Faculty of Business and Economics

Assignment Cover Sheet

FNCE90070

Experimental Methods in Decision Studies

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Research Report:

The influence of wealth effect and prosocial preference on group decision-making under risk and ambiguity

Abstract

People live in a society where their decisions made affect others in their interest circle. When making financial decisions, the wealth one owned has some influence over the tolerance to loss, risk and ambiguity for the decisions, affecting their willingness to help others in the group. Much literature has identified the "wealth effect" on decision-making via adjusting risk aversion and social preferences. However, the underlying behavioural and computational mechanisms considering personal wealth and prosocial preference have not yet been explicitly recognised. The pilot experiment indicates that subjects have a higher level of cooperative social preference in groups towards teammates with increased generosity while their wealth on hand accumulates. Risk aversion could be strengthened as wealth decreases, focusing on loss options in a risky decision, however, the wealth factor does not enhance the predictability of the classical prospect theory model with risk and loss aversions. The results demonstrate that wealth accumulation and loss could have effects on financial decision-making in a social context. I anticipate this pilot study to be a starting point for more in-depth research on group decision-making, investigating the effects of difficulty and complexity.

Introduction

Living in a society, decisions made by individuals do not affect themselves only but would also have a large impact on others, especially those who are in their social cycle or to whom they hold "responsibility". Thus, an interest group has been formed. While making financial decisions, how much wealth a person owned or will own would have some dominant power over the tolerance to loss, risk and ambiguity for the decisions, affecting their willingness to help others in the group. Here, I intend to identify the underlying behavioural and computational mechanisms considering personal wealth and prosocial preference.

Edelson et al. (2018) developed a decision paradigm in which an individual can delegate decision-making power about a choice between a risky and a safe option to their group or keep the right to decide. They found, in the experiment, that responsibility aversion is driven by a second-order cognitive process reflecting an increase in the demand for certainty about what constitutes the best choice when others' welfare is affected, while individuals who are less responsibility averse have higher questionnaire-based and real-life leadership scores.

Ahsanuzzaman et al. (2022) adopted a similar approach to the experiment involving 206 farmers in Bangladesh. They discovered that farmers exhibit higher risks and ambiguity aversions when they make choices in groups compared to choosing alone, in which group communication and group members' characteristics influence participants on their measured behavioural attributes towards risk and ambiguity. Their findings touched on the factor of "owned wealth" or timing that farmers in the sample are substantially more risk averse during the pre-harvest season (unrealised wealth) compared to the post-harvest season (owned wealth). Such influence could be attributed to the "wealth effect" in which a net relationship between risk aversion and decreasing wealth has been proven (Meeuwis, 2020).

Additionally, in group decision-making, participants could be classified into two groups: high agency level refers to the capability to influence outcomes for themselves and others (group decisions) while low agency level represents incapability of affecting the outcome (individual decisions). Meron et al. (2020) related the level of agency to social preferences among individuals and group settings. They found groups at the "high agency level" tend toward prosocial preferences – cooperative social preference, while groups at a "low agency level" tend toward (disadvantageous) inequality aversion, independent of the group size. Much literature suggests that social preferences refer to advantageous aversion to inequity given the unequal allocation of resources while inequality aversion occurs when they receive fewer resources than others (Tricomi et al., 2010). By having some responsibility over others, the decision-makers tend to perform collaboratively, avoiding uncertainty for the group.

By integrating ideas from the above literature, the experiment design would be adapted from the paradigm proposed by Edelson et al. (2018) with additional features to further investigate the "wealth effect" in group settings among group members. The changes include the display of the "Net Balance" and regular updates on the balance. In addition, the participants could interact with others to increase their success in the game.

The experiment is expected to perform a computation level of analysis. It is designed to investigate the influence of "owned wealth" and prosocial preference on group decision-making under risk and ambiguity by validating the following hypotheses:

1. Participants would have a higher level of cooperative social preference in groups towards teammates, the generosity varies according to their wealth on hand:
    a. Donation value in dollars would increase as the wealth increases;
    b. Donation value in percentage of wealth amount would decrease or keep constant.
2. Participants would adjust their tolerance level to risk/ambiguity according to their personal "wealth": the more wealth gained the higher the tolerance level.

Results

Participants

In the pilot study, 6 university students were recruited (5 females and 1 male, aged on average 25 ± 5). Nevertheless, to make the result statistically effective, a power analysis has been conducted to approximate the number of participants, equivalent to 197 (Table 1).

Table 1: Power Analysis

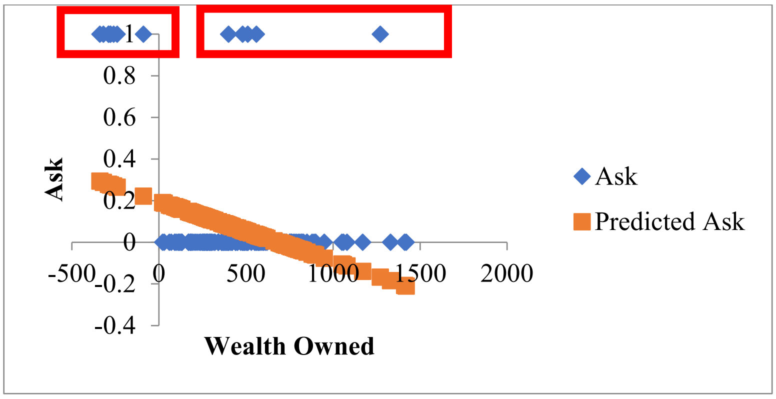
Hypothetic Mean	0.65
Standard Deviation	0.484626
Alpha	0.05
Sample Size	197.1904
Standard Error	0.034511
Right Critical Value	0.706766
Effect Size	0.177064
Acutal Mean	0.73581
Beta	0.200016
Power	0.799984

The effect size is based on Cohen's $d = \frac{|\mu 1 - \mu 2|}{\sigma}$ and beta is acceptable level of type II error.

Prosocial Preferences

1. Request for Help

Figure 1: Request for Help against Wealth Owned



As shown in Figure 1, there are two sets of situations when the subjects request help ("ASK"): 1) when their informed balance is below 0 and 2) when they are finishing off the trial. In the first situation, the subject is encountering survival issues given there are no RPs left in their balance. As such, the request is necessary for them to keep playing the game, otherwise, they would be marked as "failed to survive", negatively impacting the final group ranking. Thus, the other members of the team would have the incentive to respond to their requests and donate RPs. The majority of the participant tend not to request help as the RPs is taken from their teammates' balance. In the second situation, subjects are not in a "bad" status, however, they requested the donation at the very last opportunity. The incentive here could be attributed to the maximisation of individual wealth by exploiting the teammates' prosocial preferences. Two out of six players took this speculative opportunity.

2. Donation Decisions

In making donation decisions, it is significantly regressed against 1) being the teammate, 2) having higher wealth and 3) taking more time to decide (Figure 2a). Among donation decisions made, only 1 out of 37 donations was made to non-teammates while the rest were all made to help teammate to survive, as such avoid penalties on the group (Figure 2b). Even though Balance (Wealth Owned) was significant in the model, it has an almost zero (positive) coefficient, indicating a fairly tiny influence on the decision (Figure 2c). Subjects on average take 4.70 seconds to make a "Refuse" decision while taking longer time to think thoroughly about and weigh both sides of the decision of "Help" as well as deciding on the amount to donate (Figure 2d). Among three factors, the nature of the requestor being a teammate is the dominant factor in deciding whether to donate or not.

Figure 2: Donation Decision

a) Regression model for Donation Decisions

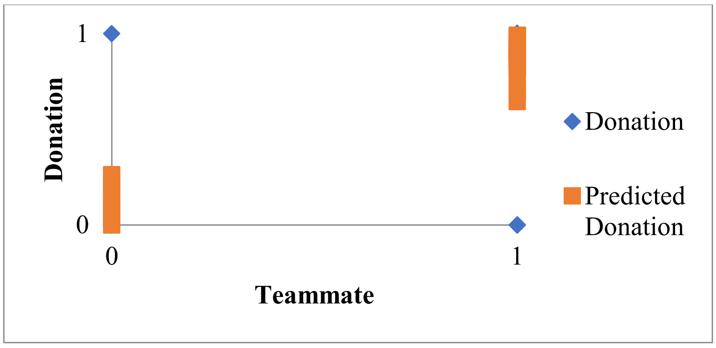
Regression Statistics	
Multiple R	0.933
R Square	0.870
Adjusted R	0.865
Standard E	0.182
Observatic	90

ANOVA

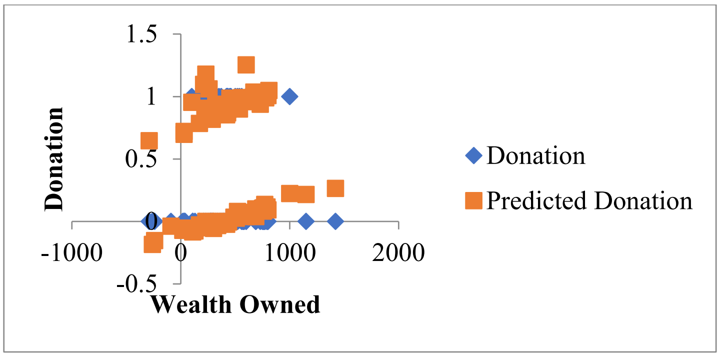
	df	*SS*	*MS*	*F*	*ignificance F*
Regressior	3	18.950	6.317	191.369	0.000
Residual	86	2.839	0.033		
Total	89	21.789			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	-0.164	0.043	-3.769	0.000	-0.250	-0.077	-0.250	-0.077
Balance	0.000	0.000	4.132	0.000	0.000	0.000	0.000	0.000
Time (s)	0.013	0.004	3.422	0.001	0.005	0.020	0.005	0.020
Teammate	0.826	0.047	17.659	0.000	0.733	0.919	0.733	0.919

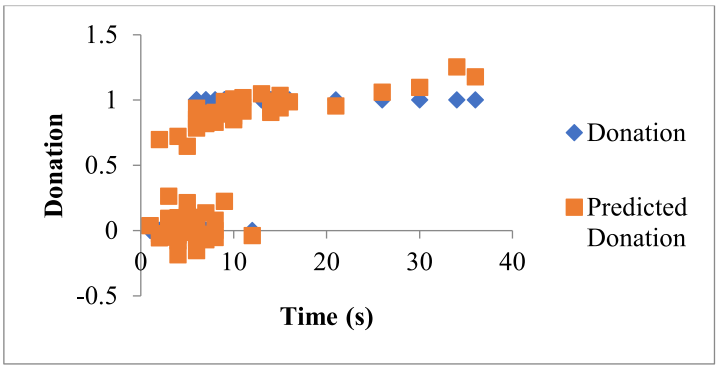
b) Donation Decision According to the Requestor



c) Donation Decision Based on Personal Wealth



d) Donation Decision Regarding Respond Time



3. Willingness to Donate

In my first hypothesis, subjects should have a higher level of cooperative social preference in groups towards teammates, and the generosity increase as their wealth on hand accumulates:

a. Donation value in dollars would increase as the wealth increases;
b. However, donation value in percentage of wealth would decrease or keep constant.

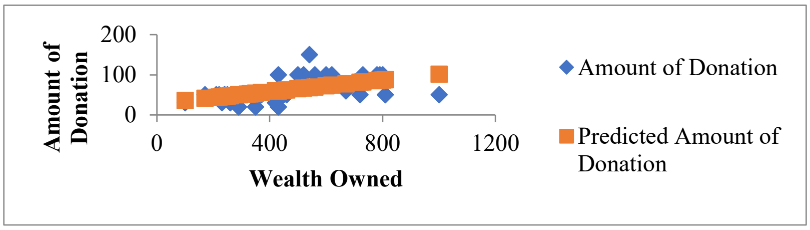
$$WTD = e^{\left(\frac{D}{W}\right)} \quad (1)$$

Willingness to Donate (WTD) is defined as the exponential function of the donation value in percentage of wealth, which is the Amount of Donation (D) over the Wealth (W).

Figure 3: Willingness to Donate

a) Donation Value in Dollars

Regression Statistics								
Multiple R	0.515							
R Square	0.265							
Adjusted R Sq	0.244							
Standard Erro	26.778							
Observations	37.000							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	1.000	9070.868	9070.868	12.650	0.001			
Residual	35.000	25096.700	717.049					
Total	36.000	34167.568						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	28.820	10.288	2.801	0.008	7.935	49.706	7.935	49.706
Balance	0.073	0.020	3.557	0.001	0.031	0.114	0.031	0.114



b) Donation Value in Percentage

Regression Statistics								
Multiple R	0.499							
R Square	0.249							
Adjusted R Sq	0.227							
Standard Erro	0.071							
Observations	37.000							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	1.000	0.058	0.058	11.597	0.002			
Residual	35.000	0.176	0.005					
Total	36.000	0.234						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	1.250	0.027	45.937	0.000	1.195	1.306	1.195	1.306
Balance	-0.000184	0.000	-3.405	0.002	0.000	0.000	0.000	0.000

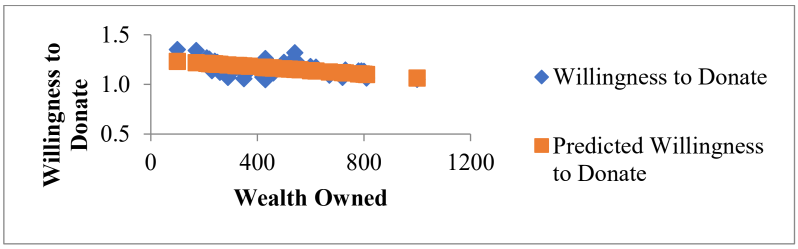


Figure 3a displays a positive relationship between wealth and the amount of donation. For every $100 increase in wealth, the donation value in dollars will increase by $7.3, which is equivalent to 7.3%.

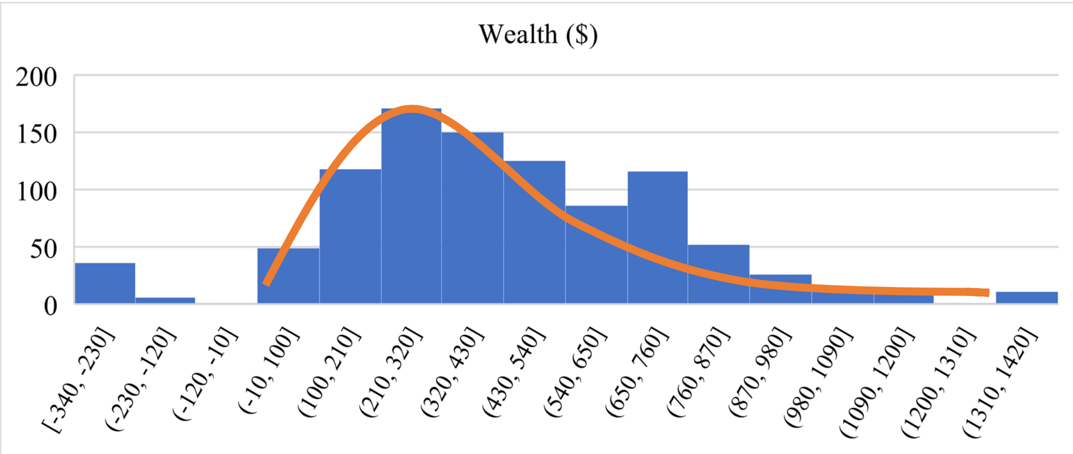
Figure 3b shows a negative relationship between wealth and the WTD. For every $100 increase in wealth, WTP will decrease by 0.0184, which is equivalent to -4% in the donation value in percentage of wealth.

Overall, I define the average change between dollar changes and percentage changes as generosity. By combining them, the generosity approximately increases by 1.65% given [7.3%+(-4%)]/2

Wealth Effect

As shown in Figure 4, wealth is normally distributed, skewed to the right.

Figure 4: Wealth Distribution



For the second hypothesis, I suppose that participants would adjust their tolerance level to risk according to their "wealth": the more wealth gained the higher the tolerance level.

To incorporate wealth as a factor in utility function adopting prospect theory. The full model deduction is present in the Modelling part in the Methods section. This section focuses on the wealth factor (ω) as the only free parameter in the model. θ and λ are fixed parameter determined by assessments in Appendix 2 and 3 for each subject. Here are three different models composing the factor. According to Table 2a, only M2 has a measurable discounting factor at 1/46 under maximum likelihood estimation in which predicting accuracy is maximised. The other two models have discounting factors approaching zero, resulting in "no effect". As such, M3 and M4 do not differentiate from M1. In M2, we could observe that risk aversion would be strengthened by losing wealth, focusing on loss options in a risky decision. By comparing models in Figure 2b, M2 has slightly lower accuracy than M1 (without wealth effect). As a result, the wealth factor would not enhance the predictability of the model.

Table 2: Wealth Modelling

a) Wealth Factor Determinations in Different Models

	Model	DF
M2	$\omega(x)\begin{cases}1+\left(\frac{Net\ Balance}{Initial\ Balance}-1\right)*Discounting\ Factor & if\ \omega\geq 0\\ 1-\left(1-\frac{Net\ Balance}{Initial\ Balance}\right)*Discounting\ Factor & if\ \omega\leq 0\end{cases}$	1/46
M3		1/1610612766
M4	$\omega(x)\begin{cases}\left(\frac{Net\ Balance}{Initial\ Balance}-1\right)*Discounting\ Factor & if\ \omega\geq 0\\ -\left(1-\frac{Net\ Balance}{Initial\ Balance}\right)*Discounting\ Factor & if\ \omega\leq 0\end{cases}$	1/536870922000
Discounting Factor is determined under Maximum Likelihood Estimation while accuracy is maximised		

b) Model Comparison

	Model	Accuracy	Precision	F1-Score	AIC	BIC	MSE
M1	$v(x)\begin{cases}x^{\theta} & if\ x\geq 0\\ -\lambda(-x)^{\theta} & if\ x\leq 0\end{cases}$	0.74	0.43	0.56	1920.96	6646.06	0.21
M2	$v(x)\begin{cases}x^{\theta} & if\ x\geq 0\\ -\lambda(-x)^{\theta\times\omega^-} & if\ x\leq 0\end{cases}$	0.73	0.43	0.56	1920.96	6646.06	0.22
M3	$v(x)\begin{cases}\omega^+x^{\theta} & if\ x\geq 0\\ \omega^- -\lambda(-x)^{\theta} & if\ x\leq 0\end{cases}$	0.74	0.43	0.56	1920.96	6646.06	0.21
M4	$v(x)\begin{cases}x^{\theta+\omega^+} & if\ x\geq 0\\ -\lambda(-x)^{\theta-\omega^-} & if\ x\leq 0\end{cases}$	0.74	0.43	0.56	1921.16	6646.26	0.26

Decision Tactics

The part is a summary of the interview session after the experiment.

The majority of subjects tend not to request help unless they feel they have to do so for survival, but one subject indicates that it is also a good opportunity to increase their wealth upon the end of the session. Half of the subjects point out that there is no difference between group decisions and individual-only decisions. Nevertheless, the others suggest that making a decision affecting the whole group would bring in a sense of responsibility and thus become more cautious in decision-making.

Only 2 out of 6 subject claims that they act aggressively when having a declining or negative balance, while the others are more cautious and risk-averse in the subsequent decisions.

Here are some strategies they use in reading the situation:

1. When the blue area (probability of loss) is greater than 50%, one tends to hesitate in taking acceptance;
2. Distribute the grey area (ambiguity) equally to orange and blue unless either orange or blue area is too tiny in that incident;
3. Ignore the grey area unless it is greater than 50%, if it is greater than 50%, then decide on the worthiness of taking the risk;
4. When the loss is greater than 50 RPs, the grey area would be regarded as the blue area; when the loss is smaller than 50 RPs, the grey area would be equally divided between orange and blue.

Discussion

To sum up the results, subjects in the competition have greater prosocial preferences in the group towards teammates as compared to strangers. During the competition, it is hard to find any incentive to support other teams. Nevertheless, one may take advantage of opportunities within the group to optimise his or her payoffs without affecting the overall performance of the group. Still, people would be self-interested to some extent.

Subjects' generosity to teammates would increase as their wealth accumulates. To avoid a penalty that would negatively affect them, each team player would intentionally be generous to a teammate in need. Given they do not know each other's balances, then the donation amount would depend on their wealth on hand (the capability to donate). In other words, they would be more generous when they have more.

In wealth models, ω has significant power in reinforcing risk aversion in valuing loss options while wealth decreases. When losing their wealth, they tend to be more cautious about decisions, thus resulting in more rejections of risky decisions. This could be attributed to the intention of avoiding worsening the current situation.

The result shows that the wealth factor does not improve the predicting power of the model. There could be two reasons for it. One is that the effect of the wealth factor is too weak to largely influence the decision. And another is that the effect of the wealth factor converges with loss and risk aversions and thus does not change the prediction. Wealth may not necessarily be an intrinsic characteristic of an individual and the experiment setting does not effectively create the real wealth sense for the subjects.

Due to limited time and resources, it might be difficult to recruit enough participants for the experiment. University students (WIERD) might not be able to represent the whole population. In designing decision scenarios, there could be more variations in terms of the colour-probability combinations and the reward-loss combinations to increase the generality of results in financial decisions. Apart from prospect theory, the risk-return decomposition of risky options would also be useful to value the risky choice options in financial decision-making, using Markowitz's approach of willingness to pay (WTP).

It would also be interesting to investigate the pressures on decision-making that affects other members of the group, such as tight time constraints, social pressure (if the discussion – real time interaction is allowed) and others. As it becomes more complicated in making group decisions due to the involvement of more stakeholders in the process, the decision-makers have to take more aspects into their consideration, possibly requiring more computational capacity and thus increasing complexity. Neuroimaging technologies such as fMRI could also be utilised to compare neural activities while making decisions for the group and oneself to spot any difference in the activation of parts of the brain.

Methods

Experiment

1. Scene Setting

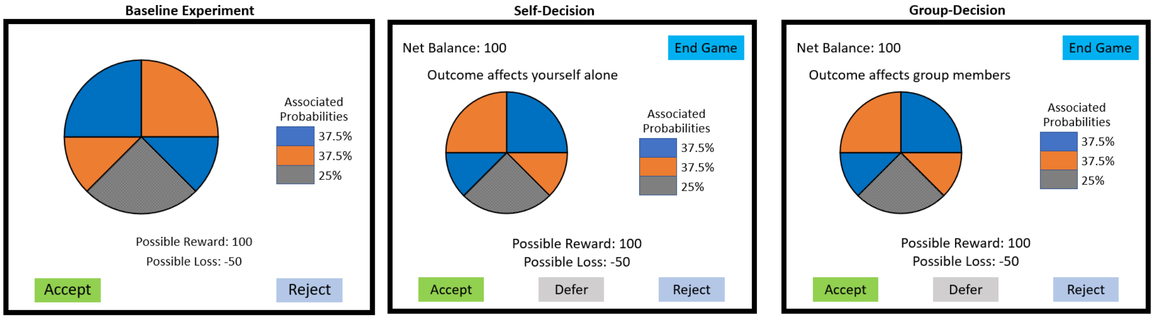
All participants would be assigned to a team of five competing with other teams. They are required to participate in a 50-day survival competition for four trials in addition to one baseline trial (35 days – individual decisions only). For each trial, the participants would be allocated a different initial balance of wealth of unknown, 100, 200, and 500 points respectively. To facilitate the decision-making, the net balance of each participant would be displayed and updated on a 5-day basis, except for the first two trials (baseline and unknown balance). They would be asked to make the financial decision on whether they accept the proposal to collect resources points (RPs), affecting the outcome payoff on either their own or the whole group. Two types of decisions are randomly mixed up.

2. Decision-Making Scenarios

Participants need to make the financial decision on whether to collect resources points (RPs), with information on a) the possible gain and loss, b) the probability of gain and loss with a level of uncertainty and four action options – accept, reject, ask for help and end the game. Noticeably, the decisions being made by participants will affect individual or group payoff.

The probability of success and failure was presented by coloured slices of a pie, green and red accordingly, with adjacent text. In each decision, a varying number of grey-coloured slices would cover part of the pie, obscuring probability information and creating ambiguity in the decision-making (Figure 1).

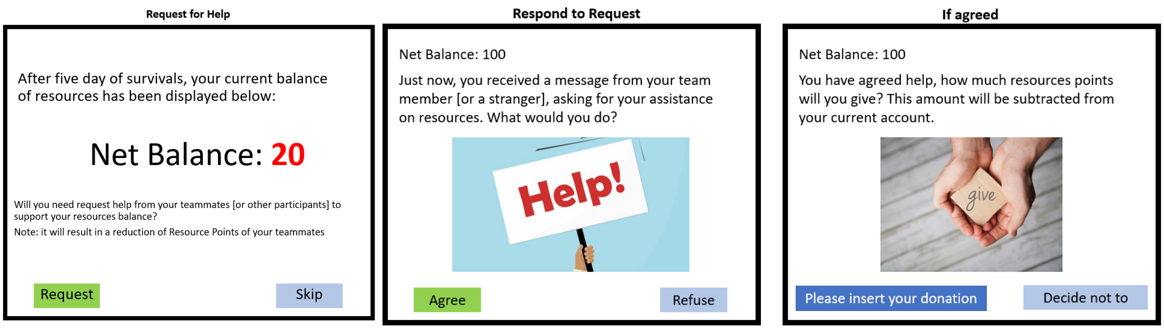
Figure 1: Decision Panel



In the Baseline Experiment, Individuals needed to select a risky option ("Accept"), or a safe option ("Reject") based on the probability of success of the risky option and the possible gain or loss if that option was chosen. Self-Decision and Group-Decision Experiments would be conducted after the Baseline Experiment. Individuals were faced with the same choices but had the additional option to "Defer" and "End Game" to the majority opinion of their group and gain access to the group's informational advantage (Figure 1). To clarify the task setting, in group decision the participant's decision would affect the payoff of all group members, while in self-decision the participant's action affected only him/herself.

During the game, each participant could ask for help from a team member or a stranger for "financial support" if the participants perceive in-survivability in the game or do not wish to fall below a certain amount of resource points ("safety level"). See Figure 2. Whenever the participants receive a request from a stranger or a teammate, he/she would need to decide whether to donate and if agrees on the donation then by how much. Each participant would have only one chance per trial to request support. If one suffers again, he or she could choose to end the game or reject all the rest decisions.

Figure 2: Group Interaction Panel



3. Rules of Resources Points Calculation

Personal RPs = RPs received in both individual decisions and group decisions

Group RPs = RPs received in group decisions of 5 team members

Reward: Additional fifty points for the team with the highest Group RPs. This encourages subjects to pay extra attention to the group decisions and find the best strategy to optimise the group returns.

Penalty: If any member of the team reached a negative balance, a -10 points penalty will be given to the Group RPs. This creates the incentive for subjects to offer help to teammates when there is a request for RPs donation.

4. Incentive Plan

All participants would receive A$10 for showing up at the experiment. All participants would be rewarded with cash at a conversion rate of 0.1 of RPs, randomly choosing any one of the outcomes from the last three trials. The average payoff would be expected to range from A$10 to A$100.

Interview

After each experiment, I conducted a 15-minute interview with each participant by asking them the following questions:

1. Do you feel any differences when making decisions between the ones affecting yourself only and the ones affecting your whole team?
2. If you have observed a negative balance or continuous decrease in the net balance, do you think to change your approach in decision making? If yes, will you become more aggressive to quickly turn over the situation or more cautious about subsequent decisions to avoid worsening the situation?
3. Does this change in strategy affect your decision-making across different sessions?
4. Do you count down the number of days until the completion of the competition?
5. How do you estimate the grey area (ambiguity)?
6. Do you have any benchmarks for determining whether you have made a gain or a loss in the session?
7. For what purposes would you request help?

Modelling

1. Expected Utility Model

This experiment would combine the classical utility modelling by Bernoulli (1954), utility and probability weighting for gains and losses by Abdellaoui et al. (2008) and the ambiguity-included prospect theory model by Edelson et al. (2018).

The expected subjective utility of the risky option would base on the assumption that

$$u = v(x_g)\pi(p_g) - v(x_l)\pi(p_l) \qquad (2)$$

where v(.) represents the utility function, x_g and x_l stand for potential gain-utile and loss-utile, p_g and $(1 - p_g)$ are corresponding probabilities of a gain and a loss, whereas $\pi(p_g)$ and $\pi(1 - p_g)$ are the subjective decision weights attached to these probabilities. The idea here is to convert ambiguity to subjective decision weights $\pi(.)$.

As the value of the safe option is normalized to zero, the expected utility of the risky prospect as given in (1) also describes the expected utility difference between the risky and the safe option. The utility function v(.) has the following properties:

$$v(x)\begin{cases} x^{\theta\sim\omega^{+}} & if\ x \geq 0\ (i.e.\ x_g) \\ -\lambda(-x)^{\theta\sim\omega^{-}} & if\ x \leq 0\ (i.e.\ x_l) \end{cases} \qquad (3)$$

where λ is the loss preference (Appendix 3), and θ is the risk aversion (Appendix 2). ω is the factor derived from the wealth of the person. To accommodate the unknown probability ($\varphi =$ ambiguity), probability (η) by which the outcome x occurs is defined by

$$\eta = \frac{1}{N}\sum_{i=1}^{N} z_i\text{, where }\begin{cases} z_i = 1\ if\ the\ piece\ of\ pie\ is\ green \\ z_i = 0\ if\ the\ piece\ of\ pie\ is\ red \\ z_i = \varphi\ if\ the\ piece\ of\ pie\ is\ grey \end{cases} \qquad (4)$$

where N is the number of slices evenly divided in the pie. Given the fact grey pie slice is equally likely to be red or green, this parameter would be 0.5 for an ambiguity-neutral agent. Probabilities are transformed by a non-linear weighting function

$$\pi(\eta) = \frac{\eta^{\gamma}}{(\eta^{\gamma}+(1-\eta)^{\gamma})^{\frac{1}{\gamma}}} \qquad (5)$$

where γ specifies the s-shaped transformation of the probability weighting function at the value of 0.9 (on average) when π is maximised via optimisation and probability of choosing the risky option for Eq. 1 adopting the logistic choice rule

$$p(u) = \frac{1}{1+e^{-\tau u}} \tag{6}$$

where τ is an inverse temperature parameter representing the degree of stochasticity in the choice process.

2. Parameter Validation

Given a total amount of 120 data points (30*4 Trials), it would be conscious to constrain the number of parameters to a reasonable amount. In the utility model, there will be a few parameters to be assessed, s-shaped probability weighting function (γ), degree of loss preference (λ) and risk aversion (θ), the inverse temperature parameter (τ), as well as newly introduced wealth factor (ω). The interaction parameter (ι) would be determined in the social preference model in addition to the utility model. See Table 3. With support from much literature, ω is the only parameter to be investigated in constructing the new model. A power analysis will be used to decide the minimal size of participants, ensuring the desired significance level and statistical power.

Table 3: Table of Input Parameters

Parameters	Determination	Sources
γ	γ > 0 in which inverse S-shaped for γ < 1; S-shaped for γ > 1. For losses, the marked probability weighting is near zero.	Verschoor & D'Exelle (2022) He et al. (2018) Goldstein & Einhorn (1987)
λ	Degree of loss preference	Edelson et al. (2018), Appendix 3
τ	Ranging from $\tau = 0$ for completely random responding and $\tau = \infty$ for deterministically choosing the highest value option.	Wilson & Collins (2019)
θ	Degree of risk aversion	Bernoulli (1954), Appendix 2
ω	ω is the factor derived from the wealth of the person, reducing risk aversion, and enhancing generosity	**The Free Parameter to Test**

3. Regression Model

The responses in the Self-Group-Decision task consisted of a set of four alternatives: [Defer (d), Risky (r), Safe (s), End (e)]. A conditional regression model would be adopted to model the choices to determine finite conditional probabilities for each option. Experiment results would also regress with the leadership scores to detect potential relationships.

3. Model Fitting and Comparisons

Various methodologies could be used to compare the models and assess the fitness of the model with data (Wilson & Collins, 2019). Maximum likelihood estimation (MLE) measures how well the given model captured the variance in the dependent variable.

$$\hat{L} = p(x|\hat{\theta}, M) \tag{7}$$

where $\hat{L}$ is the maximised value of the likelihood function of the model M and $\hat{\theta}$ are the parameter values maximising the likelihood function. x is the observed data. Based on MLE, the Akaike information criterion (AIC) serves as an estimator of prediction error with additional input of parameter numbers and thus determines the relative quality of statistical models for a given set of data.

$$AIC = 2k - 2\ln(\hat{L}) \tag{8}$$

where k is the number of estimated parameters in the model and $\hat{L}$ represents MLE for the model. In addition to AIC, the Bayesian information criterion (BIC) includes more inputs to better assess the quality of models. Thus, models could be compared across multiple models (finite amount) while the log-likelihood test can only evaluate the fittingness between two competing models.

$$BIC = k\ln(n) - 2\ln(\hat{L}) \tag{9}$$

where n is the sample size used in the model.

4. Model validation

To validate the model, mean squared error (MSE) is commonly practised.

$$MSE = \frac{1}{n}\sum(y_i - f(x_i))^2 \tag{10}$$

where n is the total number of observations, y_i are the response value of the i^{th} observation and $f(x_i)$ is the predicted response value of the i^{th} observation. However, the result of MSE can hugely depend on which observations were used in the training and testing sets. Thus, leave-one-out cross-validation (LOOCV) intervenes as an extreme case for k-fold cross-validation that maximises computational cost – fitting models many times with a different training & testing set each time and then calculating the average of all the test MSEs.

Codes and Supplementary Materials

Please refer to https://github.com/ChangfaFU/ED2022.git for full details.

Appendix

Appendix 1: Instructions for the Experiment

You are doing a 30-day survival competition for 1 baseline trial and a 50-day survival competition for 4 trials.

You are assigned to a team of 5 competing with other teams.

Initially, you will be given 0, 100, 200, and 500 points as initial owned wealth.

You will be asked to make decisions on whether to collect resources (RPs).

To make decisions, you will be given.

The possible gain and loss.

The probability of gain and loss with a level of uncertainty.

The decisions being made will affect either yourself or other group members, the decision types are randomly mixed up.

Your net balance would be updated every 5 days.

If you feel you do not have sufficient resources for survival upon balance updating, you could choose to ask for help from your team and others. You can do this only once.

Whenever your teammate or a stranger asks for help, you need to decide on

- Whether to give resources
- If yes, then by how much

You may choose to end the game during the competition if you feel unable to survive ("be reasonably paid off").

The performance is judged on personal RPs and aggregated group RPs, and thus rewarded with cash at a conversion rate of 0.1, randomly chosen one outcome from three trials.

REWARD: Additional 50 points for the team with the highest aggregated team RPs.

PENALTY: For each team member marked as "failed to survive" (Net Balance Below 0), -10 points punishment will be given to the aggregated team RPs.

Appendix 2: Assessment of Risk Aversion

Which gambles would you be willing to take? (circle whichever alternative you prefer)

☑	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $10	☐
☑	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $12	☐
☑	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $14	☐
☑	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $16	☐
☐	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $18	☑
☐	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $20	☑
☐	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $22	☑
☐	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $24	☑
☐	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $26	☑
☐	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $28	☑
☐	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $30	☑
☐	100% chance of winning $10	-vs-	50% chance of winning $0, 50% chance of winning $32	☑

The assessment is designed by Holt & Laury (2002) and adjusted by Knutson et al. (2011). I used the utility function of constant relative risk aversion (CRRA) to determine the risk aversion of the subject (Anderson & Mellor, 2009).

$$U(Y) = \frac{Y^{1-r}}{r} => \ \theta = e^{-r} \qquad (11)$$

in which r is the risk aversion parameter where Values of r < 0 or ln(r) < 1 indicate risk-seeking preferences, values of r = 0 or ln(r) = 1 indicate risk neutrality, and values of r > 0 or ln(r) > 1indicate risk aversion.

	Risk Aversion		Expected Payoff Difference	r	θ	
[redacted]						
3	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $14	3	-1.060	2.886	Risk Seeking
4	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $16	2	-0.475	1.608	
5	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $18	1	-0.179	1.196	
6	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $20	0	0.000	1.000	Risk Neutral
7	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $22	-1	0.121	0.886	Risk Averse
8	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $24	-2	0.208	0.812	
9	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $26	-3	0.275	0.760	
10	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $28	-4	0.327	0.721	
11	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $30	-5	0.369	0.691	
12	100% chance of winning $10	50% chance of winning $0, 50% chance of winning $32	-6	0.404	0.668	

Appendix 3: Assessment of Loss Aversion

Which gambles would you be willing to take? (circle whichever alternative you prefer)

☑	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $10	☐
☑	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $12	☐
☑	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $14	☐
☐	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $16	☑
☐	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $18	☑
☐	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $20	☑
☐	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $22	☑
☐	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $24	☑
☐	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $26	☑
☐	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $28	☑
☐	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $30	☑
☐	100% chance of winning $0	-vs-	50% chance of losing $10, 50% chance of winning $32	☑

The assessment is designed by Holt & Laury (2002) and adjusted by Knutson et al (2011).

Gächter (2022) specifies that an individual's implied loss aversion in the lottery choice task as below:

$$\lambda_{risky} = \frac{v(G)}{v(L)} \tag{12}$$

in which values of λ = -1indicates loss neutrality and values of λ < -1 indicate loss aversion.

	Loss Aversion		λ	
1	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $10	-1.00	Loss Neutral
2	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $12	-1.20	
3	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $14	-1.40	
4	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $16	-1.60	
5	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $18	-1.80	
6	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $20	-2.00	
7	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $22	-2.20	Loss Averse
8	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $24	-2.40	
9	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $26	-2.60	
10	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $28	-2.80	
11	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $30	-3.00	
12	100% chance of winning $0	50% chance of losing $10, 50% chance of winning $32	-3.20	

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