How Decision-Process Information Shapes Inferences in Cooperative Interactions

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Abstract

Eye movements reveal attentional processes underlying decisions, potentially enabling observers to infer hidden preferences in social interactions. We tested whether real-time gaze information improves preference inference during an interactive bargaining task, in which 79 pairs of participants were assigned to either a control group or an attention group, the latter having access to live eye tracking of buyers' fixations. Sellers adjusted subsequent offers based on buyers' response times. Buyers' first fixations signaled attribute importance, and sellers in the attention group were sensitive to this information. This benefit, however, did not result in higher earnings than in the control condition. To understand how sellers learned buyers' preferences, we developed a Bayesian learning model for the seller, its results suggest that sellers make a trade off between maximizing utility and making offers that reveal more information. These findings highlight that real-time attentional cues can reveal preference signals but may be too complex to utilize, informing our understanding of attention and decision making in social contexts.

Keywords: Decision making, Social learning, Attention, Bayesian belief updating

Introduction

Humans often infer others' private preferences, intentions, and beliefs by observing their decisions (Joiner et al., 2017; Vostroknutov et al., 2018; Charpentier et al., 2020; Wu et al., 2021). Beyond choices alone, additional cues such as response times (RT) and gaze patterns can offer insights into latent valuations and social preferences (Konovalov & Krajbich, 2019; Bavard et al., 2023; Hausfeld et al., 2021). For instance, when deciding between multiple items, people typically fixate more on the item they eventually choose (Callaway et al., 2021; Gluth et al., 2018). The present study builds upon these findings by exploring whether real-time access to a partner's eye movements improves a seller's ability to learn the buyer's hidden preferences in an iterative bargaining setup.

We hypothesized that providing the seller with live gaze information would enable more accurate inferences about which product attributes the buyer values most, leading them to make offers that the buyer is more inclined to accept. Furthermore, we expected that faster rejection would indicate particularly low offer utility, leading sellers to adjust their offers more drastically.

Methods

Participants and Design. 79 pairs (N=158; age: 24.9 ± 6.9 SD years; 113 female, 45 male)) were assigned to buyer or seller roles in an interactive bargaining task. Each pair was randomized into one of two experimental groups:
i) Attention group: Sellers saw a live display of the buyer's gaze ii) Control group: Buyer's gaze was recorded but sellers did not see the gaze data. Attribute weights that determined product utilities were manipulated in a within-subject design—in one block of trials, weights were explicitly "instructed," while in the other block they were based on participants' "natural" preferences. Participants bargained over 20 product categories (e.g., cars), each with three attributes (e.g., speed, comfort, security), choosing from 12 possible product options per category.

The bargaining task. In each trial, the seller proposed an initial product option. The buyer then either accepted or rejected. If rejected, the seller could adjust and present up to three subsequent offers. While buyers aimed to maximize their own utility (points awarded based on how well the product attributes matched their preference weights), the seller received points for each successful sale. If the buyer rejected all four offers, they received a fixed baseline payment of 50 points, while the seller earned nothing.

Results

Buyer and Seller Performance. Buyers accepted offers significantly above the 50-point baseline (60.7, SD ±7.6, $t(2397) = 68.9$, $p < .001$). Overall, sellers accumulated more points than chance (70.9, SD ± 36.0, $t(2923) = 21.99$, $p < .001$), implying some level of preference learning. Notably, "natural" preference scenarios yielded fewer negotiation steps, and higher earnings for both parties.

Effects of RT. Rejection speed correlated with how close an offer was to the buyer's preferred choice option. This was taken into account by sellers, as faster rejection RTs prompted sellers to make larger adjustments on subsequent offers (B = 2.4702, SE = 0.2181, $t(437.1342) = 11.327$, $p < .001$; Figure 1a).

Gaze Patterns. First fixations were more likely directed at attributes carrying higher weight (highest weight: 55%, 95% CI: [54, 56]; middle-weight: 26%, 95% CI: [25, 27]; lowest weight: 19%, 95% CI: [18, 20]). Last fixations showed a reversed pattern, negatively correlating with attribute weight, and total dwell time was not predictive of preference.

Comparison of Attention vs. Control Groups
Sellers in the attention group were sensitive to buyers' gaze patterns, as they adjusted their subsequent offer depending on which attribute was fixated first (M = 53.03 ± 4.22, $t(73) = -2.18$, $p = 0.0164$; Figure 1b). However, they did not earn significantly more points than sellers without gaze access (B = -3.758, SE = 2.809, $t(75) = -1.337$, $p = 0.185$).This indicates that while eye-movement information is meaningful, it may be difficult to utilize effectively in real-time negotiations.

Cognitive Modeling To understand the computational processes by which the seller could learn the buyer's preference, we developed a choice model for the buyer and a learning and choice model for the seller. Buyers followed a sigmoid relationship between utility and choices (B = 0.160 , SE = 0.004, $p < .001$). The sellers were modeled as a Bayesian learner, who can learn from buyers' choices and update their beliefs over preferences. Furthermore, the sellers were assumed to make a tradeoff between making offers that maximize utility and making offers that reveal more information about the buyer's preferences (using a tradeoff parameter λ.) Seller's overall offer value was a sum of λ * information gain + ($1-\lambda$) * utility. Bayesian modeling suggested a non-zero value of λ (0.18 ± 0.044, 95% CI: [0.10, 0.26]), suggesting that sellers did take information gain into account, but were more driven by utility.

Discussion

Our findings highlight how decisions, response times, and visual fixations each provide distinct clues about hidden preferences in a buyer–seller bargaining framework. Sellers did appear to factor in buyers' RT, adjusting offers more sharply following quick rejections. However, harnessing gaze data in real time to translate attentional signals into consistently more profitable outcomes proved challenging. Complex fixation trajectories such as the discrepancy between first and last fixation patterns likely complicated the seller's interpretation of the buyer's true priorities.

Figures

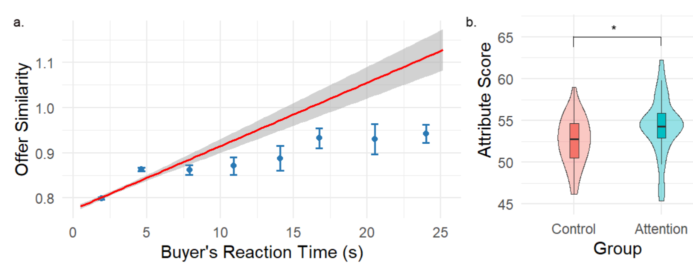

Figure 1. a) Sellers' offers are sensitive to buyer's RT. The similarity between consecutive offers increases the longer the buyer takes to reject an offer. b) Seller's with access to buyer's eye movements learn from which attribute buyers look at first. The attribute score of the first fixated attribute is higher in the Attention group as compared to the control group.

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