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Intrinsic Motivation and Altruism under Rational Inattention: Do We Perform Better When We Care?

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Abstract
Under the rational inattention framework, we explore the relationship between intrinsic motivation, altruism, information (attention) cost, and decision performance using perceptual tasks. We find counterintuitive results: higher intrinsic motivation leads subjects to perform worse. Furthermore, a high level of altruism is associated with lower decision performance when information acquisition benefits others. These observations are attributed to a positive relationship between altruism, intrinsic motivation, and information cost. Our findings highlight the complex trade-offs between intrinsic motivation, altruism, and cognitive limitations. They challenge the common assumption that increased motivation may lead to better outcomes. Meanwhile, we find that the net expected utility and the cost of information acquisition do not vary across different decision contexts. These results suggest that cognitive constraints may depend less on how subjects are paid and more on how the experiment is designed.

JEL Classification: C91; D60; D80; E20

Keywords
altruism — rational inattention — intrinsic motivations — perceptual tasks

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Introduction

Attention serves as a fundamental catalyst for information processing, and recognizing it as a precious yet limited resource becomes essential for its efficient allocation in economic analysis (Davenport and Beck, 2001; Kalil et al., 2023; Maćkowiak et al., 2023). The theory of rational inattention (RI hereafter) (Sims, 2003) posits that individuals maximize expected utility net of information (or attention) costs. The cost function is often rooted in Shannon's mutual information (Cover, 1999; Shannon, 1948), which quantifies the reduction in the average distance between priors and posteriors (Caplin et al., 2022; Matějka and McKay, 2015).

The majority of experimental studies testing RI theory employ explicit monetary rewards as incentives for participants who accurately complete choice tasks (Civelli et al., 2022; Dean and Neligh, 2023; Dewan and Neligh, 2020). These experiments are analogous to what we refer to as the self-interested incentives situation. Yet, whether the RI framework extends to contexts where incentives are structured differently – particularly when individuals' attention allocation benefits others – remains an open question. Psychological and economic studies highlight that intrinsic motivations, as well as altruistic preferences, can shape attention allocation (Ciccarone et al., 2025; Deci and Ryan, 2003; Sohlberg and Mateer, 1989). Specifically, Robinson et al. (2012) shows that individuals with stronger intrinsic motivations exhibit decision patterns that are less responsive to financial incentives.

The aim of this paper is to shed light on choice behavior using the RI framework in both self-interested (T1) and pro-social (T2) decision contexts. In the former case, an individual can choose to acquire costly information to reduce uncertainty, which in turn increases her expected monetary payoff. In the latter case, the individual's expected monetary payoff depends only on the decisions of others, while her correct choices (made through costly information acquisition) generate monetary benefits for her peers. This payoff structure naturally introduces altruistic motives, making T2 an ideal environment in which to investigate the joint role of altruism and intrinsic motivation in attention allocation.

In both decision contexts, we examine how non-monetary components of utility interact with information acquisition constraints to shape decision performance. More specifically, we investigate the interactions among enjoyment, altruism, attention cost, and decision performance. Finally, we compare whether attention costs differ across decision contexts.

To address our questions, we use a published experimental dataset collected by Toumi and Rafaï (2018). The experiment employed visual perceptual tasks,[1] which are widely used in the RI experimental literature (Civelli et al., 2022; Dean and Neligh, 2023; Dewan and Neligh, 2020). However, unlike our

[1] These tasks required participants to process visual stimuli—such as counting differently colored dots on a computer screen—and then make a state-dependent decision. Correct decisions depended on attention-intensive processing of the stimuli.

analysis, Toumi and Rafaï (2018) relied solely on response time as a proxy for attention allocation. In contrast, our paper diverges from their approach in three key respects. First, our analysis is grounded directly in RI theory, which allows us to interpret choice behavior within a structural framework. Second, rather than relying on proxy measures, we estimate the attention cost parameter, which quantifies the cognitive cost of processing information, and analyze its relationship with intrinsic motivation, altruism, and decision accuracy. Third, in the T2 treatment, we explicitly estimate an altruism parameter that captures the utility weight subjects assign to others' payoffs. Together, these features allow us to assess how intrinsic and social motivations jointly influence attention allocation under cognitive constraints.

Our findings challenge the conventional assumption that higher motivation improves performance: for example, in our setting, greater enjoyment and stronger altruistic preferences are associated with higher information costs, which leads individuals to perform worse-off. This is because a higher information cost decreases the degree of accuracy rate. Meanwhile, we show that net expected utility and information costs do not differ significantly between treatments, implying that cognitive constraints are robust to changes in incentive structures.

Our paper contributes to both the rational inattention and social preference literatures. First, it extends the experimental RI literature, which has traditionally focused exclusively on self-interested scenarios (Civelli et al., 2022; Dean and Neligh, 2023; Dewan and Neligh, 2020). We provide novel evidence on how intrinsic motivation and altruism correlate with attention costs and decision accuracy across both T1 and T2. Second, we offer a new interpretation of altruistic behavior. Previous studies on social preferences typically analyze altruism using well-established experimental paradigms such as the dictator game (Forsythe et al., 1994), the ultimatum game (Camerer and Weber, 1992; Güth et al., 1982), or the public goods game.[2] In these frameworks, altruism is generally quantified by the percentage given (in dictator and ultimatum games) or the amount contributed (in public goods games). By contrast, to our knowledge, our study is the first to investigate altruism through visual perceptual tasks grounded in the RI framework.[3]

In our setting, altruistic behavior is not defined as a direct sacrifice of one's own monetary payoff to increase the payoff of others, but rather as a willingness to incur cognitive costs by allocating additional attention in order to improve accuracy, thereby generating monetary benefits for peers. This perspective enriches the interpretation of altruism by linking it to the cost of information acquisition. Our structural estimations show that altruism is positively correlated with information cost and negatively correlated with accuracy, suggesting that prosocially motivated individuals process more information, pay higher cognitive costs, but paradoxically perform worse. This counterintuitive finding mirrors the role of intrinsic motivation in our results, where greater enjoyment also raises attention costs and reduces accuracy.

The measurement of altruism in classical social games is often affected by confounding factors such as reciprocity (Cox, 2004), social pressure (Zizzo and Fleming, 2011), or beliefs about others' strategies (Fischbacher and Gächter, 2010). Perceptual tasks, by design, mitigate many of these concerns, since decisions involve effortful information processing rather than redistributive choices. Accordingly, our framework provides a cleaner environment in which to study altruism, emphasizing its cognitive underpinnings and its interaction with attention costs. In this way, we offer a fresh interpretation of prosocial behavior that links social preferences to rational inattention and cognitive constraints.

The remainder of the paper is organized as follows. Section 2 describes the experimental data. Section 3 presents our behavioral hypotheses. Section 4 reports the empirical results. Section 5 concludes the paper.

Experimental Data

We used lab-experiment data provided by Toumi and Rafaï (2018). The experiment was conducted at the Laboratoire d'Économie Expérimentale de Nice (LEEN) at Université Côte d'Azur in April and May 2016. The experimental setup was similar to the visual perceptual tasks used in studies such as Caplin and Dean (2015); Civelli et al. (2022); Dean and Neligh (2023); Dewan and Neligh (2020).

In simple terms, subjects need to allocate their attention to reveal the states of nature. If state S_B occurs, the correct choice is B; if state S_W occurs, the correct choice is W. The experiment included two treatments in a between-subjects design[4]: a self-interested scenario (T1) and a pro-social treatment (T2). The Intrinsic Motivation Inventory (IMI) has been used to measure intrinsic motivation (Deci and Ryan, 2003; McAuley et al., 1989; Plant and Ryan, 1985; Ryan, 1982; Ryan et al., 1983). Complete experimental instructions can be found in the online Appendix-Instructions.

Behavioral Hypotheses

In this section, we formulate our behavioral hypotheses, which are directly derived from the experimental design and the RI model. Readers can find detailed information regarding the theoretical modeling and experimental design in the Online Appendix – Supplemental Material.

Table 1 shows our treatment-dependent utility functions. In the T1 treatment, selecting the correct choice resulted in earning 6 Experimental Currency Units (ECU), where 100 ECU was equivalent to 1 euro; otherwise, the subject earned 0

[2] See Andreoni et al. (2010) for a review of experimental studies on social games.

[3] Toumi and Rafaï (2018) introduced a pro-social treatment with perceptual tasks but did not specifically analyze altruistic behavior within the RI framework.

[4] The experiment conducted by Toumi and Rafaï (2018) also included a "No-Incentives (T0)" treatment. However, we did not use the data from this treatment because it is irrelevant to our study.

ECU. Where "Enjoyment" represents self-reported enjoyment, and β is a parameter to be estimated.

Treatments	Utility functions u
T1	6 ECU + β_{T1} × Enjoyment$_{T1}$
T2	E(ECU) + β_{T2} × Enjoyment$_{T2}$ + α × 6 ECU

Table 1. Utility functions.
Note: The utility functions represent the utility that subjects obtain from making correct choices.

In the T2 treatment, each subject was randomly paired with two other players for each choice task. Choosing correctly generated 3 ECU for the two matched players, with no earnings otherwise. Meanwhile, a subject's monetary rewards depended on the decisions of her two group members. However, the dataset provided by Toumi and Rafaï (2018) lacked precise information regarding this aspect. We replace the subject's monetary rewards with the expected value that she may obtain: $\text{E(ECU)} = 0.25 \times 6\,\text{ECU} + 2 \times 0.25 \times 3\text{ECU} = 3\,\text{ECU}$. This is because, the subject may receive 0 ECU if both of her two group members made the incorrect choice, 3 ECU if only one of her group members made the correct choice, or 6 ECU if both of her two group members made the correct choice. Therefore, if the subject was rational, she may consider that she had an equal probability (25%) of obtaining 0 or 6 ECU in a choice task, and she had a 50% chance of obtaining 3 ECU. Furthermore, the correct choice made by the subject generated 3 ECU for each of her two group members, resulting in a total of 6 ECU. Therefore, an additional component of altruism, α, is introduced into the utility function (Levine, 1998; Rotemberg, 2014). The parameter α ranges from 0 to 1, where 0 indicates that the subject did not care at all about others' monetary rewards.

For simplicity, we denote λ as the marginal information cost of processing information in the RI model, and $\gamma(\cdot)$ as subjects' posterior belief about the states of nature after information acquisition. One can also interpret $\gamma(\cdot)$ as the accuracy rate. For example, given that B (W) is the correct choice in state S_B (S_W), the conditional probability that S_B occurs, given B is chosen, $\gamma(S_B|B)$, is referred to as the accuracy rate for state S_B. According to the RI model and our treatment-dependent utility functions, several hypotheses can be derived.

H1: β is positively related to λ in both treatments.

- Dean and Neligh (2023) reported that the marginal information cost λ increases with utility u[5]. A higher enjoyment β leads to a greater u. Therefore, we assume that β is positively related to λ.

H2: λ is negatively related to $\gamma(\cdot)$ in both treatments.

- We assume that a higher marginal information cost λ results in lower accuracy $\gamma(\cdot)$. This hypothesis is reasonable according to the prediction of the RI model.

H3: β is negatively related to $\gamma(\cdot)$ in both treatments.

- Higher enjoyment (β) results in lower accuracy ($\gamma(\cdot)$). Although our H3 may seem counterintuitive, it is plausible: larger stakes (i.e., higher utility) can lead to bigger mistakes (Ariely et al., 2009). Furthermore, according to H1 and H2, if λ and β increase together, and λ decreases $\gamma(\cdot)$, it is reasonable to assume that β is negatively related to $\gamma(\cdot)$.

H4: β_{T2} is positively related to α in the T2 treatment.

- In the T2 treatment, we assume that if a subject is pro-social (i.e., has a high α), she should enjoy the experiment and make correct choices that benefit other players.

H5: α is positively related to λ_{T2} in the T2 treatment.

- Higher altruism (α) leads to greater u. Therefore, we assume that α is positively related to λ_{T2}.

H6: α is negatively related to $\gamma(\cdot)$.

- Our H6 might be counterintuitive. However, according to H5 and H2, if the level of altruism (α) and information cost (λ_{T2}) increase together, and λ_{T2} decreases accuracy $\gamma(\cdot)$, it is reasonable to assume that α is negatively related to $\gamma(\cdot)$.

H7: The marginal information cost, λ, differs between T1 (λ_{T1}) and T2 (λ_{T2}).

- To our knowledge, there is no evidence showing how the information cost λ varies across different decision situations. However, in the RI model, the value of λ is a function of utility u and accuracy $\gamma(\cdot)$ (see Caplin et al. (2022) for the Invariant Likelihood Ratio condition). Therefore, to infer the ranking of λ_{T1} and λ_{T2}, it is necessary to examine how utility and accuracy vary between the two treatments.

Results

The experiment included a total of 75 subjects (36 in T1 and 39 in T2), each of whom completed 100 choice tasks, resulting in a total of 7,500 observations. The average age of participants was 23.64 years, with a standard deviation of 6.77 years. 36% of the subjects were reported as male.

[5]The Invariant Likelihood Ratio (ILR) condition (Caplin et al., 2022) states that the information cost is a function of utility and accuracy. In our experimental setting, the ILR condition implies that:

$$\lambda = \frac{u(B, S_B)}{\ln \gamma(S_B) - \ln \gamma(S_W)}.$$

The model predicts that accuracy should increase proportionally as utility increases; therefore, the information cost remains stable. However, Dean and Neligh (2023) reported experimental evidence that information cost increases with utility. Hence, the experimental findings contradict the model's prediction.

Statistical Results

We first present some statistical results comparing subjects' choice behavior in the two treatments. Figure 1 shows subjects' decision accuracy in the two treatments.

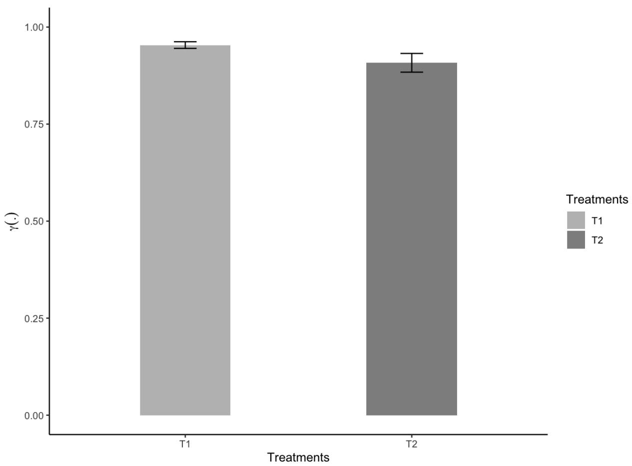

Figure 1. Accuracy.

Note: $\gamma(\cdot)$ represents subjects' actual posterior regarding the true states of nature, which we interpret as accuracy.

The average accuracy was 0.954 and 0.908, with standard errors of 0.008 and 0.024 in the T1 and T2 treatments, respectively. We conducted a simple t-test showing that the accuracy in T1 was not statistically significantly different from T2 ($t = 1.781, p = 0.081$). This result is consistent with Toumi and Rafaï (2018), who reported that the error rates in the two treatments were not statistically significantly different.

Figure 2 shows the comparison of decision time between the two treatments. Decision time represents the duration from when a subject began a choice task until she made her choice in that same task.

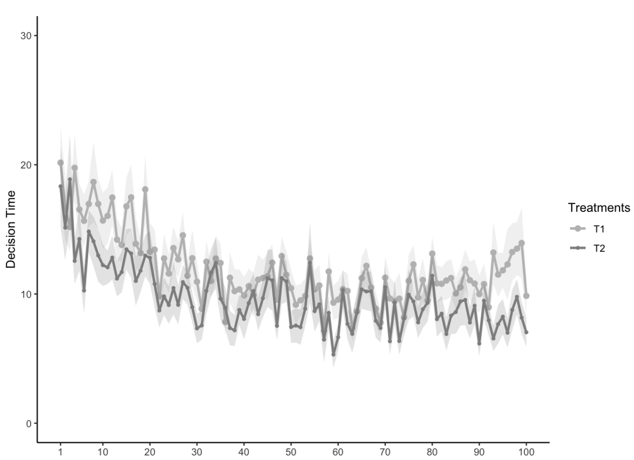

Figure 2. Decision time.

Note: The decision time represents the average time spent on a particular choice task across all subjects.

On average, the decision time in the T1 treatment was 11.976 seconds across all choice tasks, with a 95% confidence interval ranging from 10.318 to 13.634 seconds. In the T2 treatment, it was 9.722 seconds, with a confidence interval ranging from 8.170 to 11.273 seconds. A simple t-test shows that the decision time in T1 was statistically significantly different from that in T2 ($t = 6.111, p < 0.001$). Therefore, subjects appeared to spend more time in T1 than in T2.

Note that Toumi and Rafaï (2018) used decision time as a measure of attention allocation and concluded that subjects allocated more attention in T1 than in T2 due to longer decision times. However, in our paper, we use the RI model, in which attention allocation is measured by Shannon mutual information. Therefore, decision time alone cannot serve as a reliable index to infer that T1 attracted more attention than T2. To determine the underlying ranking between the marginal information costs λ_{T1} and λ_{T2} (i.e., H7), we must examine how net expected utility and accuracy vary between the two treatments (see Online Appendix – Supplemental Material).

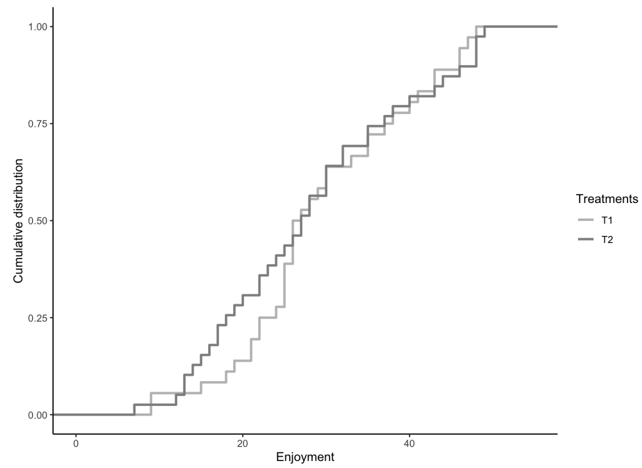

Figure 3. Enjoyment.

Note: "Enjoyment" represents subjects' self-reported enjoyment after they completed all choice tasks.

Figure 3 shows the cumulative distribution of self-reported enjoyment in the two treatments. In this paper, we use enjoyment as the sole index of intrinsic motivation[6]. On average, the self-reported enjoyment was 29.444, with a standard deviation of 0.167, in the T1 treatment. In the T2 treatment, it was 28.154, with a standard deviation of 11.530. A simple t-test shows that the self-reported enjoyment was not statistically significantly different between the two treatments ($t = 0.508, p = 0.612$). Toumi and Rafaï (2018) also found that self-reported enjoyment did not differ between the two treatments. Therefore, they concluded that decision situations (treatments) had no impact on intrinsic motivation. However, there was no evidence on how intrinsic motivation interplays with attention allocation. In this paper, we address this gap by investigating the relationship between the information cost λ and the parameter associated with enjoyment, β.

[6]This approach aligns with Toumi and Rafaï (2018), who similarly used enjoyment as the sole measure of intrinsic motivation.

Rational Inattention

The RI model predicts that the optimal accuracy for rationally inattentive subjects should be less than 1 and greater than 0.5.

Accuracy $\gamma(\cdot)$	T1	T2
$\gamma(\cdot) = 1$	9	3
$0.5 < \gamma(\cdot) < 1$	27	35
$\gamma(\cdot) \leq 0.5$	0	1
Total	36	39

Table 2. Category of subjects.
Note: Individual-level accuracy was computed as the total number of correct choices divided by the total number of choice tasks (e.g., 100 trials).

In the T1 treatment, 75% (27 of 36) of subjects exhibited rationally inattentive behavior, while 25% exhibited ”full attention”. In the T2 treatment, 89.7% of subjects were rationally inattentive and 7.7% exhibited ”full attention”, with only one subject showing accuracy below 0.5. Note that we classify subjects with perfect accuracy (e.g.,$\gamma(\cdot) = 1$) as exhibiting ”full attention”, though this does not imply they are not rationally inattentive. This occurs because these subjects may face a substantially lower marginal information cost (λ), enabling them to achieve maximum accuracy. To determine whether a subject is rationally inattentive, we must examine whether an information cost exists for that subject.

A subject is rationally inattentive if her choice behavior satisfies both the No Improving Attention Cycles (NIAC) and No Improving Action Switches (NIAS) conditions (Caplin and Dean, 2015). The NIAC condition requires that posterior accuracy be a non-decreasing function of stimulus strength. The NIAS condition stipulates that the (revealed) posterior probability associated with the true state of nature must exceed those of alternative states. However, our experimental design does not allow testing the NIAC condition, as neither the T1 nor T2 treatment incorporates varying stimulus strength. Nevertheless, our setup enables verification of whether the NIAS condition is satisfied.

The NIAS condition in our experimental setting requires testing the following two inequalities: $\gamma(S_B|B) \geq \gamma(S_W|B)$ and $\gamma(S_W|W) \geq \gamma(S_B|W)$. Here, $\gamma(S_B|B)$ represents the conditional probability of state S_B occurring given that action B was chosen.

Figure 4 indicates that the NIAS condition was satisfied at the aggregate level in both treatments. In the T1 treatment, the average $\gamma(S_B|B)$ was 0.943, with a standard deviation of 0.069. The average $\gamma(S_W|B)$ was 0.036, with a standard deviation of 0.048. The average $\gamma(S_W|W)$ was 0.963, with a standard deviation of 0.047. The average $\gamma(S_B|W)$ was 0.056, with a standard deviation of 0.069. A paired t-test shows that the NIAS condition is satisfied, as the revealed posterior associated with the true state of nature is statistically significantly different from the alternative states of nature ($t = 52.961, p < 0.001$). In the T2 treatment, the average $\gamma(S_B|B)$ was 0.893, with a standard deviation of 0.161. The average $\gamma(S_W|B)$ was 0.074, with a standard deviation of 0.148. The average $\gamma(S_W|W)$ was 0.926, with a standard deviation of 0.148. The average $\gamma(S_B|W)$ was 0.107, with a standard deviation of 0.161 ($t = 16.995, p < 0.001$).

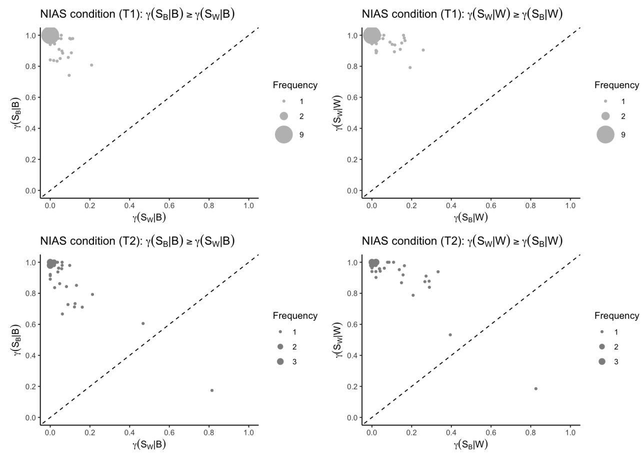

Figure 4. No Improving Action Switches (NIAS) condition.
Note: $\gamma(S_B|B)$ is computed as the number of occurrences in which state S_B and action B co-occur, divided by the total number of times action B was chosen.

Only one subject in the T2 treatment violated the NIAS condition. Therefore, we excluded this subject from our analysis.

Parametric Estimation

In this section, we study our behavioral hypotheses presented in Section 3 by exploring the relationship between information cost λ, intrinsic motivation β, altruism α, and accuracy $\gamma(\cdot)$. As mentioned earlier, for subjects who achieved maximum accuracy ($\gamma(\cdot) = 1$), the marginal information cost (λ) should theoretically equal zero. However, in practice, these subjects might face only a substantially lower information cost rather than none at all. To avoid identification issues, we used an accuracy threshold of $\gamma(\cdot) = 0.99$ for subjects who reached the maximum observed accuracy level.

Figure 5 shows the relationship between the estimated λ and β at the individual level[7]. We conduct a simple paired Pearson correlation test and find that β_{T1} is significantly positively related to λ_{T1} ($t = 19.108, p < 0.001$). We find the same result between β_{T2} and λ_{T2} ($t = 6.049, p < 0.001$).

These results confirm our H1 and have a direct behavioral interpretation. If a subject enjoys the experiment, she will spend more attention counting colored dots to learn the states of nature, which increases the information cost. Thus, intrinsic motivation plays an important role in attention allo-

[7] Our estimation approach involves a nested optimization procedure (Dean and Neligh, 2023). For each candidate pair of parameters β and λ, we numerically solve for the optimal accuracy $\gamma(\cdot)$ by maximizing net expected utility (See Online Appendix - Supplemental Material). This optimal accuracy is then used to compute the likelihood of observed choices. Maximum likelihood estimation then identifies the parameter values that best fit the data.

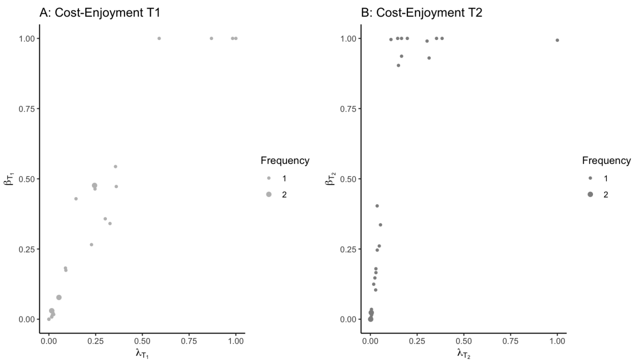

Figure 5. H1: λ and β.

Note: We set a lower bound of 0 and an upper bound of 1 for β in our estimation. When β equals zero, self-reported enjoyment does not contribute to utility. The estimated λ is normalized to a range from 0 to 1 to simplify the comparison.

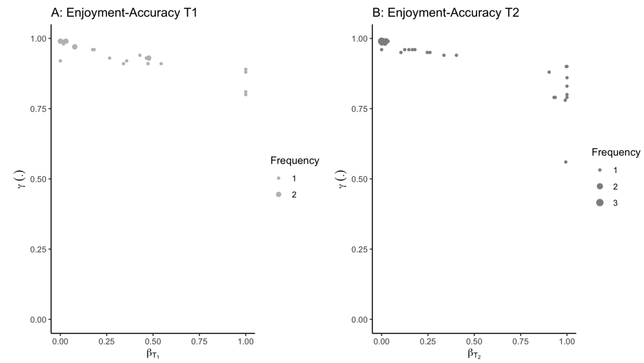

Figure 7. H3: β and $\gamma(\cdot)$.

Note: We set a lower bound of 0 and an upper bound of 1 for β in our estimation. When β equals zero, self-reported enjoyment does not contribute to utility.

cation regardless of decision situations. Furthermore, because Figure 3 does not show differences in self-reported enjoyment between the two treatments, the estimated β_{T1} and β_{T2} should not differ significantly from each other. A simple t-test confirms this hypothesis ($t = 1.112, p = 0.269$).

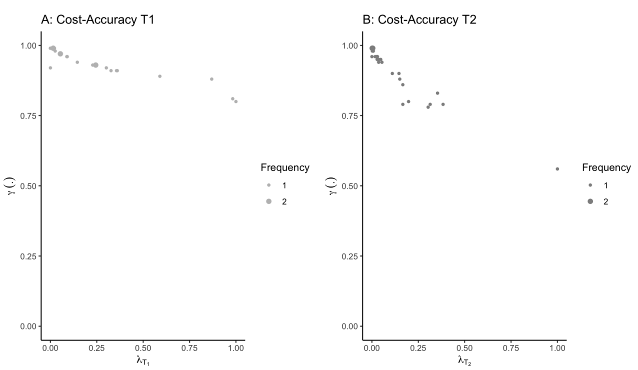

Figure 6. H2: λ and $\gamma(\cdot)$.

Note: $\gamma(\cdot)$ represents subjects' actual accuracy, computed as the number of correct choices divided by the total number of choice tasks (i.e., 100 choice tasks).

Figure 6 shows the relationship between actual accuracy $\gamma(\cdot)$ (or posterior) and information cost λ. The paired Pearson correlation test reveals a significant negative correlation between $\gamma(\cdot)$ and λ in T1 ($t = -16.555, p < 0.001$) and T2 ($t = -17.693, p < 0.001$). The RI model predicts that a more precise posterior results in a higher cost. Our results confirm this prediction. Previous studies (Civelli et al., 2022; Dean and Neligh, 2023; Dewan and Neligh, 2020) also find a negative relationship between $\gamma(\cdot)$ and λ in a self-interested incentive decision situation (T1). Our results confirm that such a negative relationship also holds in a pro-social incentive decision situation (T2).

Figure 7 shows the relationship between the estimated β and accuracy $\gamma(\cdot)$. The Pearson correlation test reveals a significant negative relationship between these two variables in T1 ($t = -13.349, p < 0.001$) and in T2 ($t = -9.4773, p < 0.001$). Therefore, these results confirm our H3.

At first glance, these results seem counterintuitive. In standard rational economic theory, where there is no information cost or cognitive constraint, higher enjoyment leads subjects to process all relevant information, resulting in higher accuracy. However, in the RI model, higher enjoyment motivates subjects to process more information, which increases the information cost and ultimately reduces accuracy. Thus, higher enjoyment indirectly reduces accuracy.

As mentioned before, these results (Figures 5, 6, 7) can also be interpreted as a violation of the Invariance Likelihood Ratio condition (Caplin et al., 2022), which predicts that $\gamma(\cdot)$ should increase proportionally with u, keeping λ stable. However, Dean and Neligh (2023) reports experimental evidence that λ increases with u, implying that the actual $\gamma(\cdot)$ increases more slowly than the optimal accuracy predicted by the model. In our study, since u is an increasing function of β, the actual accuracy $\gamma(\cdot)$ may also increase more slowly than the optimal accuracy predicted by the model as β increases. As λ rises with β (Figure 5), the marginal cost of processing additional information increases, discouraging subjects from fully capitalizing on the increased enjoyment to improve accuracy.

Figure 8 shows, in the T2 treatment, the relationship between the estimated altruism parameter α and the estimated enjoyment β_{T2} (Panel A), the estimated cost λ_{T2} (Panel B), and the actual accuracy $\gamma(\cdot)$ (Panel C).

A paired Pearson correlation test shows that β_{T2} is significantly positively related to α ($t = 30.21, p < 0.001$), suggesting that subjects who are altruistic also tend to enjoy the choice task of counting colored dots. Therefore, our H4 is confirmed. Meanwhile, α is significantly positively related to λ_{T2} ($t = 5.865, p < 0.001$). This observation is not surprising, as pro-social behavior leads subjects to allocate more effort (i.e., process more information) during the experiment, thereby increasing information cost. However, the increased information cost incurred by the subject benefits her group members by enabling them to earn higher monetary rewards.

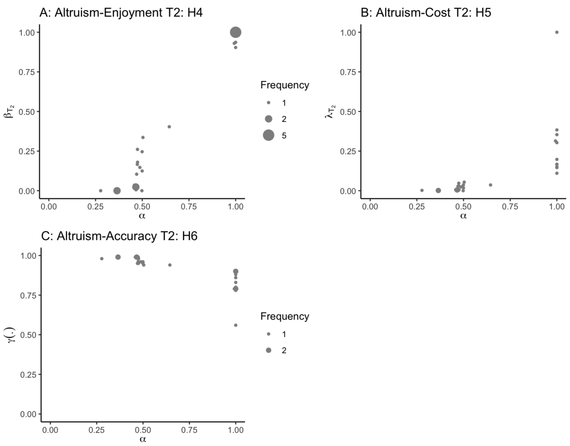

Figure 8. H4, H5, and H6: Altruism.

Note: We constrained α to the interval $[0,1]$ in our estimation. When $\alpha = 0$, the subject does not consider their group membership's monetary payoff at all.

Thus, our H5 is also confirmed. Finally, α is significantly negatively related to accuracy $\gamma(\cdot)$ ($t = -8.999, p < 0.001$). While this result may seem counterintuitive, it is plausible. The interpretation of this final result is equivalent to that of the relationship between enjoyment and accuracy shown in Figure 8.

Figure 9 shows the comparison of net expected utility (Panel A) and information cost (Panel B) between the two treatments. The net expected utility is computed based on Equation (A4) (See Online Appendix Supplemental Material) and the estimated parameters λ, β, and α at the individual level. $\gamma(\cdot)$ is replaced by the actual accuracy.

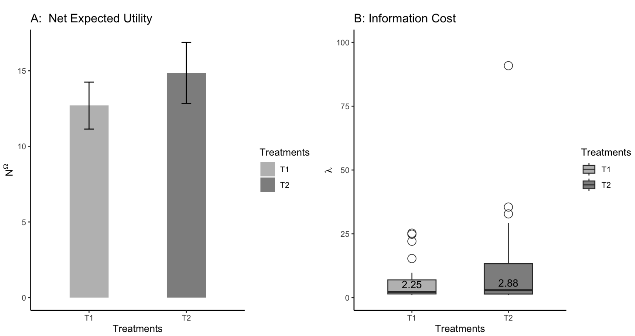

Figure 9. H7: λ_{T1} and λ_{T2}.

Note: Panel A, the net expected utility was computed using Equation (A4) (See Online Appendix-Supplemental Material). Panel B, the boxplot shows the estimated λ without normalization. The numbers represent the median estimated cost in two treatments.

The average net expected utility in T1 was 12.696 (se = 1.553), while in T2 it was 14.858 (se = 2.014). We use the Mann-Whitney U test to compare the net expected utilities, avoiding potential influence from outliers. The results show that the net expected utilities are not significantly different between the two treatments ($W = 696$, $p = 0.901$). This result implies that the marginal information cost should also remain stable across the two treatments (i.e., $\lambda_{T1} = \lambda_{T2}$). To see this, according to Equation (A4), the actual accuracy $\gamma(\cdot)$ is equal in the two treatments (see Figure 1), and the net expected utility N^{Ω} also remains stable between the two treatments. Therefore, we must have $\lambda_{T1} = \lambda_{T2}$.

Figure 9, Panel B, compares the information costs between the two treatments. The average λ in T1 was 5.406 (se = 1.105), while in T2 it was 9.667 (se = 2.702). The Mann-Whitney U test shows no significant difference between the treatments ($W = 651$, $p = 0.725$). This result contradicts Toumi and Rafaï (2018), who reported that treatment T1 attracts more attention than T2 due to longer decision times in the former. However, our parameter estimation reveals equal information costs between the two treatments, indicating similar attention allocation patterns in both decision situations.

Conclusion

This paper shows that intrinsic motivation and altruism increase the subjective cost of attention and decrease performance, in line with the rational inattention framework. Our study contributes to the social preference literature by using perceptual tasks to investigate altruistic behavior. This method has been employed in other disciplines, such as psychology and neuroscience (Mukherjee et al., 2018; Tankersley et al., 2007; Vekaria et al., 2017). To the best of our knowledge, however, we are the first to study altruism using visual perceptual tasks in economics. In our study, subjects who display altruism indicate their willingness to sacrifice limited attention to benefit others, rather than sacrificing monetary rewards to enhance others' financial gains. This innovative approach may provide new insights for research in economics and sociology.

Furthermore, our novel interpretation of altruism holds important economics implications. For example, on streaming platforms such as Twitch, the funding model for content creators relies on the altruism of viewers. Programs are financed either by donations or by the advertising viewed. The creator can choose when advertising appears, and must often play a balancing act between earning extra money and degrading the viewer experience. Sometimes this is done in consultation with viewers, and it's not uncommon to observe viewer communities requesting advertising out of pure altruism, and thus supporting creators not with their own money but with a donation of attention. The same type of behavior can be seen on VOD (Video On Demand) platforms like YouTube, where some ad-block[8] users voluntarily deactivate their ad-block to view ads and support creators. The French membership platform Utip[9] has made this attention-altruism relationship the core of its business model. In this way, users could view advertising in their spare time and earn money for the con-

[8] An ad-block is a browser extension available for download that blocks advertising on the Internet, particularly effective on VOD platforms. A user who is not subjected to video advertising is a user who does not generate any money for the platform and the content creator.

[9] This platform had to close in 2023 due to financial problems.

tent creator of their choice. The platform had over 500,000 users by 2020. So, with the rise of streaming and VOD platforms, altruistic attention has become a major issue for the financing of a number of web-based projects. In February 2024, french TikTok witnessed a surge in students monetizing videos exceeding one-minute length with over 10,000 subscribers, utilizing the hashtag #LaMinuteEtudiante[10], driven by financial necessity. This trend highlights a shift towards altruistic attention in social media content creation, indicative of the evolving altruistic dimension within digital platforms reliant on user attention monetization.

We also believe that our interpretation of altruism holds important policy implications. In everyday life, altruistic behavior cannot solely be represented by the act of sharing or giving "money", as demonstrated in the public good game or dictator game. For example, when policymakers aim to develop a new policy to enhance social welfare at the aggregate level, they undertake various preparatory steps. These include collecting field data, conducting research, consulting professionals, and selecting specific experimental zones, etc. All these preparatory efforts are directed toward gaining acceptance from the population. Nevertheless, all these preparatory steps necessitate policymakers to allocate a considerable amount of attention to achieve a high quality of new policy. Therefore, how policymakers balance the cost of attention allocation with the final quality of the developed policy may indirectly impact the satisfaction level of the population. The quality of the policy ultimately depends on the amount of attention invested by policymakers in various preparatory steps. Finally, we argue that additional experimental and empirical studies are necessary to test the internal and external validity of analyzing altruism based on perceptual tasks.

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[10]The hashtag #LaMinuteEtudiante, commonly used on TikTok, signifies content posted by students aiming for monetization. It serves as a marker indicating participation in this trend, facilitating recognition within the platform's community.

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Appendix - Additional Results

Table 3 presents simple linear regression analyses, controlling for repeated observations per individual, that summarize our findings. Hypotheses H1 to H6 are supported, whereas H7 is not.

	Dependent variable:									
	β_{T1} (1)	β_{T2} (2)	γ_1 (3)	γ_2 (4)	β_{T1} (5)	β_{T2} (6)	β_{T2} (7)	α (8)	α (9)	λ_{T1} (10)
	H1	H1	H2	H2	H3	H3	H4	H5	H6	H7
λ_{T1}	0.046^{***}		-0.007^{***}							
	(0.002)		(0.0004)							
λ_{T2}		0.018^{***}		-0.005^{***}				0.011^{***}		
		(0.003)		(0.0003)				(0.002)		
γ_1					-5.966^{***}					
					(0.447)					
γ_2						-3.859^{***}			-2.271^{***}	
						(0.407)			(0.252)	
α							1.642^{***}			
							(0.054)			
λ_{T2}										4.261
										(2.979)
Constant	-0.006	0.168^{***}	0.989^{***}	0.977^{***}	5.919^{***}	3.917^{***}	-0.673^{***}	0.515^{***}	2.721^{***}	5.406^{**}
	(0.021)	(0.057)	(0.004)	(0.006)	(0.426)	(0.379)	(0.036)	(0.034)	(0.235)	(2.135)
Obs	36	38	36	38	36	38	38	38	38	74
R^2	0.915	0.504	0.890	0.897	0.840	0.714	0.962	0.489	0.692	0.028
Adjusted R^2	0.912	0.490	0.886	0.894	0.835	0.706	0.961	0.474	0.684	0.014

Table 3. Regression results for hypotheses H1 to H7.
Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. *Standard errors in parentheses.*