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MEASURING RISK ATTITUDES FOR STRATEGIC DECISION-MAKING IN A COLLABORATIVE ENGINEERING DESIGN PROCESS

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ABSTRACT

This paper evaluates a questionnaire-based risk attitude assessment method to quantify individual risk attitudes for strategic, multi-actor design decisions. A lottery-equivalence questionnaire elicits a utility curve for risky payoffs which is fit to a Constant Absolute Risk Aversion (CARA) model. Secondary data from a multi-actor design experiment provides observations of strategic decisions in two-actor design games for validation. 124 participants complete the risk attitude questionnaire and a series of 29 experimental tasks. Assuming participants follow the risk dominance equilibrium selection criterion, a risk-neutral utility function accurately predicts 62.2% of decisions. Incorporating risk attitudes elicited from the questionnaire only increases the accuracy to 63.3% while incorporating risk attitudes inferred from observations increases the accuracy to 77.5%. While participants exhibit differential risk attitudes in design tasks, results show the lottery-equivalent questionnaire does not provide risk attitudes consistent with strategic design decisions. Results support findings that risk in the engineering domain is contextual. This paper concludes that risk attitude is an important factor in understanding strategic decisions in interactive engineering design settings and understanding risk attitudes can help create more efficient design processes.

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1 INTRODUCTION

Technological innovations contribute to the design, manufacture, and operation of increasingly complex products in today's world. The increased complexity incentivizes groups of engineers and stakeholders, who might have different interests, to work together simultaneously to reach multiple objectives [1]. Collaboration enables two or more actors to work together to achieve a goal that is beyond the capabilities of any one member if they work individually [1]. Collaborative engineering is a human-centered process in which engineers and engineering companies aim to align efforts to maximize individual gains.

Information systems and tools can support collaborative design processes. For example, companies like Canon report significant reductions in design iterations, total costs, and lead time by using a collaborative design tool to more efficiently exchange design information [2]. Technical solutions can improve design efficiency; however, it must be borne in mind that social and human dynamics influence decisions in collaborative design processes [1]. Collaborative design processes are human-centered activities where the actions of one affect the gains of others, making risk inseparable from the design process. Engineers can recognize and take certain precautions when there is a quantifiable or physical risk; however, there is no universally correct decision because the normative decision for each designer changes based on their *risk attitudes* [3–6].

In engineering design, risk is characterized by the likelihood and consequences of an undesirable scenario [7] and risk management aims to reduce the probability of occurrence and magnitude of loss in these situations [8]. However, as identified by Van Bossuyt et al., risk analysis methods fail to consider risk attitudes of engineers in design processes [6]. Including risk attitude in the risk analysis and management process would help to fit normative decisions to each designer [9].

Strategic sources of risk in collaborative design focus on specific types of uncertainty across organizational boundaries, namely, comparing the upside potential of successful collaboration with the downside risk of coordination failure. Designers qualitatively assess risk based on their experience, provided information, and beliefs about other designers' actions. Further, they may employ strategic behaviors such as retaining essential technical information or distorting information about their intentions to guard against potential threats. Limitations to available information across organizational boundaries makes identifying the normative choice even more challenging in collaborative settings [10]. In general, collaborative solutions benefit from aligning strategic decisions; however, the potential for coordination failure generates risk. In this type of scenario, engineering firms need to make strategic decisions considering possible gains and losses depending on their objectives. Understanding differential risk attitudes prior to these strategic decision-making processes can improve risk-informed decision-making.

In collaborative design processes, decision-makers could benefit from communicating their risk attitudes to better understand differences in perception and objectives and build more effective collaborative designs tailored to each actor [7]. For example, a risk-seeking actor perceives relatively higher upside potential and lower downside risk to uncertain collaboration compared to a risk-neutral perspective. In contrast, a risk-averse actor perceives relatively lower upside potential and higher downside risk. Management and psychological literature show that actors can perceive situations as less risky by changes in the context and framing of the problem [4, 11, 12], which can potentially help to achieve successful collaboration. Accordingly, focusing on risk-averse actors and decreasing their perceived risk levels can maximize gains for all actors. Understanding risk attitudes can also help conduct training to normalize risk experts' opinions with peers, harmonizing an engineer's professional perception of risk with the organization's risk perception and expectations [6].

This paper measures risk attitudes using a lottery-style questionnaire assessment method and compares results to observed risk attitudes in secondary data from a multi-actor strategic design experiment. The questionnaire adopts a lottery-equivalent risk attitude assessment from management science [4] to quantify designer risk attitudes. Participants complete the questionnaire prior to the experiment, and their responses are analyzed to form a utility curve to fit a Constant Absolute Risk Aversion (CARA) model. Analysis follows a risk dominance criterion to determine normative choice and compares observed and expected strategies

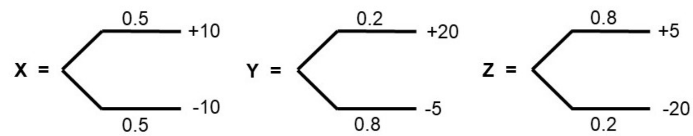

FIGURE 1: An example of payoffs for three risky alternatives with equal mean (0) and variance (100)

with risk attitudes obtained from the questionnaire and risk attitudes obtained from the experimental tasks to understand the validity of the lottery-style questionnaire in capturing risk attitude.

2 LITERATURE REVIEW

2.1 Risk Preference and Risk Perception

Risk perception is not stable and individuals can perceive different levels of risk in the same situation. The example in Fig. 1 shows probabilistic payoff outcomes for risky alternatives of X, Y and Z with equal expected value $E[X] = E[Y] = E[Z] = 0$ and equal variance $Var[X] = Var[Y] = Var[Z] = 100$. However many people do not consider these options as equally risky; many judge alternative Z as the least risky. Changing the scale of payoffs can also influence risk perception; for example, people perceive gaining or losing 10 pennies less risky compared to gaining or losing 10 dollars.

People perceive riskiness of an alternative differently depending on their reference point, and this perception can be manipulated in ways such as outcome framing [11]. Changes in risk perception and risk preference are not the same thing and can cause different choice behavior [4]. From management literature, Hausch et al. give the example of betting behavior in racetracks [12]. A risk-return decomposition of changing utility functions allows for an alternative interpretation that the perception of what constitutes a risky option may change as a function of outcome feedback. According to this interpretation, betting behavior changes not because of changes in risk preference but because of changes in the perception of what constitutes a risky horse. A person's risk preference may remain the same over the racing day, but the perception of what constitutes a risky horse will change. Cooper et al. show that differentiating risk perception and risk attitude is important. For instance, the decision-making behavior difference between entrepreneurs and managers is not caused by entrepreneurs' greater preference of risks but instead their overly optimistic perception of the risks involved [13].

The relative emphasis put on probability versus magnitude of outcomes when judging risk can vary as a function of demographic characteristics associated with wealth levels [4]. Weber and Milliman question if different people can perceive risk differently in the same situation, then it may also be possible for a given individual to perceive the risk of the same alternative differently at different times or in different contexts.

2.2 Risk Attitude

People judge the riskiness of a situation by considering both the probability and magnitude of adverse effects [14]. In economic theory, a utility function $U(x)$ expresses a decision-maker's preference for alternative x. For uncertain or risky outcomes, the expected utility hypothesis states that decision-makers choose the alternative with highest expected utility computed as $E[U(x)] = \sum_k p_k U(x_k)$ where outcome x_k occurs with probability p_k [15]. While the utility function models each decision-maker's preferences, the expected utility hypothesis does not accurately model observed human behavior under all conditions but rather models normative decisions only for the given utility function. Thus, it is essential to identify the *right* utility function for each actor.

A decision-maker's preferences among risky alternatives reveals their utility function $U(x)$ [3] and the shape of this model describes their risk attitude [5]. Risk averse preferences form a concave curve while risk seeking preferences form a convex curve [4]. More specifically, the Arrow–Pratt measure of absolute risk aversion $R(x) = -U''(x)/U'(x)$ measures the concavity of U at the point x, representing risk aversion of a decision-maker [5]. A constant absolute risk aversion (CARA) model

$$U(x) = \begin{cases} \frac{1}{a}\left(1-\exp(-a \cdot x)\right) & a \neq 0 \\ x & \text{otherwise} \end{cases} \tag{1}$$

assumes constant risk aversion $R(x) = a$ for risk seeking ($a < 0$), risk avoiding ($a > 0$), or risk neutral ($a = 0$) preferences.

Dyer and Sarin introduce the notion of *strength of preference* referring to the *intensity of an individual's preference for an alternative or a consequence* [16]. They explain that a decision-maker's strength of preference can show variations based on their starting point and reward. Dyer and Sarin give the example of a decision-maker who has the same strength of preference for acquiring three oranges when they have none and acquiring five more oranges when they have three. Then decision-maker's indifference between receiving three oranges for sure and a lottery can be explained by the decreasing marginal value that they place on oranges, meaning the introduction of risk in the form of a lottery has no impact on decision-makers preferences. For explaining these risk attitudes, Dyer and Sarin introduce the term *relative* risk attitude, suggesting the decision-maker in the example should be described as a relative risk neutral individual rather than a risk averse individual. A decision-maker's preferences for risky alternatives, relative to their strength of preference for these certain consequences, are neutral to the introduction of risk [16]. They state that there are at least two identified factors affecting decision-makers' decisions in risk involving situations, first varying preference differences for incremental changes in the amount of the attribute and second, the attitude toward risk-taking.

2.3 Risk in Engineering

In engineering, risk is defined by the effect of uncertainty on objectives [17]. Martin further defines risk as the probability of occurrence of an event multiplied by the severity of the consequences [18]. NASA guidelines define risk as the likelihood and consequences of an undesirable scenario that could endanger the mission objectives [7]. Based on these descriptions, risk can be represented with three variables: an undesirable scenario, its probability of occurrence, and its severity or consequences.

Literature shows that an acceptable risk threshold varies for different engineers; this is also true for different engineering organizations [9]. While some companies are more risk-taking (and this attitude is necessary for their creative, innovative structure), others are risk-averse. Accordingly, risk attitude varies for different companies and engineers and analyses should be handled differently depending on each organization. Furthermore, literature shows engineering risk attitude is domain-specific and suggests risk attitudes are multifaceted and cannot be captured by a single index [6]. Toh and Miller suggest the risk attitude of team members affects creative concept selection in engineering design settings [19]. Literature also shows engineering decision-makers incorporate feedback into decisions under objective risk conditions [20].

Van Bossuyt et al. uses a single criterion decision-based design approach adapted from risk attitude utility functions to transform engineering risk data in the expected value domain into risk attitude domain [21]. They develop a model *E-DOSPERT* to quantify decision-maker's risk decisions, differentiating appropriate uses of E-DOSPERT-derived risk-utility functions and lottery-derived risk-utility functions. They conclude that while lottery methods are suitable for later stages of the complex conceptual design process and beyond into physical design, E-DOSPERT-derived risk-utility functions based on an exponential utility function can be used in the early phases of complex conceptual design where practitioners are hypothesized to exhibit constant risk aversion. Van Bossuyt et al. test the scale with the six predicted domains of engineering risk including engineering practice and processes, product functionality, legal, engineering ethics, product testing, and training [22]. They conclude that the scale is suitably reliable to measure engineering risk attitude in two domains, including processes, procedures, and practices. For the other domains, it is marginally suitable or not statistically significant.

2.4 Research Objective

Previous papers in engineering design identify risk attitude assessment methods [6, 21, 22] but focus on early phases of design processes when new designs are created. In the early phases of the design processes, where the focus is on investigating design options, risk mainly arises from technical sources such as capabilities and resources. However, collaborative design processes require multiple actors working together, resulting in frequent interaction. As each actor concentrates on their gains, decision-makers can choose to retain some essential information, adding another level of uncertainty to the process. In collaborative engineering design processes, designers need to evaluate both technical and social risks to make a strategic decision. This paper differs from previous studies by investigating a suitable instrument to understand the impacts of risk attitudes of designers in the strategic decision-making phase when gain of an actor depends on actions of other actors. Identifying such an instrument could help understand how designers' preferences for collaboration change based on their risk attitude.

The paper adapts a risk attitude assessment questionnaire from management science [4] to reveal risk attitude as utility function curvature in the strategic decision-making stage of the engineering design process when actors are choosing whether to pursue uncertain collaboration with a partner. The questionnaire uses a lottery-equivalence method to assess utility functions in both gain and loss domains. Assuming strategic decisions follow the risk dominance equilibrium selection criterion, analysis investigates if a lottery-based risk attitude assessment method can provide insights to understand strategic decisions in engineering design tasks. A lottery-based risk attitude assessment method assesses strategic risk and provides a numerical value in the risk attitude scale, helping to differentiate attitudes of decision-makers.

This paper hypothesizes that risk attitudes of designers affect their strategic decisions in a bi-level collaborative engineering design process. The paper tests this hypothesis by adapting a questionnaire specifically for a collaborative engineering design experiment and uses secondary data to compare strategic decisions of participants in the experiment with the obtained individual utility functions from the questionnaire.

3 STUDY METHODOLOGY

3.1 Design Experiment

This paper uses secondary data from a design experiment constructed to study strategic design decision-making [23] that includes 29 two-player bi-level design tasks conducted between a human participant and a computer agent. Participants earn experimental currency units (ECUs) from the outcomes of each task, aiming to maximize their earnings.

The experiment is similar to a two-actor version of an earlier problem studied by Stern et al. [24] which considers a network of system actors in a technology transition problem who each have a choice between strategies s_i in the space $\mathcal{S}_i = \{\phi_i, \psi_i\}$, where ϕ_i and ψ_i are actor i's "existing technology" and "new technology" strategies respectively. The "existing technology" option provides low (or no) risk and low reward outcomes while the "new technology" option provides high risk and high reward outcomes. Nash equilibria $\phi = (\phi_1, \phi_2)$ and $\psi = (\psi_1, \psi_2)$ represent the "independent" and "collaborative" strategy sets, canonically referred to as "stag hunting" and "hare hunting" in game theory.

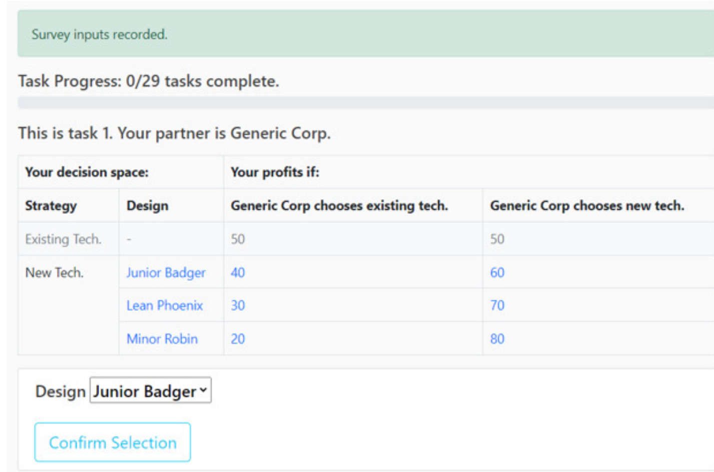

FIGURE 2: Screenshot of lower-level design decisions initially available to participants. Each alternative gives different payoffs contingent on the partner's selected strategy.

Table 1 displays normal form payoffs $V_i^{s_i, s_j}$ for an example stag hunt game modeled in Ref. [24] with "existing" and "new" strategy labels [23]. Strategic sources of risk arise from the uncertain strategy selected by each actor. While the new technology option provides upside potential for both actors under successful collaboration (i.e., $V_i^{\psi_i, \psi_j}$ is the payoff maximizing outcome), it also exhibits downside risk due to coordination failure (i.e., $V_i^{\psi_i, \phi_j}$ is the payoff minimizing outcome). In contrast, the existing technology option provides a low- or no-risk outcome.

For each task, participants first make a lower-level decision by selecting a design from three different possible implementation options of a new wireless communication technology shown in Fig. 2. Payoff values quantify the ECUs earned under different strategic contexts. All tasks have static payoffs for existing technology alternatives ($V_i^{\phi_i, \phi_j} = V_i^{\phi_i, \psi_j} = 50$). The downside payoffs corresponding to the three new technology options under failed collaboration (i.e., the partner chooses existing technology, $V_i^{\psi_i, \phi_j}$) vary for each task, whereas all tasks have consistent upside payoffs under successful collaboration (i.e., the partner also chooses new technology, $V_i^{\psi_i, \psi_j} = \{60, 70, 80\}$).

Next, participants make an upper-level strategic decision (s_i) shown in Fig. 3 between implementing the selected new technology design ($s_i = \psi_i$) or the existing technology ($s_i = \phi_i$). At this stage, participants can also see their partner's conditional payoff

TABLE 1: Normal form payoffs for a symmetric two-actor technology transition game from [24].

	$u_1 = u_2 = \frac{2}{3}$, $R = 0.69$	Actor 2 (s_2): Existing (ϕ_2)	Actor 2 (s_2): New (ψ_2)
Actor 1 (s_1)	Existing (ϕ_1)	$V_2^{\phi_2,\phi_1} = 5$; $V_1^{\phi_1,\phi_2} = 5$	$V_2^{\psi_2,\phi_1} = 1$; $V_1^{\phi_1,\psi_2} = 5$
	New (ψ_1)	$V_2^{\phi_2,\psi_1} = 5$; $V_1^{\psi_1,\phi_2} = 1$	$V_2^{\psi_2,\psi_1} = 7$; $V_1^{\psi_1,\psi_2} = 7$

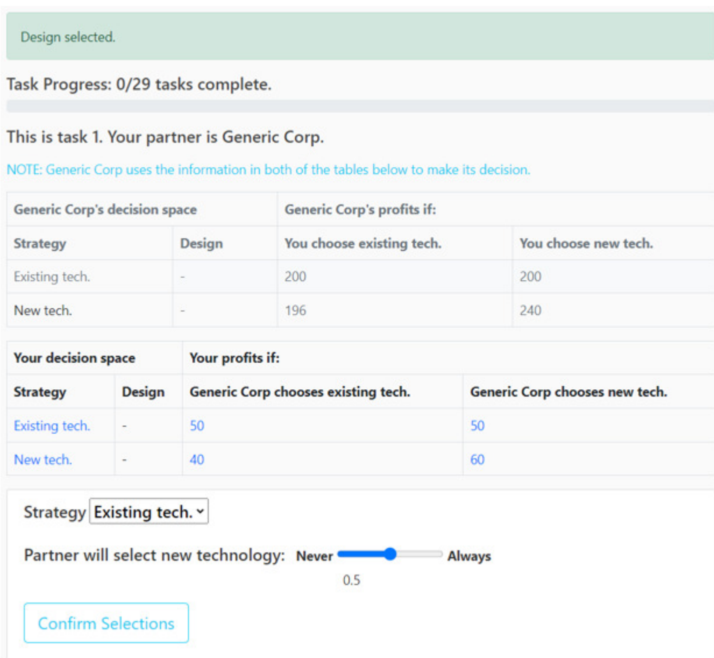

FIGURE 3: Screenshot of upper-level strategy decisions available to participants. The partner's payoff table is also visible.

table ($V_j^{\phi_j,\phi_i}, V_j^{\phi_j,\psi_i}, V_j^{\psi_j,\phi_i}, V_j^{\psi_j,\psi_i}$) which is pre-selected to produce a range of collaborative dynamics. After selecting a strategy, participants provide their belief about their partner's (computational agent) cooperation probability. The computational agent selects a strategy (s_j) based on the weighted-average log measure of risk dominance (R) assuming both players are risk neutral. Finally, the participant earns the corresponding number of ECUs based on joint strategic decisions (s_i, s_j). ECUs earned from each task are hidden from participants until the end of the experiment when cumulative score and percentile are revealed.

3.2 Risk Attitude Assessment

The risk attitude assessment adapts a questionnaire from Weber and Milliman [4] to the design experiment. Participants complete lottery-style questions to estimate their CARA-modeled risk attitude a before the experimental design tasks. The method does not use the relative risk attitude and directly uses risk attitude because participants have constant wealth as in each question. The questionnaire asks participants to select a probability q from a slider that would make them indifferent to earning or losing a stated amount of ECUs (Δx_b) relative to a status quo (x_0) compared to an alternative Δx_a with given probability p. Sample questions in the gain and loss domain include:

- Gain domain (Question 1): *"Your current design earns a baseline of 50 ECUs and has an opportunity for improvement. Following process a) has an 80% chance of earning 5 extra ECUs. Following process b) has a Q% chance of earning 40 extra ECUs. Select the value Q from the slider below that makes both options equivalent to you."*
- Loss domain (Question 8): *"Your current design earns a baseline of 50 ECUs but faces a crisis. Following process a) carries an 80% chance of decreasing value by 20 ECUs. Following process b) carries a Q% chance of decreasing value by 100 ECUs. Select the value Q from the slider below that makes both options equivalent to you."*

The questionnaire includes eight questions listed in Table 2, four in the gain domain and four in the loss domain. The expected utility hypothesis in Eq. 2 equates the expected utility of alternatives a) obtaining $x_a = x_0 + \Delta x_a$ with probability p or x_0 with probability $1-p$ and b) obtaining $x_b = x_0 + \Delta x_b$ with probability q or x_0 with probability $1-q$.

$$p \cdot U(x_a) + (1-p) \cdot U(x_0) = q \cdot U(x_b) + (1-q) \cdot U(x_0) \quad (2)$$

From this equilibrium, Eq. 3 calculates the $U(x_a)$ values from the elicited probability q and given probability p, assuming $U(50) =$

TABLE 2: List of Risk Attitude Lottery Question Parameters

Question	x_0	p	Δx_a	x_a	Δx_b	x_b
1	50	0.8	5	55	40	90
2	50	0.8	15	65	40	90
3	50	0.8	25	75	40	90
4	50	0.8	35	85	40	90
5	50	0.8	-80	-30	-100	-50
6	50	0.8	-60	-10	-100	-50
7	50	0.8	-40	10	-100	-50
8	50	0.8	-20	30	-100	-50

50, $U(90) = 90$, and $U(-50) = -50$.

$$U(x_a) = \frac{(p-q)\cdot U(x_0) + q\cdot U(x_b)}{p} \tag{3}$$

Calculations provide estimates of utility function points $U(x_a)$ for each question, forming a utility curve $U(x)$ for values from -30 to 85 for each participant. Analysis fits the elicited utility curves to a CARA utility function to quantify the risk aversion a for each participant.

3.3 Participant Demographics

Prior to the experiment, demographic questionnaire items collect participant information of age, gender, English language ability, and academic status. A total of 124 participants (44 female and 80 male) completed the questionnaire and finished the experiment. Participants ranged from 18 to 44 years of age. 107 participants reported they are native/fluent English speakers, 16 participants reported TOEFL (>90) or IELTS scores (>7.5) and one participant reported a Duo-Lingo score (=125). 92 of the participants are first-year students and 32 participants are junior year or above undergraduate, graduate, or have already graduated from a STEM field.

4 ANALYSIS AND RESULTS

4.1 Equilibrium Selection

Harsyani and Selten's theory of equilibrium selection criteria [25] identifies Nash equilibria as payoff dominant (the equilibrium that generates higher payoffs for all actors) and risk dominant (the equilibrium that appears less risky under strategic uncertainty) [25, 26]. Selten frames the normative strategy for each actor based on an indifference point, the *normalized deviation loss* (u_i) in Eq. 4, which is the minimum probability of cooperation (p_j) required to pursue the payoff-dominant strategy subject to the decision-maker's utility function U_i.

$$u_i = \frac{U_i\left(V_i^{\phi_i,\phi_j}\right) - U_i\left(V_i^{\psi_i,\phi_j}\right)}{U_i\left(V_i^{\phi_i,\phi_j}\right) - U_i\left(V_i^{\psi_i,\phi_j}\right) + U_i\left(V_i^{\psi_i,\psi_j}\right) - U_i\left(V_i^{\phi_i,\psi_j}\right)} \tag{4}$$

Selten formulates a global risk dominance measure (R) in Eq. 5 as a weighted average logit of u for each player [27, 28].

$$R = \frac{1}{2}\ln\left(\frac{u_1}{1-u_1}\right) + \frac{1}{2}\ln\left(\frac{u_2}{1-u_2}\right) \tag{5}$$

This paper uses R as a normative strategy selection criterion, i.e., $R > 0$ indicates $\phi = (\phi_1, \phi_2)$ should be selected as the risk dominant equilibrium while $R < 0$ indicates $\psi = (\psi_1, \psi_2)$ should be selected based on both risk and payoff dominance.

4.2 Normative Strategies with Elicited Risk Attitudes

Analysis first fits the participant utility functions elicited from the risk attitude assessment questionnaire in Eq. 3 to the CARA model in Eq. 1 to model a risk-aware utility function with a single parameter, a. Equation 6 applies a positive affine transformation with scale parameter $s > 0$ and translation parameters $x_{min} = \min(x) = -30$ and $U_{min} = \min_x U(x)$ for each participant.

$$U_{CARA}(x) = \begin{cases} \frac{s}{a}\left(1 - \exp(-a\cdot(x - x_{min}))\right) + U_{min} & a \neq 0 \\ s\cdot(x - x_{min}) + U_{min} & \text{otherwise} \end{cases} \tag{6}$$

Analysis uses the `scipy.optimize` package and the `curve_fit` function to perform a non-linear least squares to find the optimal value of a and s to fit the CARA curve to the obtained utility curves from the questionnaire responses. Example Fig. 4 shows the utility curve obtained from the questionnaire and the model CARA fit for one participant.

Next, Eq. 4 calculates normalized deviation loss (u_i) values using the fitted CARA parameter a for each participant and the observed payoffs ($V_i^{\phi_i,\phi_j}, V_i^{\phi_i,\psi_j}, V_i^{\psi_i,\phi_j}, V_i^{\psi_i,\psi_j}$) for each task. The same calculation computes normalized deviation loss for the computational agent using $a = 0$ and the payoffs revealed to the participant ($V_j^{\phi_j,\phi_i}, V_j^{\phi_j,\psi_i}, V_j^{\psi_j,\phi_i}, V_j^{\psi_j,\psi_i}$). Finally, Eq. 5 obtains risk dominance values (R) for each task using the u_i values computed for the participant and agent. The normative strategy for $R < 0$ is ψ whereas, the normative decision for $R > 0$ is ϕ.

The analysis first obtains R values assuming risk-neutral behavior for each participant to predict the expected strategic decision (S_e) for each task. S_e is then compared with the observed

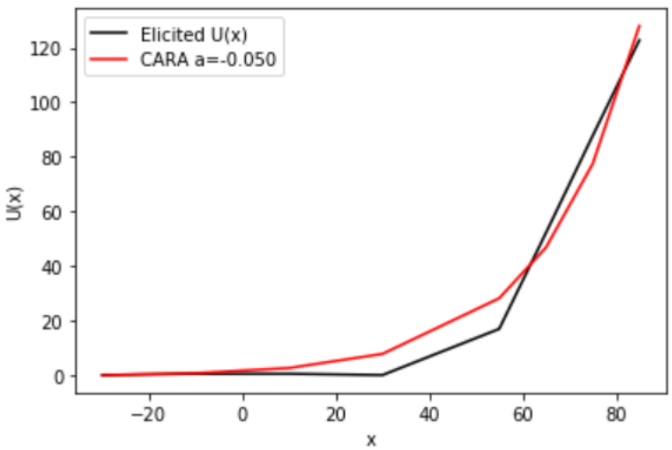

FIGURE 4: Plot shows utility curve obtained from the questionnaire and the CARA fit for one participant.

strategic decisions of participants (S_p). Results show 2238 of 3596 cases (62.2%) match the risk dominance expected strategy. Then, R values are re-computed using each participant's risk attitude (as measured by the questionnaire) to obtain risk-informed expected strategic decision (S_a). Comparison of S_p and S_a shows that risk attitude informed R-values only explain 2278 of 3596 cases (63.3%). Consequently, risk attitudes obtained from the questionnaire do not substantially help explain the participants' strategic decisions.

4.3 Observed Strategies and Implied Risk Attitudes

Risk attitudes can also be implied by experiment tasks following an inference procedure to fit a values to the participant's observed strategy selection behavior. The analysis process first calculates R values and obtains an expected strategy ($S_e(a)$) parameterized by unknown a for the 29 tasks completed by each participant. Then the process compares observed strategies (S_p) from the experiment tasks with the expected ones and aims to minimize the root mean square deviation (RMSD) in Eq. 7.

$$a^{\star} = \arg\min_{a} \sqrt{\frac{\sum (S_p - S_e(a))^2}{N}} \tag{7}$$

Results typically give one or more ranges of $a^{\star}$ values that minimize RMSD because of the binary response variable for each task and finite number of observations. Analysis considered values of a between -0.5 and 1.0. The following procedure selects a single value of a for each participant. For participants that could not be distinguished from extreme risk avoiders (i.e., $a = 1.0$ minimized RMSD), the smallest value in $a^{\star}$ was selected. Similarly, for participants that could not be distinguished from extreme risk seekers (i.e., $a = -0.5$ minimized RMSD), the largest value in $a^{\star}$ was selected. For all other participants, the median value in $a^{\star}$ was selected.

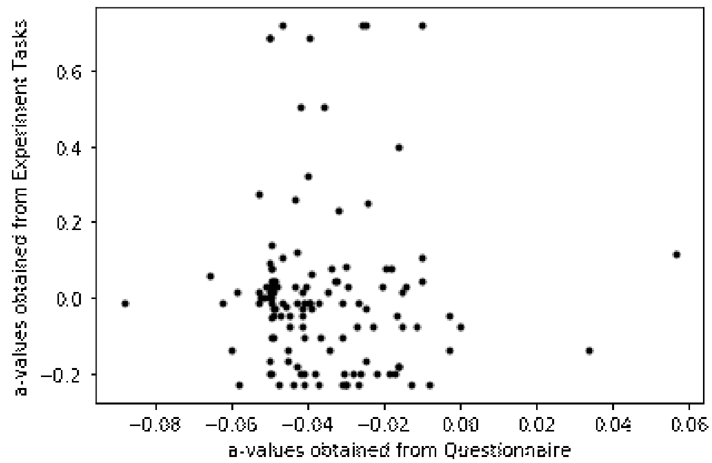

FIGURE 5: Plot shows comparison of a-values obtained from the experiment and a-values obtained from the questionnaire for each participant.

The expected strategies are calculated using R values based on obtained a values from the experimental data. Results show 2787 of 3596 cases (77.5%) align with the risk dominance expected strategy which is substantially better than the risk-neutral assumption (62.2%). Figure 5 compares the a values obtained from the questionnaire and from the experiment.

5 DISCUSSION

5.1 Comparing Elicited and Observed Risk Attitudes

Results show that CARA risk attitudes elicited from the questionnaire mostly range in a narrow region between $a \in [-0.06, 0.00]$. Only two participants show positive (risk-avoiding) a values. Results suggest that the participants cluster on the risk-seeking scale, but after considering the scale of the obtained a values, many results are close to risk-neutral. Indeed, when comparing to a risk-neutral model, results indicate that the created lottery-style questionnaire only slightly explains strategic decisions made by the participants in the experiment ($\approx 1\%$ improvement in accuracy).

Analysis of observed strategic decisions in the experiment tasks can also imply risk attitudes of participants. The observed risk attitudes range from $a \in [-0.3, 0.8]$, capturing more diverse risk attitudes than those obtained through the questionnaire. Based on the a-values obtained from the experiment, most participants made more risk-neutral and slightly risk-seeking strategic decisions. However, a few participants made extremely risk-averse strategic decisions, clustering between a value range between 0.6 and 0.8.

Comparing the elicited risk attitudes from the questionnaire with the observed risk attitudes in Fig. 5 shows nearly zero correlation (Pearson's $r = 9.43 \cdot 10^{-4}, p = 0.955$). In other words, the risk attitudes elicited from the questionnaire have almost no relationship to the risk attitudes implied from observations. There are several potential explanations for why the risk attitudes obtained from the questionnaire cannot capture the strategic decisions of participants during the experiment.

First, the questionnaire frames decisions from a static lottery perspective, presenting exogenous uncertainty to participants. In contrast, experimental participants engage with a more interactive and potentially endogenous uncertainty during the design tasks because their payoff depends also on the agent's decisions. Participant internal belief of more (less) "collaborative" agent behavior would contribute to smaller (larger) observed risk aversion values as seen in some participants.

Second, the questionnaire responses may suffer from instrument bias due to social desirability effects. Participants were aware they were answering a risk attitude assessment questionnaire and could potentially provide risk-neutral answers by calculating expected values from the numeric payoff and probability values provided. A risk-neutral attitude could be seen as a socially-desirable behavior, especially in technical disciplines such as engineering. This effect would explain the clustering of questionnaire responses close to the $a = 0$ risk-neutral point on the scale.

Third, the questionnaire uses separate items to elicit participant utility functions in the gain and loss domains. However, the experimental tasks are more complex and include both gain and loss domains in each decision, e.g., participants often consider trading a modest potential gain under successful collaboration with a large potential loss under coordination failure. Participants may exhibit more extreme risk attitudes for problems combining gain/loss domains compared to independent effects measured in the questionnaire.

Finally, the questionnaire items are presented as abstract decision problems with a short text narrative. In contrast, the experimental tasks are more contextual with staged decisions between the participant and the computer agent. The lack of context in the questionnaire items may present a barrier to eliciting the type of information useful to understand later decisions.

5.2 Limitations

Results from this study are subject to several limitations. First, analysis uses the risk dominance criterion to identify the normative strategy choice for a prescribed utility function. Risk dominance both evaluates the effectiveness of risk attitudes elicited from the questionnaire in Sec. 4.2 and infers the risk attitudes from participant decisions in Sec. 4.3. Some alternative decision policies, such as "always collaborate" or "always defect" will manifest as small or large risk attitudes, respectively. Other decision policies, such as maximizing expected value assuming a fixed probability of agent collaboration or even random selection, add noise to the results. Even assuming risk-neutral utility functions, participants follow risk dominance in 62.2% of tasks which provides greater accuracy than trivial policies such as "always collaborate" (56.6% accuracy) and is similar to the global policy of "maximize expected value assuming a 50% chance of agent collaboration" (62.7% accuracy).

Second, analysis in this paper only considers the CARA utility function to model risk attitudes with a scalar parameter, a. The CARA model was selected based on its simplicity. While there is a significant body of literature that differentiates between absolute and relative risk attitude (e.g., to distinguish from diminishing marginal value) and more complex utility functions resulting from prospect theory, these factors are mitigated somewhat by the experimental design. All of the questionnaire items and experimental tasks adopt a "status quo" value of 50 ECUs and participants do not know the results of prior tasks until the end of the experiment to obfuscate wealth effects.

Further, the experiment task payoffs range between -175 and 80 to cover a fuller range of strategy dynamics; however, the questionnaire only evaluates the utility function shape over a narrower range of payoffs between -30 and 85. The narrow range was elicited using only eight questions due to time limitations. Considering a wider range of elicited utility function points, especially with replication to mitigate response variation, would help to better represent participant preferences.

Finally, the population sampling frame poses a limitation for this study because most (74%) of the participants are first-year students while the others (26%) are junior year or above undergraduate, graduate, or have already graduated from a STEM field. Due to institute policies, the first-year students were not eligible for performance-based compensation which may limit the accuracy of the questionnaire and task responses to true preferences. While this paper does not highlight differences across sub-populations, Stern and Grogan find some differences in decision policy: first-year students more frequently follow noisy decision policies while the other participants more frequently follow risk dominance [23]

6 CONCLUSION AND FUTURE WORK

Risk attitude is an important factor in understanding strategic decisions in interactive engineering design settings. Lottery-style questionnaires have been used in the literature [4]; however, the risk attitudes obtained from the questionnaire implemented for this paper did not match the implied risk attitudes, which might be due to fundamental differences between dynamic and static uncertainty or simply due to the implementation.

A lottery-style questionnaire is able to capture different risk attitudes; however, it is not effective to model strategic decisions in the multi-actor engineering design tasks considered. Risk attitudes obtained directly from experiment tasks provide more reliable information to explain strategic decisions of participants. These results support claims that risk in the engineering domain is contextual, not a fixed property, which is supported by findings of Van Bossuyt et al. [22].

Future work can revisit the adaption or implementation of a questionnaire with items that can more closely capture the dynamics of a strategic problem. Rather than directly eliciting a utility curve via lottery-equivalence questions, further studies can investigate if existing assessments such as E-DOSPERT can provide more accurate correlation results for explaining strategic decisions. Future questionnaires should be contextual and also consider whether risk attitudes are a function of a partner in engineering design settings.

From these results, it can also be discussed that rather than adopting questionnaires for risk attitude assessments, training tasks that include the same dynamics and context can be included in the design processes for obtaining the risk attitudes of designers prior to the design tasks. This approach also has limitations, such as leveraging the learning curve of individuals and the additional cost of having more tasks; however, this method would provide valid risk attitude assessment results, as shown in this paper.

Future work can focus on developing a method that can accurately assess risk attitudes prior to the strategic decision-making process. Further understanding risk attitudes prior to strategic decisions can help actors make more reliable decisions with the provided information and create more efficient engineering design collaborations. In collaborative design processes, communication of risk attitudes would help to understand and anticipate other actors' perceptions, identify design options that are of mutual interest, and provide more clarity on the actor's preferences.

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