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Risky decision making in a computer card game: An information integration experiment

Information integration in risky decision making was studied by using a functional measurement approach. Participants (N=84) played a computerized risky card game incorporating a within-subject design with the 3 factors (a) probability of negative or positive outcome, (b) amount of gain, and (c) amount of loss. Results on the group level showed mainly additive patterns of integration. Observed deviations from the general pattern could be explained more detailed by the results of the individual analyses: There was a wide range of different strategies from centration to additive and mixed additive-multiplicative strategies. The most frequent rules of integration were additive; pure multiplicative rules were rarely found. These findings give support to additive models in risky decision making. However, individual differences in risky decision making strategies appear to be a topic that deserves further study.

Keywords: risky decision making, information integration, cognitive algebra, risk taking, risky choice

When dealing with risky situations in everyday life, people often have at hand three pieces of information on which they can base their decisions: (1) amount of possible gains, (2) amount of possible losses, and (3) probabilities of the possible gains and losses. In order to come to a decision, for example whether to show risk-seeking or risk-averse behavior, one has to somehow integrate these pieces of information.

As to the kind of the integration process, there are different views: Normative mathematical models of expected value describe a multiplicative way of integrating probabilities and values like gains and losses. The dominant model in psychological theory about dealing with risky situations has been the expected utility model. Both in its original version (Von Neumann & Morgenstern, 1944) and its further developments like prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), these models also assume a multiplicative integration of the value and the probability component. Although there are some models with additive integration (e.g., Payne, 1973; Sokolowska & Pohorille, 2000), most

theories assume a multiplicative combination (Mellers, Chang, Birnbaum, & Ordonez, 1992).

Indeed, it has been shown that even children as young as 6 years integrate probability and value multiplicatively in forming expected value (Schlottmann, 2001). On the other hand, there are substantial findings that have cast doubt upon the assumption of a general multiplicative integration. Mellers, Chang et al. (1992) and Mellers, Ordonez, and Birnbaum (1992) found that the integration rule varied with the response mode: Multiplicative integration was found when buying or selling prices were used as dependent variables, whereas additive integration was found when attractiveness or risk ratings were used as dependent variables. Other studies found influences of the stimulus context and the complexity of the tasks: Both participants' attractiveness ratings (Mellers, Ordonez et al., 1992) and their risk ratings (Mellers & Chang, 1994) switched from an additive to a multiplicative rule of integration when zero or near-zero values of probability or amount were included in the stimulus design. Joag, Mowen, and Gentry (1990) found multipli-

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cative integration of probability and value in risk ratings only when the decisions had *multiple* plays (e.g., the outcome is the sum of a gamble that is played independently 100 times). In the case of *single-play* decisions (when the gamble is played just once), integration followed an additive rule. Sokolowska and Pohorille (2000) tested different multiplicative and additive models to see which of these would best fit their data consisting of risk ratings. In their findings, additive models outperformed multiplicative models. Furthermore, the estimated parameters for the best-fitting *multiplicative* models led to a nearly additive integration in these originally multiplicative models as well.

All of these studies have in common that they investigated risky decision making by focussing on risk perception and risk estimates: Risk ratings were used by Joag et al. (1990), Mellers, Chang et al. (1992), and Sokolowska and Pohorille (2000); attractiveness ratings were used by Mellers, Chang et al. (1992), Mellers, Ordonez et al. (1992), and Schlottmann (2001); and buying and selling prices were used by Mellers, Chang et al. (1992) and Mellers, Ordonez et al. (1992). That is, participants' responses were ratings on judgment scales. In contrast, in everyday life risky decision making often is about *choices*, e.g. whether to take or leave a risk.

Our goal was to extend the investigation of cognitive algebra in risky decision making from risk estimates to risky choices. Accordingly, we wanted to measure the risky decision making process more directly – in a manner similar to Slovic (1966): Children were presented 10 switches. The children knew that 9 were “good” switches, each of them leading to a win of a spoonful of candies. But there was also a “disaster switch”: If a child pulled this one, then all of the candies already won would be lost. The children had to make consecutive decisions whether they wanted to take their chance with another switch – although the probability for the disaster switch increased with each switch already pulled – or whether they would prefer to stop. Thus, with every decision children had to make a trade-off between the potential win of more candies and the risk of losing everything. Just like in Slovic's experiment, our idea was to combine the benefits of the more naturalistic choice task with the advantages of a non-dichotomous continuous response scale as used in the studies on risky decision making mentioned above.

Thus, the study aimed at two main points: The first aim was to explore the information integration and the involved cognitive algebra in risky decision making. A design with functional measurement (Anderson, 1982) was adopted, allowing analyses both on the group and the

individual level. The second aim was to measure risky decision making directly, extending the existing research from risk perception and risk judgment to risky choice: Participants should make decisions in a risky situation, choosing their individually appropriate degree of riskiness. These two aims led to the development of a computerized card game that combined Slovic's (1966) attempt to measure risk-taking propensity with a design involving functional measurement.

Method

In the experiment, participants played a computerized card game making risky decisions depending on 3 pieces of information. Every participant played a total of 63 rounds that differed on the 3 factors (a) probability of positive and negative outcome, (b) amount of gain, and (c) amount of loss. The dependent variable was the number of cards chosen in each of the rounds of the game.

Procedure

Experiments were conducted individually. The experimenter explained the rules of the card game in a standardized manner. The game screen on the computer was explained and the experimenter told the participants that they just had to indicate which card they wanted to choose next and to say stop when they did not want to choose any further cards. The computer was handled by the experimenter throughout the whole experiment in order to avoid possible biases coming from participants' differing familiarity and practice with computers. After the experiment, participants were debriefed and given the opportunity to ask further questions.

Design and stimuli

The game monitor consisted of 32 cards. At the beginning of each trial, all cards were shown face down. By clicking on a card, it was turned over, revealing whether it was a winning or a losing card. At the top of the game monitor, participants could see the following information: number of hidden losing cards, amount of gain per winning card, amount of loss in case of clicking on a losing card, and number of the current round of the game. This information changed with every round of the game, according to the factorial design of the game. Furthermore, participants could see their actual score of points, changing with every card chosen. The task for the participants was to gain as many points as possible during the 63 game trials. This means they subsequently chose one card after the other until they decided that it was getting too risky and it would be better to stop. If the participants decided to stop the current round or if they clicked on

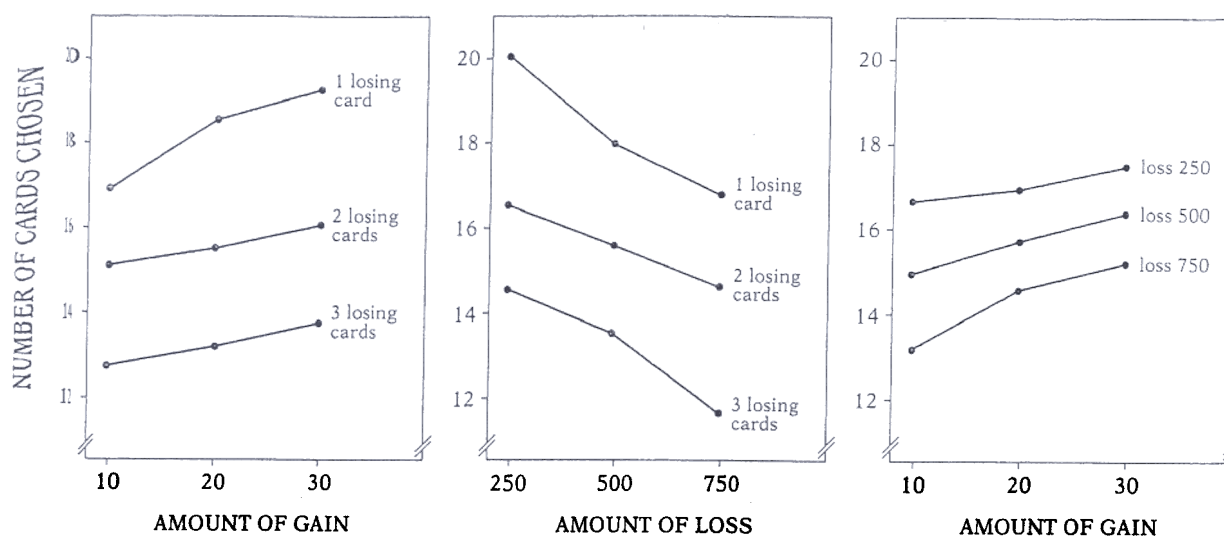


Figure 1. Mean number of cards chosen. Each graph shows the integration of two factors, collapsed over the respective third factor. Left: Amount of gain and probability. Middle: Amount of loss and probability. Right: Amount of gain and amount of loss. The patterns are mainly parallel, indicating additive integration; observable deviations from parallelism do not result in linear fan patterns as would be expected if integration was multiplicative.

a losing card, all of the remaining cards were turned over to show which of the other cards were winning or losing cards, respectively. Then, the next round was started.

According to functional measurement methodology (Anderson, 1982), a full factorial within-subject design was used with the factors (a) probability (1, 2, or 3 hidden losing cards), (b) amount of gain (10, 20, or 30 points per winning card), and (c) amount of loss (250, 500, or 750 points); each factor had 3 levels. Each combination was presented twice, resulting in 54 experimental trials, with the trials randomly ordered within each of the two blocks. These experimental trials were manipulated in order to have the same feedback conditions for each participant: The game was programmed in a way that the losing cards would always be the last possible cards (e.g., in the case of two hidden losing cards, only the last one of 31 cards chosen would be a losing card). To maintain the impression of a real game of chance, a second manipulation was used: Evenly distributed among the 54 experimental trials, there were 9 additional trials. These 9 additional trials – the so-called losing trials – were programmed in a way that every participant clicked on a losing card with very high probability (independently of the choices of the participants, e.g., the third card chosen was a losing card)¹. These two manipulations worked

together well; only 3 participants suspected a manipulation. Data of these 3 participants had therefore to be excluded from further analyses and were replaced with the data of 3 additional participants.

Participants

There were 84 participants, 42 women and 42 men, aged 26 to 79 years (mean age 50 years). Nearly all of them had University education, in fields other than psychology.

Results

Group analyses

The 3 panels in Figure 1 present the mean number of cards chosen dependent each on two factors, collapsed over the respective third factor. As can be seen, the patterns are mainly parallel, indicating additive rules of integration. However, there are observable deviations from strict parallelism. This indicates that at least some of the participants followed non-additive rules of integration. These deviations from parallelism do not seem to come from multiplicative rules of integration: If integration had been multiplicative, linear fan patterns would have been expected. Thus, despite some deviations from parallelism, visual inspection on the group level seems to suggest mainly additive patterns of integration.

The results from the statistical analyses are similar to the conclusions from visual inspection: Significant effects were found for all 3 factors and for all interactions: probability, gains, losses, probability \times gains, probability \times losses, gains \times losses, and probability \times gains \times losses. The respective statistics are (all $p < .001$): probability

¹The total sum of 63 trials consisted of the $3 \times 3 \times 3 \times 2 = 54$ experimental trials and the 9 additional losing trials. The factors' levels of these 9 losing trials were randomly chosen among the 27 different combinations of the full factorial design. Since these losing trials only served to maintain the impression of a real game of chance, these data were not included in further analysis.

$F(2, 166)=192.35, \eta^2=.699$; gains $F(2, 166)=38.15, \eta^2=.315$; losses $F(2, 166)=54.45, \eta^2=.396$; probability \times gains $F(4, 332)=12.95, \eta^2=.135$; probability \times losses $F(4, 332)=8.52, \eta^2=.093$; gains \times losses $F(4, 332)=6.61, \eta^2=.074$; probability \times gains \times losses $F(8, 664)=10.76, \eta^2=.115$. As in the visual inspections, results are not fully unequivocal: Significant interactions on the group level are required for the assessment of multiplicative rules of integration and therefore may indicate multiplicative rules of integration on the individual level (Anderson, 1970; Anderson, 1982; Anderson & Shanteau, 1970). However, given both the largely parallel patterns in Figure 1 and the corresponding small effect sizes for the interaction terms, again, the better assumption seems to be a mainly additive rule of integration. The significant interactions do not seem to come from general multiplicative rules of integration but might come from the aggregation over different strategies in the group analyses. To investigate this point, the group analyses should be confirmed by individual analyses – as suggested by different authors (e.g., Anderson, 1982; Wilkening, 1979).

Individual analyses

For every participant, an individual analysis of variance was calculated according to functional measurement methodology (Anderson, 1970, 1982). The factors probability, amount of gain, and amount of loss again served as independent variables. An α -level of $p < .10$ was adopted for these analyses in order to minimize possible β -errors, i.e. reducing the risk to overlook more complex integration rules – like adding instead of centering rules or multiplying instead of adding rules.

From the whole sample, 28.6% took all 3 factors into account ($n=24$), 16.7% took 2 factors into account ($n=14$), and 39.3% centered on 1 factor ($n=33$; all of these participants centered on the factor probability, except one centering on the factor loss). The remaining 15.5% of the participants have not taken into account any factor consistently ($n=13$). When looking at the proportion of participants taking into account 2 or 3 factors ($n=38$), the following picture emerges: Most of them applied a purely additive rule of integration ($n=22$), another portion followed a mixed rule consisting of adding and multiplying (total $n=14$; $n=8$ for 2 additive combined with 1 multiplicative integration; $n=6$ for 1 additive combined with 2 multiplicative integrations), and only 2 participants followed a pure multiplicative rule of integration, both with significant effects of probability, losses, and probability \times losses.

Thus, two points can be stated from the individual analyses: First, the mainly additive

pattern seen in the group analyses is not an artifact stemming from different rules of centeration. Second, the assumption of an additive model in the group analysis is further supported since more participants followed additive than multiplicative rules of integration.

Discussion

Looking at our results, several findings deserve to be noted: (1) The factors probability and amount of loss had stronger effects and were more often taken into account than the factor amount of gain. This is in agreement with previous research (Coombs & Lehner, 1980; Slovic, 1967; Sokolowska & Pohorille, 2000; Weber, Anderson, & Birnbaum, 1992). (2) On the individual level, we found a wide range of different strategies instead of one general integration rule. These strategies ranged from centering to adding and to mixed strategies of adding and multiplying. (3) However, the most frequent rules of integration – omitting the non-integrating rules – were *not* multiplicative, but additive ones. (4) On the group level, the mixture of strategies led to the observed patterns that were mainly additive. Taking these two findings together, it seems reasonable to assume an additive model of integration from our data – giving further support to the line of research that doubts multiplicative integration of probability and value in risky decision making (Joag et al., 1990; Mellers, Chang et al., 1992; Mellers, Ordonez et al., 1992; Schlottmann, 2001; Sokolowska & Pohorille, 2000). Besides replicating these findings, our experiment broadened the existing database on cognitive algebra in risky decision making by extending it from risk perception and risk judgment to the more naturalistic domain of risky choice. On the other hand, individual differences appear to be an important issue: A model describing risky decision making should therefore be able to explain (a) who is adopting (b) which strategy (c) under which circumstances. These questions cannot be answered from our experiment, of course, but they surely deserve further study.

References

- Anderson, N. H. (1970). Functional measurement and psychophysical judgment. *Psychological Review*, 77, 153–170.
- Anderson, N. H. (1982). *Methods of information integration theory*. New York: Academic Press.
- Anderson, N. H. & Shanteau, J. C. (1970). Information integration in risky decision making. *Journal of Experimental Psychology*, 84, 441–451.
- Coombs, C. H. & Lehner, E. P. (1984). Conjoint design analysis of the bilinear model: An application to judgments of risk. *Journal of Mathematical Psychology*, 28, 1–42.

- Joag, S. G., Mowen, J. C., & Gentry, J. W. (1990). Risk perception in a simulated industrial purchasing task: The effect of single versus multi-play decisions. *Journal of Behavioral Decision Making*, 3, 91-108.
- Kahneman, D. & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47, 263-292.
- Mellers, B. A. & Chang, S. (1994). Representations of risk judgments. *Organizational Behavior and Human Decision Processes*, 57, 167-184.
- Mellers, B. A., Chang, S., Birnbaum, M. H., & Ordonez, L. D. (1992). Preferences, prices, and ratings in risky decision making. *Journal of Experimental Psychology: Human Perception & Performance*, 18, 347-361.
- Mellers, B. A., Ordonez, L. D., & Birnbaum, M. H. (1992). A change-of-process theory for contextual effects and preference reversals in risky decision making. *Organizational Behavior and Human Decision Processes*, 52, 331-369.
- Payne, J. (1973). Alternative approaches to decision making under risk: Moment versus risk dimensions. *Psychological Bulletin*, 80, 439-453.
- Şchlottmann, A. (2001). Children's probability intuitions: Understanding the expected value of complex gambles. *Child Development*, 72, 103-122.
- Slovic, P. (1966). Risk-taking in children: Age and sex differences. *Child Development*, 37, 169-176.
- Slovic, P. (1967). The relative influence of probabilities and payoffs upon perceived risk of a gamble. *Psychometric Science*, 9, 223-224.
- Sokolowska, J. & Pohorille, A. (2000). Models of risk and choice: Challenge or danger. *Acta Psychologica*, 104, 339-369.
- Tversky, A. & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5, 297-323.
- Von Neumann, J. & Morgenstern, O. (1944). *Theory of games and economic behavior*. Princeton, NJ: Princeton University Press.
- Weber, E. U., Anderson, C. J., & Birnbaum, M. H. (1992). A theory of perceived risk and attractiveness. *Organizational Behavior and Human Decision Processes*, 52, 492-523.
- Wilkening, F. (1979). Combining of stimulus dimensions in children's and adults' judgments of area: An information integration analysis. *Developmental Psychology*, 15, 25-33.

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