adopting new information technology infrastructure and applications [3].

Contrary to these plausible mechanisms of social context affecting the private use of algorithmic assistance, research on algorithmic adoption/aversion commonly adopts the "decision trials" paradigm [4], in which a user's willingness to utilize ADS is measured on a sequence of instances of a task performed alone. With the existence of emergent phenomena in both human collectives and in the interaction of humans and algorithmic agents [5], it likely follows that understanding their combination–collectives of humans, each utilizing their own ADS–requires simultaneous manipulation of both the unit of analysis (individual/collective) and the availability of algorithmic tools, as described in Figure 1. In this study, we seek to answer the question of *how social context affects an individual's willingness and effectiveness in utilizing ADS, relative to individuals operating in isolation*.

Experimental Design

An ideal situation to measure the impact of social context might be one in which there were collections of individuals and groups, with agents in both collections completing the same tasks and having access to the same algorithmic assistant. It is hard to imagine a real-world scenario with these properties for several reasons, the most obvious of which is the requirement of task and ADS similarity. However, even if that requirement were fulfilled, our inference would be impaired by the fact that whether an agent belongs to a group or not is highly endogenous – workers who choose to be freelancers, for example, likely differ from company employees on key factors such as skill, education, and experience, and workers also self-select into specific companies based on organizational culture and values.

Instead, we approach this question experimentally, with the ability to finely control the properties of the decision-making task and algorithmic assistant, while exogenously manipulating membership, structure, and communication modes within a group. We describe a between-subjects design in Figure 2, in which participants are randomized to either complete tasks individually or within a group. To answer our question of the average effect of the social context on an individual's willingness to utilize ADS, our dependent variable is a measure of the degree of delegation to the algorithmic assistant (e.g. a binary variable in the case of complete delegation, or "weight of advice" for a continuous measure of delegation, as appropriate for each decision-making task), while the effectiveness of ADS utilization is measured by performance outcomes (e.g. accuracy, time taken, and efficiency).

The study is in progress, and is being executed in Empirica [6], an open-source virtual lab framework designed for large-scale multiplayer experiments, with participants recruited from Prolific and Amazon Mechanical Turk – a screenshot of the group experimental interface is shown in Figure 3. The experiment allows for task types, algorithmic design factors (e.g. algorithm accuracy, transparency, feedback [7]), and group interaction factors (e.g. chat capability, status indicators, group hierarchy, and incentive structure) to be systematically varied, increasing the robustness of our findings, allowing us to explore potentially interesting interactions, and introducing a novel dataset of algorithmically assisted decision-making behavior across a wide range of conditions.

References

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		Unit of Analysis	
		Individual	**Collective**
Algorithmic Aid	**Without algorithmic aids**	Individual Decision-making	Group Decision-making
	With algorithmic aids	"Decision Trials" Paradigm	**Current Study**

Figure 1. Experimental design dimensions: The main dimensions manipulated in this study are the unit of analysis and the availability of ADS. Holding the unit of analysis as the individual, the algorithmic aversion/affinity research program studies emergent human-AI interaction phenomena when introducing algorithmic aids. Without introducing algorithmic aids, social psychologists and sociologists study emergent decision-making behaviors when going from an individual to a collective unit of analysis. To understand the utilization of ADS in collectives (the current study), it is unlikely that we can simply add the insights of these two research programs; thus, we manipulate the dimensions simultaneously to capture the emergent behavior of the algorithmically-empowered collective.

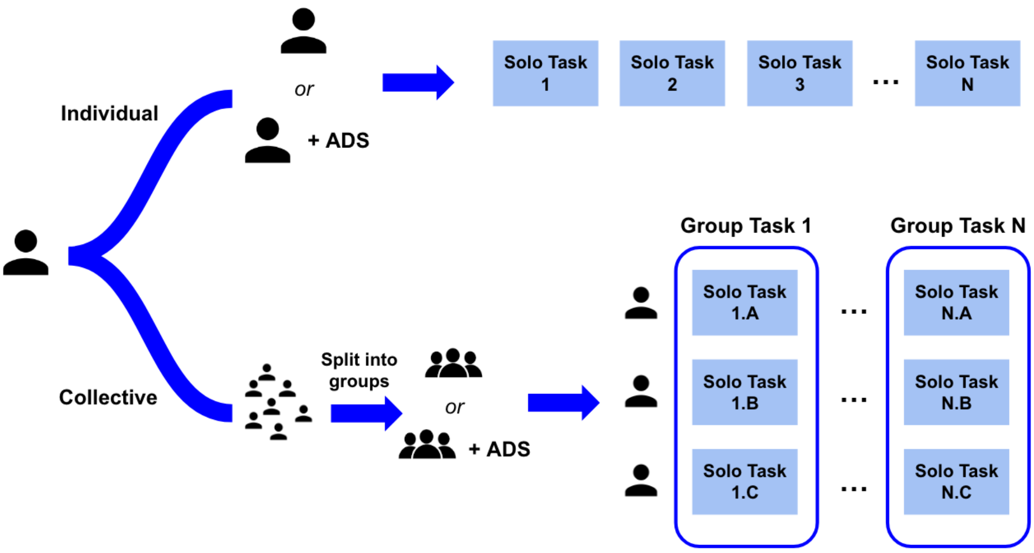

Figure 2. Between-subjects experimental design: Participants are first randomized into either the individual or collective condition; individuals and groups are then randomized into units that have access to an ADS tool, and units that do not. Participants in the individual condition complete a series of tasks alone (with or without ADS) and are rewarded based on their cumulative performance across tasks. Participants in the group condition simultaneously complete sub-tasks (which are identical to the tasks completed by those in the individual condition) of a "group task" individually (with or without ADS), but can interact with each other in different ways. The group is then rewarded based on their cumulative performance across group tasks, while the group's performance on each group task is an aggregate function of its members' performance on their individual sub-tasks.

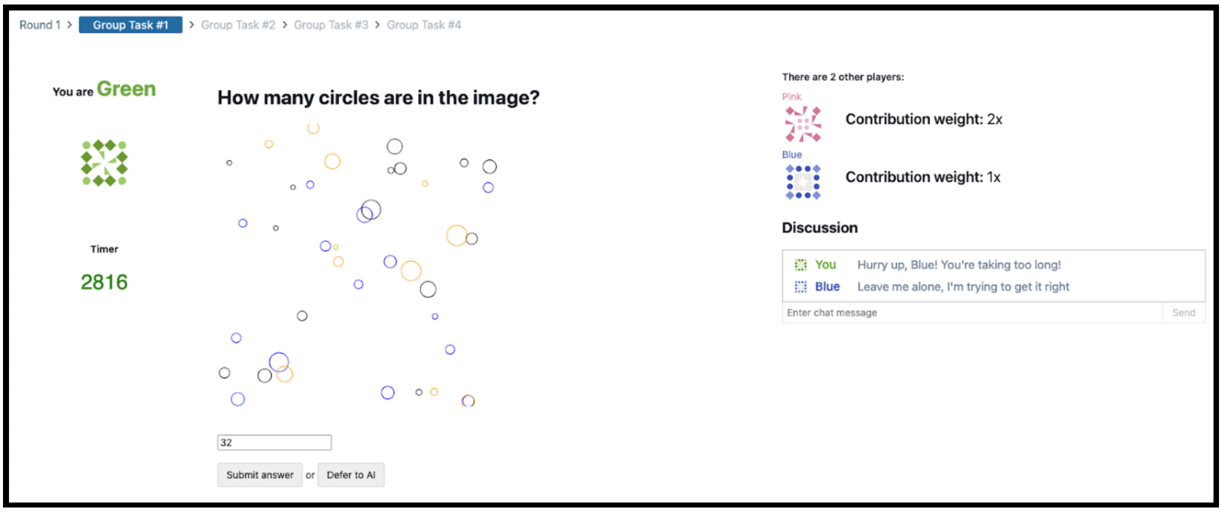

Figure 3. Screenshot of group task interface: In this experiment, participants in both the individual and group conditions complete a series of tasks; this screenshot shows the interface while completing one such task as a group. The focal player (Green) is tasked with counting the circles in the image presented, with the time limit shown on the left, and information about her group members (Pink and Blue) shown on the right, along with the chat window. Green can choose to either complete the task manually and submit a count of circles, or click the "Defer to AI" button to have an algorithmically-generated answer submitted on her behalf. Participants in the individual condition are shown an identical interface, with the group-related elements (right sidebar) removed.