IMPACT OF RISK VISUALIZATION FORMATS ON DECISION MAKING

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IMPACT OF RISK VISUALIZATION FORMATS ON DECISION MAKING

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DECLARATION OF ORIGINALITY

I, Burcu Avcı, certify that

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- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
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ABSTRACT

IMPACT OF RISK VISUALIZATION FORMATS ON DECISION MAKING

This thesis investigates how exponentially increasing risks are understood and how this understanding leads to decisions. This research is grounded in two literatures: (lack of) understanding of exponential growth and risk visualization. It is well known that exponential trends are conceptually hard to grasp and many critical natural phenomena show exponential growth (e.g. viral spread, forest fires, cancer cell division). In many cases, exponential growth leads to exponential increases in risk and one efficient way to communicate such increasing risk is via visualizations. The present thesis investigated risk perception and decision-making when exponential risk information is presented in different formats. Participants completed a modified Balloon Analogue Risk Task (BART), in which they had to evaluate a number of scenarios with an already pumped balloon. The balloon's popping probability always increased exponentially but depending on the type of the balloon the riskiness of each pump varied. The risk probabilities for each pump were presented in either a table or a line graph. Participants reported their risk perception for each scenario and whether they would pump the balloon. As expected, highly-educated participants were less likely to "pump" balloons as the popping probability and the riskiness of the balloons increased. However, visualization format had no effect on risk perception or decision-making. This finding suggests that participants were able to extract the critical information in a similar manner from both line graphs and tables and responded relying on both quantitative and visual information.

ÖZET

RİSK GÖRSELLEŞTİRME BİÇİMİNİN KARAR VERMEYE ETKİSİ

Bu tezde üstel artan risklerin nasıl anlaşıldığını ve bu anlamlandırmanın verilen kararları nasıl yönlendirdiğini araştırdık. Araştırma iki literatürün bulgularına dayanmaktadır: üstel büyümenin anlaşıl(ama)ması ve risk görselleştirmeleri. Üstel trendlerin kavramsal olarak zor anlaşıldığı bilinmektedir ve birçok önemli doğal olayda üstel büyüme gözlemlenebilmektedir (örn. virüs yayılımı, orman yangınları, kanser hücresi bölünmesi). Çoğu zaman, üstel büyüme riskte de üstel artışa yol açar ve bu risk bilgisinin etkili bir şekilde iletilebilmesinin bir yolu risk görselleştirmeleri kullanmaktır. Bu çalışmada, üstel artan risk bilgisi farklı görselleştirme biçimlerinde sunulduğundaki risk algısı ve karar verme süreçleri araştırıldı. Katılımcılara Balloon Analogue Risk Task (BART)'ın değiştirilmiş bir versiyonu verildi. Bu görevde katılımcıların önceden şişirilmiş balon senaryoları değerlendirmeleri gerekiyordu. Balonun patlama ihtimali hep üstel şekilde artıyordu ancak balonun türüne göre her şişirişin riskliliği farklılık gösteriyordu. Her şişirişteki risk ihtimalleri tablo veya çizgi grafiği ile sunuldu. Katılımcılar her senaryo için algıladıkları riski ve balonu bir sefer daha şişirip şişirmeyecekleri kararını bildirdiler. Beklendiği gibi, yüksek eğitimli katılımcılar, balonun o şişirişteki patlama ihtimali ve genel riskliliği arttıkça balonu "şişirme"ye daha az eğilimlilerdi. Fakat, görselleştirme biçiminin risk algısı ve karar vermeye etkisi gözlemlenmedi. Araştırmanın bulgularından yola çıkarak, katılımcıların hem tablo hem de çizgi grafiklerinden önemli bilgileri benzer şekilde çıkardığı ve hem sayısal hem de görsel bilgilere dayanarak karar verdikleri çıkarımı yapılabilir.

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CHAPTER 1

INTRODUCTION

Information communication is important for many fields and our lives consist of a series of decisions and their execution. How and to what extent we understand the information presented to us may affect the subsequent decisions. How we present information also affects understanding and perception of the information by the receiver (Spiegelhalter, 2017). Most of the time, our decisions are based on information that is incomplete or uncertain (Baron, 2008). Furthermore, the future, is by definition full of uncertainty. Therefore, we behave in ways dictated by what we have learned from our previous experiences and probabilistic outcome information, i.e. the likelihood of certain outcomes under certain conditions. One of the main goals of this thesis is to investigate how individuals evaluate probabilistic information about risks and make decisions. I specifically focus on individuals' understanding of exponentially increasing probabilistic risk information. Particularly, I am interested in investigating how visualization format affects perception of exponential risk and how this perception affects decision-making. Research on exponential risk recently increased with the 2019 Pandemic, mainly focusing on future forecasting (Fansher et al. (under review); Lammers et al., 2020). Previous research on risk probabilities and visualization format are more focused on either comparing the format or the risk, investigating how visual format aids understanding risk (Schapira et al., 2006; Chua et al., 2006; Harvey & Bolger, 1996); and exponentially increasing trends are not the main focus on these studies. Rather, studies on exponential trends mainly focus on understanding exponential growth (Stango & Zinman, 2009; Ebersbach & Wilkening, 2007; Mullet & Cheminat, 1995;

Wagenaar & Sagaria, 1975). To our knowledge, not much has been investigated about how exponentially increasing risks are perceived at specific time points; how those risks are impacting decisions and whether perception of such risks is impacted by format.

Below I will separately review the literature on uncertainty and risk perception, the difficulty of understanding exponential trends, and how risk visualizations are useful tools to communicate such information. Then, I will present the motivation for the present study at the intersection of these three broad areas of research.

1.1 Risk perception, risk understanding, and risk-taking

Risk may evoke different meanings in different contexts and to different people, Slovic and Weber (2002) list 4 common definitions of risk: risk as a hazard, as a probability, as a consequence, and as a potential adversary or threat. Taking risks or making decisions on whether to take risks is an inevitable part of life as the future is full of probabilities and possibilities. While possibilities are qualitative and define whether an event may or may not happen; probabilities are the quantitative part of possibilities, indicating the likelihood of the possibility of an event. If the probability of an event is not 100%, it is uncertain, and the magnitude of the event's uncertainty might alter how we make decisions about it.

Risk probability (i.e. magnitude of the uncertainty) is one of the most commonly communicated aspects of risk, even though it is one of the many aspects of risk information. Risk probability information can be disclosed in various forms like frequencies, percentages, rates, and verbal expressions (Positive/negative framing, comparative risks, evaluative labels, etc.) and how risk is communicated may bias or affect risk perception (for a review see Visschers et al., 2009; Spiegelhalter, 2017). For instance, when the same information is presented with either a positive or negative frame, this systematically affects people's choices (McNeil et al., 1982; Tversky & Kahneman, 1981). Specifically, positively framed risks (i.e. presentation of survival as opposed to death rates) lead to lower levels of perceived risk; this leads to shifts in endorsement decisions for the positively framed option, which in fact is no different from the negatively framed option in terms of the statistical facts (Kahneman & Tversky, 2008).

Another factor that impacts perceived risk is context. Contextual effects on risk perception may be related to individual differences in domain expertise. For instance, while asserting risk, experts tend to rely on factual information and depend less on dread risk; laypeople tend to rely on signal potential of the event which differentiates how they make their judgment of the risk (Slovic & Weber, 2002). The affective responses the context might elicit also affect how risk judgments are made (Slovic, 2018; Slovic, 1987). The signal potential of an event signifies the potential social impact of risk which is related to where it can be classified in a two-factor space: The dread risk and system familiarity (known/unknown risk) (Slovic & Weber, 2002; Slovic, 1987). The dread risk and system familiarity (known/unknown risk) combinations affect how we perceive an event's riskiness. Typically highly dreadful events for which people have limited knowledge (high unknown) are considered as higher risk carrying events. For example, while nuclear reactor accidents are perceived as more high-risk (highly dreadful, highly unknown); bicycle accidents are perceived as low-risk (low dreadfulness, low unknown). (Slovic, Fischhoff & Lichtenstein, 1981; Slovic, 1978). In light of these reasons, in studies of risk perception, researchers try to control context to ensure participants are likely to have similar levels of familiarity and show similar affective reactions to the context of the presented event.

In laboratory studies on risk perception and decision making (risk-taking behavior), to alleviate concerns regarding contextual influences, one option is to use tasks with an "intuitive game-like character" (Schmitz et al., 2016, p.34). One of these frequently used games is the Balloon Analogue Risk Task (BART; Lejuez et al., 2002). In the BART task, on each trial, participants are given a balloon to pump, and their goal is to pump the balloon as large as possible without popping it. For each successful pump, the participants gain (virtual) money but if they end up popping the balloon, they then lose everything on that trial. After every pump, participants decide whether to put their earnings to the bank or to pump the balloon again. Participants are typically not given explicit/overt information about the balloon's probability of popping or how to gain maximum earnings; they are supposed to implicitly learn these patterns. Critically, the balloons' popping probability increases exponentially with each consecutive pump (e.g. If the balloon has a pumping range between 1 and 128 -the blue balloon-, at the first pump it has 1/128 popping probability, and at the nth pump it has 1/128-n popping probability). Risk-taking behavior is measured by the number of pumps made on successful trials, i.e. on the ones in which the balloon did not pop. This value captures how participants react when pumping a balloon which enables them to accumulate money while risking of losing it with every pump. Due to the risk probabilities increasing exponentially, the best strategy for gaining the highest-earning possible is to pump the balloon half of its pumping potential. Otherwise, the participant takes small risks and gains a smaller amount of money, or they take larger risks and may lose the money they accumulated. In essence, successful performance on BART necessitates that participants find a balance between risk-taking and gaining money as the probability of the risk exponentially increases.

Studies have shown that performance on BART is correlated with risk-related measures such as sensation-seeking, impulsivity and behavioral constraint as well as self-reported risk-taking tendencies (Lauriola et al., 2014, Lejuez et al. 2002). The task has an easy-to-understand context and, it is close to real-world decision-making as it is affected by emotional arousal, and the decisions are made sequentially (Schmitz et al., 2016). Therefore, BART is considered a behavioral measure of risky behavior and continuous decision-making. In this project, I used a BART-like task to investigate how risky decisions are influenced by the format of exponentially increasing risk information.

1.2 Exponential relationships

In the present study, I plan to investigate risk-taking behavior using a BART-like task in which participants need to evaluate exponentially increasing risk information prior to making a decision. Therefore, below I provide a brief overview of the challenges associated with understanding exponential growth (or decay) and of the limited research that looks at how graphic depictions of format impacts understanding of exponential growth.

Exponential growth patterns are abundant in nature. For instance, population growth (overpopulation), carbon dioxide, viral spread, food spoilage, reproduction of invasive species, forest fires, division of cancer cells, and smartphone sales can happen with exponential growth (Some examples are from 10 Real Life Examples of Exponential Growth, n.d.), in which an exponential relation is positive. In all these examples, a quantity increases with time; critically though, the rate of growth increases each time. It is well known that people have a hard time grasping exponential growth conceptually (Ebersbach & Wilkening, 2007, Mullet & Cheminat, 1995, Wagenaar & Sagaria, 1975). Exponential patterns are not immediately apparent at the beginning of sequentially unfolding events; however, the increase or decrease can have high impact within a short period of time. Compared to linear relationships where change per unit time is constant, in exponential trends, change per unit time is variable and therefore it may be harder to correctly estimate this value. In fact, researchers have identified a tendency to misestimate exponential growth, a bias known as the Exponential Growth Bias (Stango & Zinman, 2009). Exponential Growth Bias is characterized by thinking that an exponentially increasing relationship is growing in a linear fashion. (Cordes et al., 2019, Wagenaar & Sagaria, 1975). As a consequence, people tend to underestimate growth. Recently Lammers et al. (2020) found that when asked to estimate the total number of coronavirus cases in five days, participants misestimated the growth of the COVID19; their case forecasts followed a linear pattern as opposed to an exponential, leading to an underestimation of the number of cases. However, following a brief instruction stating the increase of coronavirus cases is not "steady and constant" but "doubling every three days" and task (past and future estimations) interventions, participants were less likely to underestimate and consequently show greater support for social distancing measures. Thus, Lammers et al. demonstrate that brief instructional interventions may help to reduce exponential growth bias.

1.3 Presentation of (exponential) risk information

Risk information can be presented in various ways, verbally, visually, or both. The configuration of these presentations can affect how people perceive the risk and how they regulate their behavior according to this perception (Padilla et al. 2018). Visschers et al. (2009) and Spiegelhalter's (2017) reviews on risk communication give summarized tips on how to communicate risk information. These tips mainly emphasized ways to increase the processing efficiency of the information, which enables a more immediate and more effortless cognition and decision-making. The format we choose should depend on what kind of task we have in hand and what kind of understanding we want the observers to have. There is not one single way of presenting information but knowing how the format and the features of visualizations affect the perception of information is important.

Critical to the purposes of this research, we believe that the recommendations on how to best depict trend information may be informative. It is suggested that while line graphs facilitate interpreting trends over time and cumulative information (e.g. Zacks & Tversky, 1999); bar graphs and pictographs (icon arrays) facilitate comparing; and pie charts to compare proportions (Lipkus & Hollands, 1999; Meyer, Shinar & Leiser, 1997; cited by Visschers et al., 2009).

Since the focus in this particular project is decisions based on exponentially increasing risk contexts, the presentation format of risk information should display how the whole trend looks like in time: Exponential growth generally shows a trend where growth/increase is initially small, and it seems small in consecutive order; however, as observations increase the growth/increase gets larger multiplying each observation. Therefore, presenting the data as a time series is necessary to present exponential growth. The two most optimal formats to present the set of risk probabilities at each time point/event are via tables and line graphs: The information visualization literature suggests that, although performance depends on the task, people can quickly and accurately depict trends and change of trends upon viewing line graphs (for a review see Visschers et al., 2009; Lipkus & Hollands, 1999; Meyer, Shinar & Leiser,1997; Meyer, Shamo & Gopher,1999; Hollands & Spence,1992). When presented with tables, participants have faster reaction times than when presented with bar and line graphs across various tasks such as reading exact values, identifying the maximum value, comparison of values, and reading of trends (increasing or decreasing); tables also enabled similar accuracy at reading trends as line graphs (Meyer et al., 1997). Furthermore, Shamo et al. (1996) and Meyer et al. (1999) found that line graphs have an advantage over tables in tasks requiring predicting and perceiving trends, especially if the relationship is structured. Therefore, both line graphs and tables can provide essential information to understand trends. However, understanding of different parts of exponentially increasing trends might be affected differently by presentation format (i.e. table and line graphs).

Recently a few studies investigated forecasts of exponential growth in the context of Covid19 using tables and line graphs. Fansher et al. (in revision) found people were more accurate at forecasting the number of Covid cases when they were presented a table than when the data was presented as a line graph. Furthermore, in the same study, they reported that forecasts based on tables were underestimates. In the current study, I investigate how risk probabilities are perceived when they are presented in a line graph versus in a table. In that sense, this current study is different than recent studies comparing forecasting outcomes across different formats. As exponential growth has a structure more apparent as observations increase, tables and line graphs might lead to different levels of understanding or perception of risk probabilities in different phases of the information presented. Specifically, the visual presence of the overall trend in line graphs may help viewers more easily realize the higher risk at later time points in exponentially increasing risk trends.

1.4 Current study

This thesis study plans to integrate findings of risk perception, decision making and information visualization literature by investigating the perception of exponential risk probabilities and decision-making when these risk probabilities are presented with different visual formats. In the current study, I used a task similar to BART but with adaptations that planned to help address my questions directly and would be suitable for online data collection. I gave participants different risk scenarios with different risk probabilities and asked them to evaluate risk information that is presented either in table or line graph format. Then participants made decisions to either pump the balloon or take points.

Studies using the original BART focuses on how people behave during sequential and cumulative risk events. However, in the present study, rather than focusing on how people learn sequential and cumulative risks, I am interested in risk-taking behavior when the risk is clearly increasing, a pattern that characterizes the later sections of exponential growth patterns. Lejuez et al. (2002) reported that most of the participants behave in a risk-averse manner and that participants do not make the average number of pumps that would reach the highest-earning strategy limit, even with low-risk balloons. Additionally, in the original BART task, the balloon might pop if the participant is taking risks thus observing high-risk scenarios can be hard. To deal with this problem, I chose to present participants with snap-shot scenarios and prompt participants to report whether they would pump the balloon carrying a certain level of risk (high or low-risk balloon), at a particular point in the risk continuum. This approach is similar to that employed in another risk-behavior task- the Bomb Risk Elicitation Task (BRET); in BRET, on each trial participants report how many boxes to collect from out of 100 boxes, one of which has a bomb in it and the bomb explodes after the choice is made (Crosetto & Filippin, 2013). Thus, unlike in BART, in BRET, participants' risk-taking intent is observed. Critically, in BRET each box has an equal probability of exploding meaning that the risk probabilities are not exponentially increasing. In that regard, the original BRET is not suitable for the main question of interest of this thesis.

Another advantage of using snapshot scenarios is that this approach allows us to observe the behavior of all participants under the same scenario. In this regard, my approach is different from both BART and BRET, because in both of those the task design allows for participants to stop the process based on idiosyncratic factors. While I am aware that measuring intentions given particular scenarios may not always reflect actual behavior, we believe that the modified task has the potential to demonstrate viewers' risk understanding across different risk presentation formats by measuring potential differences in intention. Furthermore, different presentation formats might lead to different understandings of different parts of exponentially increasing trends. I would like to explore how different parts of the exponentially increasing trends affect risk perception and decision-making when the risk probabilities are presented in table and line graph formats.

In summary, this task, which is a modified version of BART, mainly plans to use BART as the context of scenarios to investigate decision-making upon being presented with sequential risk information. BART as a context can control for familiarity and affect for its easy-to-understand and game-like nature. As I wanted to investigate people's risk perceptions and decision making when they arrive towards later pumps without the balloon popping, scenarios where they are at an n^{th} pump were given to participants accompanied by the popping probability information at all the pumps of a balloon with either a table or a line graph. There were two types of balloons: One balloon was a low-risk balloon with an exponentially growing popping probability at each pump and has a limit of 90 pumps; the other balloon was a high-risk balloon with also an exponentially growing popping probability but with a limit of 30 pumps. While my main focus is on the risk-taking behavior under different risk contexts and while the risk is presented in different formats, I also know that these types of decisions are not only a function of the data presented in these formats, but also perceived risk and the affective responses these decisions might evoke (see pages 3-4).

In this study, I manipulated the visualization format, risk probability (risk progress) and riskiness of balloons to determine their interactive effects on decisions. The two main observations were risk-taking and risk perception. I expect risk-taking decision and risk perception to be probably highly correlated. Critically, I expected visualization format to impact risk perception: In line graphs, the sharp increase in the mid-later phases would be much more apparent than tables therefore, I expected higher risk perception and less risky behavior. Also, I expected higher risk perception and less risky behavior at the high-risk balloon block, as the risk probabilities are much higher quantitatively. Same for the risk progress, as the risk probabilities increased, I expected higher risk perception and less risky behavior. Participants with higher risk-taking scores at Dospert-25 would be more likely to make more decisions to pump the balloon in both visualization groups and both balloon types.

CHAPTER 2

METHODOLOGY

2.1 Participants

312 participants consented to participate in the Qualtrics experiment. 240 participants completed the survey and 228 of these participants (141 women and 81 men, M_{age} = 24.6; Mdn_{age} = 21; SD_{age} = 8.72) responded correctly to attention check questions. I recruited participants with the Boğaziçi University Research Participation System (N = 126) with course credit compensation and by snowballing on social media (N = 102); current and graduated students from Boğaziçi University also participated with snowballing on social media. The sample size was determined according to the recommendations from Bujang et al. (2018). They recommended two rules of thumb: Event per variable of 50 or 100 + (50 x number of independent variables in the final model). The current study has three predictors: one between-subjects and two within-subjects: The sample size was appropriate for the first rule of thumb as there were at least 90 participants in each condition; however, the sample size should have been slightly larger to conform to the second rule of thumb, as the sample size needed would be 250.

2.2 Materials and stimuli

The experiment was programmed on Qualtrics. This study was approved by the Boğaziçi University Ethics Committee for Master and Ph.D. Theses in Social Sciences and Humanities (SOBETİK) on the 12th of December, 2020 (Appendix A). The tables and line graphs were prepared in Excel and exported as .png. They were grey-toned except for the risk probability cues which were red. The table and line graphs (Appendix B, C, D and E) presented what is the probability of the balloon popping in each pump (thus, not the cumulative risk of the balloon's popping probability until that pump). There were two variants of each visualization as there are two balloon types: low-risk (90 pump-limit) and high-risk (30 pump-limit) balloon. The tables had the same number of rows (30); the low-risk balloon had 3 columns for the n^{th} pump and the probability of popping. The line graphs' x-axis is the n^{th} pump and the y-axis shows the probability of popping (%). The line graphs' x-axis had the same distance for each unit. Thus, the high-risk balloon had a shorter x-axis as the axis has 30 units while the low-risk balloon's x-axis had 90 units.

The participants were given scenarios where they would make decisions, these scenarios depended on risk probability which is the number of pumps already made. As the main objective of the study was to understand behavior during the increasing part of exponential growth, I chose risk probabilities after half of the maximum pumps for each balloon, which still covers the more flatter part of the exponential growth trend. Risk progress from the 50, 60, 70, 80 and 90 percentages were selected along with the highest risk scenarios which are the last-second pumps (L2, two pumps before the last, and L1, the penultimate pump- one pump before the last pump, see Table 1); making 7 trials for each balloon. This way three of the risk popping percentages across balloons was also equated (10%, 33% and 50%). In original BART, 50% risk progress plays an important role as a strategy where pumping the balloon until half of its capacity leads to the highest earnings. However, the highest-earning strategy works in cumulative and continuous risk-taking scenarios; and in this experiment, the participant is given singular balloons that did not pop until a given position making this strategy less important than the original version.

Table 1. Risk Progress and Risk Probabilities of the Balloon Scenarios

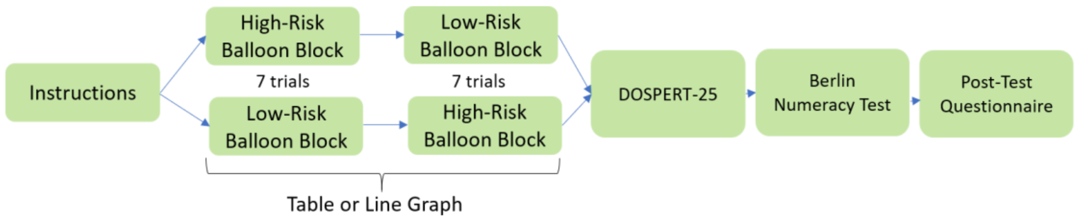
High-Risk Balloon (max 30 pumps)			Low-Risk Balloon (max 90 pumps)		
Risk Progress (%)	n^{th} Pump to Decide	Risk of Popping (%)	Risk Progress (%)	n^{th} Pump to Decide	Risk of Popping (%)
50	15	6.25%	50	45	2.17%
60	18	7.69%	60	54	2.70%
70	21	**10.00%**	70	63	3.57%
80	24	14.29%	80	72	5.26%
90	27	25.00%	90	81	**10.00%**
L2	28	**33.33%**	L2	88	**33.33%**
L1	29	**50.00%**	L1	89	**50.00%**

Note: The risk probability scenarios chosen for the experiment for the high-risk balloon and the low-risk balloon are shown in the table below. The high-risk balloon can be pumped up at most 30 times and the low-risk balloon can be pumped at most 90 times. The bold percentages show the risk progress trials where the risk of popping (risk probability) is the same for both balloons.

2.3 Design and procedure

The experiment is a mixed-design study with three variables. Information Visualizations Format is the between-subjects variable: The information was presented as a table to one group and as a line graph to the other group. They included the same content: What is the probability of the balloon popping (%) at each pump. Balloon Type and Risk Probability are within-subjects variables. All participants were presented both low and high-risk balloons; all the risk probability scenarios in a blocked manner. The order of low and high-risk balloons was counterbalanced across participants and the scenarios appeared in a continuously increasing manner (see Figure 1).

In the online format programmed in Qualtrics, each trial consisted of four to five pages (see Figure 2 to see one of the trial pages). The first page showed a colorless balloon, the number of times the balloon was pumped and the amount of points accumulated for that balloon. It also emphasized the balloon being a new balloon. On the next pages, the information visualization (table or line graph)



		Trial Order						
		1	2	3	4	5	6	7
High-Risk Balloon Max 30-pumps	Risk Progress (%)	50	60	70	80	90	L2	L1
	n^{th} Pump to Decide	15	18	21	24	27	28	29
	Risk of Popping (%)	6.25%	7.69%	**10.00%**	14.29%	25.00%	**33.33%**	**50.00%**
Low-Risk Balloon Max 30-pumps	Risk Progress (%)	50	60	70	80	90	L2	L1
	n^{th} Pump to Decide	45	54	63	72	81	88	89
	Risk of Popping (%)	2.17%	2.70%	3.57%	5.26%	**10.00%**	**33.33%**	**50.00%**

Figure 1. The experiment procedure and the trials in the experimental conditions

and the question was given. The current risk probability for the scenario was highlighted in red bold in both visualization formats. The questions were as followed, in Turkish, in the same order and on separate pages: (1) In your opinion, how risky is it to pump the balloon this time? (risk perception; Tr: Sizce bu sefer balonu şişirmek ne kadar risklidir?; response as percentage slider); (2) Would you pump this balloon one more time? (decision making; Tr: Siz bu balonu bir defa daha şişirir miydiniz?; response as binary yes/no choice); (3) How comfortable were you while making the previous decision? (affective factor; Tr: Bu kararınızı verirken içiniz ne kadar rahat şekilde verdiniz?; response as percentage slider). There was also the risk-taking intent question (4^{th} Question) and it was only showed when the participant responded with “Yes” to the decision-making question (2^{nd} Question): If you were given the chance, how many times would you like to pump the balloon after the X^{th} pump? (risk-taking intent; Tr: Size bu olanak tanınsa, X. şişirişten sonra bu balonu kaç kez daha şişirmek isterdiniz?; response as number input for the amount of pumps).

This balloon has been pumped 20 times
Accumulated Points: 20

(n^{th} pump) n. Şişiriş	(Probability of Popping at Pump) Şişirişte Patlama İhtimali (%)
1	3.33%
2	3.45%
3	3.57%
4	3.70%
5	3.85%
6	4.00%
7	4.17%
8	4.35%
9	4.55%
10	4.76%
11	5.00%
12	5.26%
13	5.56%
14	5.88%
15	6.25%
16	6.67%
17	7.14%
18	7.69%
19	8.33%
20	9.09%
21	10.00%
22	11.11%
23	12.50%
24	14.29%
25	16.67%
26	20.00%
27	25.00%
28	33.33%
29	50.00%
30	100.00%

Would you pump this balloon one more time?

Yes

No

Figure 2. Question 2 of the high-risk balloon table trial at 70% risk progress

After accepting the conditions of the consent form and answering demographic questions (age, gender, department/job and statistic course participation), participants received instructions. In the instructions, how the balloon scenario task works was explained. Then experimental trials began. The participants were presented either a table or a line graph. After the experimental trials, the DOSPERT-25 Risk Taking scale adapted to Turkish (Blais & Weber, 2006; Dinç & Tez, 2019; Appendix F) and then the Adaptive Berlin Numeracy Task for highly educated samples (Cokely et al. 2012, Appendix G) was to be completed. Finally, participants gave feedback about the visualizations and the task and saw a thank-you screen (Figure 1 summarizes the experiment's progress). The participants were instructed to start and finish the experiment in one sitting and once. There were two attention checks in the experimental blocks. One of them was a catch trial with a high-risk balloon scenario in which the balloon was pumped 29 times and pumping the balloon one more time will definitely pop. The other one was choosing “2” in the likert scale.

CHAPTER 3

RESULTS

The analysis of the data was done after excluding participants who did not complete the experiment and who did not respond to attention check questions correctly. The data was organized so that each row in the spreadsheet contained the trial information (format, balloon type, risk progress, popping probability), responses (decision, risk perception, affect, risk intent, DOSPERT score, Berlin Numeracy Test score) and participant information (subject number, balloon block order, age, gender, statistics course and participation recruit) for each participant's trials in separate rows. I did the analyzes on jamovi (The jamovi Project, 2021; R Core Team, 2020) and used the GAMLj package by Galluci (2019). I started building logistic regression models starting from the most general way to more specific models: Model A includes all the scenario conditions (risk progress), risk-taking tendency score from DOSPERT and participants' affective response reports. In the following models, I adjusted the sample by excluding participants who responded with "no" to the pumping question and also excluded the first two scenarios (50% and 60% risk progress).

First, I will give the results of the logistic regression models predicting the decisions, followed by the results of the linear regression models predicting risk perception ratings, and finally, I will explain participant strategies with descriptive statistics of coded responses. Two versions of the sample were used in the analyzes: The first sample contains all the participants who fit the inclusion criteria and the second sample is the filtered version of all the participants in which participants who did not choose to pump the balloon in the first two scenarios (Risk progress 50 and

60) of the balloons were excluded. We believe that these individuals showed rather high levels of risk aversion, refraining from pumping the balloon when the cumulative popping probability was relatively very low and nearly all of the participants decided to pump the balloon (see Table 4). The second sample will be referred to as "the less risk averse sample" (see Table 2 and Table 5).

Table 2. Frequencies of Participants in the Line Graph and Table Conditions

		All Sample		Less Risk Averse Sample	
		Line Graph	Table	Line Graph	Table
Order	High Risk - Low Risk	61	57	54	49
	Low Risk - High Risk	55	55	42	44
	Total	116	112	96	93

In Table 3, I summarized the descriptive statistics of the individual difference variables. Although participants excluded from the Less Risk Averse Sample behaved risk averse during the first two scenarios, DOSPERT-25 scores showing risk-taking tendency of the All Sample were slightly lower from the Less Risk Averse Sample. The two samples had very close individual difference features. For both samples, the youngest participant was 18, the oldest participant was 70 years old; most of the participants were between 18-30 years old (*Mdn* = 21).

Table 3. Descriptive Statistics of Individual Difference Variables

		All Sample (N = 228)		Less Risk Averse Sample (N = 189)	
		M	*SD*	*M*	*SD*
Age		24.60	8.72	24.60	9.06
DOSPERT		3.44	.72	3.48	.70
Berlin Numeracy		2.93	1.16	2.99	1.13
		N	%	*N*	%
Gender	Woman	141.00	61.80	120.00	63.50
	Man	81.00	35.50	65.00	34.40
	Other Gender	1.00	.40	1.00	.50
	Does not want to indicate	5.00	2.20	3.00	1.60
Statistics Course	Yes	84.00	36.80	68.00	36.00
	No	144.00	63.20	121.00	64.00

Note: DOSPERT-25 scores are between 0-7 (no risk-taking tendency to high risk-taking tendency) and Berlin Numeracy scores are between 0-4 (low risk literate/ numeracy to high-risk literate/ numeracy).

3.1 Decision-making

Participants were asked whether they would pump the balloon one more time for each scenario and responded as either “yes” or “no”. According to the instructions they were given, responding “yes” meant that they would take the risk of the balloon popping to gain one more point and “no” meant they did not take the risk of gaining one more point to preserve accumulated points. Table 4 and Table 5 shows the frequencies and percentages of “yes” responses in the all sample and the less risk averse sample, respectively (For the line graphs showing the “no” response percentages, see Figure 3 and Appendix H, respectively). As expected, the number of participants who responded “yes” to pumping the balloon one more time decrease as the risk progress proceeds (the probability of the balloon popping increases) and low-risk balloon scenarios have more “yes” responses than high-risk balloon scenarios in both samples. These patterns are more apparent after the first two scenarios as the 50% and 60% risk progress scenarios were responded with “yes” by more than 90%

of the participants in all the conditions which is why the second sample (the less risk averse sample, $N = 189$) was included in the analyses.

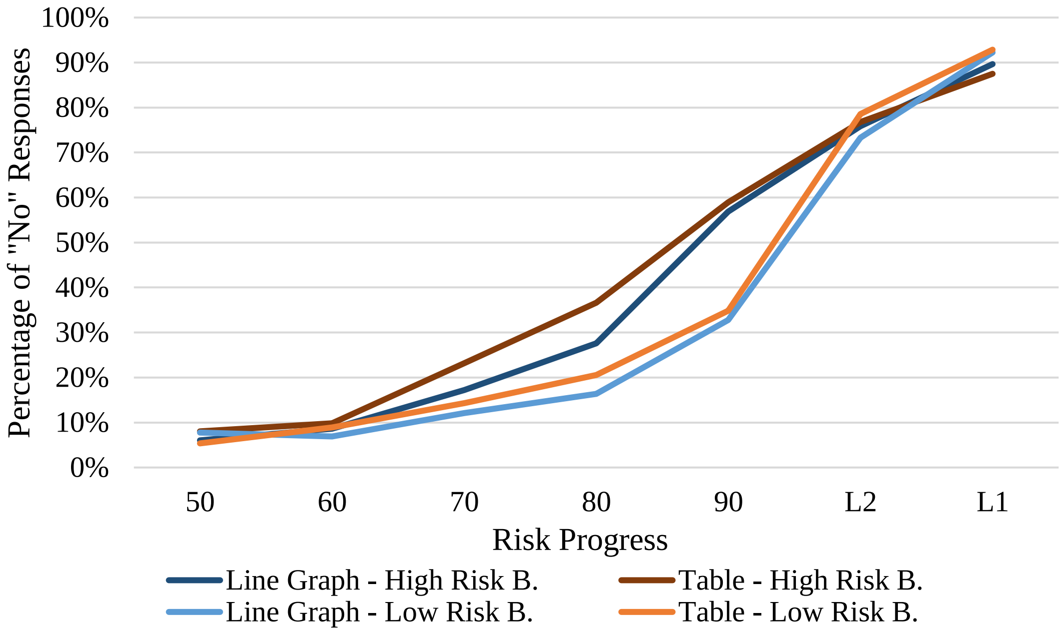


Figure 3. Line graph showing the percentages of "No" responses in the All Sample

Table 4. Frequencies and Percentages of "Yes" Answers to Question 2 in the All Sample

		Format			
		Line Graph		Table	
Balloon	Risk Progress	N	%	N	%
High Risk	50	109	93.97	103	91.96
	60	106	91.38	101	90.18
	70	96	82.76	86	76.79
	80	84	72.41	71	63.39
	90	50	43.10	46	41.07
	L2	28	24.14	26	23.21
	L1	12	10.34	14	12.50
Low Risk	50	107	92.24	106	94.64
	60	108	93.10	102	91.07
	70	102	87.93	96	85.71
	80	97	83.62	89	79.46
	90	78	67.24	73	65.18
	L2	31	26.72	24	21.43
	L1	9	7.76	8	7.14

Note: Question 2 is "Would you pump this balloon one more time?"

Table 5. Frequencies and Percentages of "Yes" Answers to Question 2 in the Less Risk Averse Sample

		Format			
		Line Graph		Table	
Balloon	Risk Progress	N	%	N	%
High Risk	70	86	89.58	79	84.95
	80	78	81.25	65	69.89
	90	48	50.00	43	46.24
	L2	26	27.08	24	25.81
	L1	9	9.38	14	15.05
Low Risk	70	92	95.83	85	91.40
	80	89	92.71	82	88.17
	90	72	75.00	68	73.12
	L2	28	29.17	24	25.81
	L1	7	7.29	8	8.60

Note: Question 2 is "Would you pump this balloon one more time?"

Separate binary logistic models were fitted to the data to test whether format, risk progress and balloon type predicted the decision to pump the balloon one more time; and all the models had similar results with different fits. Therefore I will be reporting three models in detail and the tables showing the results of all models can be found in the Table 7, Table 9 and Appendices I-N; and the goodness of fit statistics for the logistic regression models can be seen in Table 6. Akaike's Information Criterion (AIC) is a statistical measure that is "corrected for model complexity" for goodness-of-fit measure; and Schwarz's Bayesian Criterion (BIC) is also a goodness-of-fit measure similar to and more conservative than AIC (Field, 2018). Both measures are used to compare models and between the models, the ones with the smaller values are estimated to have a better model fit to the sample. Marginal and Conditional R2 indicate variance explained in the model: marginal R^2 is "variance explained by fixed factors" and conditional R^2 is "variance explained by both fixed and random factors (Nakagawa and Schielzeth, 2013).

Table 6. The Goodness of Fit Statistics for the Logistic Regression Models

	Model A	Model B	Model C	Model D	Model E	Model F
Model Description	Full Model	Full Model (Less Risk Averse Sample)	Continuous Risk Progress Model	Later Risk Scenarios Model	Risk Probability Model (All Sample)	Risk Probability Model (LRAS)
AIC	1864.61	1306.41	815.98	968.83	1075.46	892.23
BIC	2070.94	1422.844	861.28	1034.26	1122.45	937.54
R^2_{marg}	0.56	0.51	0.23	0.35	0.42	0.47
R^2_{cond}	0.88	0.87	0.8	0.85	0.83	0.82
Sample	All Sample	LRAS	LRAS	LRAS	All Sample	LRAS

The first model, Model A (Appendix I), is a three-predictor logistic model with three covariates and was fitted to the all sample ($N = 228$, Observations = 3192): The model predicted the odds of responding with "yes" by format (Table - Line), balloon type (low-risk balloon - high-risk balloon), risk progress (50, 60, 70, 80, 90, L2, L1) and all the interactions of these predictors with each other; affect response (Question 3), DOSPERT score and Berlin Numeracy Test score as covariates, two-way interactions of format with affect response and the DOSPERT score. Risk progress contrasts were repeated, conditions were compared with the subsequent condition. Based on the marginal R-square, $R^2_{marg} = .56$, the error of approximation of the data decreases 56% due to the fixed effects and based on the conditional R-square, $R^2_{cond} = .88$, it decreases 88% due to all effects. The package gave an error of convergence, the model might contain too many factors. Contrary to our expectations, format did not significantly predict decision-making, $\chi^2(1) = .80$, $p = .37$. As expected, balloon type, $\chi^2(1) = 30.18$, $p < .0001$, and risk progress, $\chi^2(6) = 495.56$, $p < .0001$, predicted balloon pumping decision. Interaction between balloon type and risk progress was found to be a significant predictor of decision-making, $\chi^2(6) = 51.10$, $p < .0001$. Among the covariates, Berlin Numeracy test scores did not significantly predict decisions, $\chi^2(1) = .05$, $p = .83$; while DOSPERT scores, $\chi^2(1) = 10.31$, $p = .001$, and affect responses, $\chi^2(1) = 129.16$, $p < .0001$, significantly predicted decisions. However, they did not interact with the format. Thus, in the following models, we did not include these covariates. For Model B (Appendix J), when we exclude the covariates and the model is fitted to the less risk averse sample (N = 189, Observations = 1890), the R-square fits remained in similar levels (R^2_{marg} = .51, R^2_{cond} = .87) and the fit criteria improved for both AIC (Model A: 1864.61; Model B: 1306.41) and BIC (Model A: 2070.94; Model B: 1422.84).

In the third set of analyses, I specifically wanted to focus on the group of participants who are not particularly risk aversive to test the effects of format along with more directly with the impact of balloon type and risk progression. Model C (Appendix K) is a three-predictor logistic model. Model C was fitted to the less risk averse sample (N = 189, Observations = 1134) and predicted the odds of responding with "yes" by format (Table - Line), balloon type (low-risk balloon - high-risk balloon), risk progress (70, 80, 90 as a continuous predictor) and the three-way interactions of these predictors. 24% of the data fits the model due to fixed effects, R^2_{marg} = .24, and 80% of the data fits the model when grouping is also taken into account (all effects), R^2_{cond} = .80. Similar to the previous models, contrary to our expectations, the format did not significantly predict participants' balloon pumping decisions, $\chi^2(1) = 2.14$, $p = .14$. As expected, balloon type, $\chi^2(1) = 51.37$, $p < .0001$, and risk progress, $\chi^2(1) = 96.02$, p < .0001, predicted decisions. However, the interaction between balloon type and risk progress was not found to be a significant predictor of decision-making in this model, $\chi^2(1) = 2.03$, $p = .15$. Model C predicts there is 99% probability of making a pumping decision at low-risk balloons, 95% CI [.97, .99], and 91% probability at high-risk balloons, 95% CI [.83, .95]. It also predicts the odds of responding "yes" is .82 as the risk progress proceeds, 95% CI [-.24, -.16]: As the scenarios progress participants are less likely to respond "yes" when asked whether they would pump the balloon one more time. Despite having better model fit criteria than the previous models, AIC = 815.98 and BIC = 861.28, the fixed effects explain 24% of the model fit to the data. This might be due to the frequencies of "yes" responses being similar and high in these three scenarios included in the analysis. Therefore, for Model D (Table 7), I selected the scenarios with 80%, 90% and L2 (second to the last pump) risk progress to increase the variability of responses. As risk increased, we expected participants to refrain from further pumping the balloon more often.

Table 7. Logistic Regression Results of Model D

Predictor		Estimate	*SE*	*p*	OR	95% Confidence Interval Lower	Upper
Intercept		.88	.27	< .0001	2.41	.35	1.41
Format	Table - Line Graph	-.58	.53	.28	.56	-1.62	.46
Balloon	LR - HR	1.67	.24	< .0001	5.30	1.19	2.15
Risk Progress	80 - 90	2.66	.33	< .0001	14.31	2.02	3.31
	90 - L2	3.44	.34	< .0001	31.33	2.78	4.11
Format x Balloon	Table - Line Graph x LR - HR	.09	.46	.85	1.09	-.81	.98
Format x Risk Progress	Table - Line Graph x 80 - 90	-.88	.60	.14	.41	-2.05	.29
	Table - Line Graph x 90 - L2	-.17	.56	.76	.84	-1.27	.93
Balloon x Risk Progress	LR - HR x 80 - 90	-.30	.56	.59	.74	-1.39	.79
	LR - HR x 90 - L2	2.47	.52	< .0001	11.83	1.46	3.48
Format x Balloon x Risk Progress	Table - Line Graph x LR - HR x 80 - 90	.48	1.12	.67	1.61	-1.71	2.67
	Table - Line Graph x LR - HR x 90 - L2	.26	1.00	.80	1.29	-1.70	2.22

Model D is a three-predictor logistic model fitted to the less risk averse sample (N = 189, Observations = 1134): The model predicts the odds of responding with "yes" by format (Table - Line), balloon type (low-risk balloon - high-risk balloon), risk progress (80, 90, L2) and all the interactions between these predictors. Risk progress contrasts consisted of the comparison of the condition with the subsequent condition. Model D's model fit criteria were slightly worse than Model C's, AIC = 968.83 and BIC = 1034.26. However, both fixed effects, $R^2_{marg} = .35$, and all effects $R^2_{cond} = .85$, explained the model fit to the data better than Model C. The fixed effects predictions were similar with Model A and Model B: Format did not significantly predict decisions; there was 76.3% probability to respond "yes" in the line graph condition, 95% CI [.60, .87], and 64.3% in the table condition, 95% CI [.46, .79], $\chi^2(1) = 1.192$, $p = .28$. Balloon type, $\chi^2(1) = 46.64$, $p < .0001$, and risk progress, $\chi^2(2) = 158.90$, $p < .0001$, are significant predictors of decisions. Model D predicted that there is an 85% probability of responding "yes" in the low-risk balloon scenarios, 95% CI [.75, .91], and 51% in the high-risk balloon scenarios, 95% CI [.38, .65]. According to the model predictions for risk progress, at 80% the probability of responding "yes" is 98%, 95% CI [.95, .99]; at 90% it decreases to 76%, 95% CI [.63, .85]; and at L2, second to last scenario, it becomes 9%, 95% CI [.05, .16]. The interaction between balloon type and risk progress significantly predicts risk decisions, $\chi^2(2) = 25.41$, $p < .0001$ (probabilities and confidence intervals can be seen in Table 5 and the predicted probabilities in Figure 4).

Table 8. Predicted Probability to Respond "Yes" at Balloon Type and Risk Progress Interaction in Model D

				95% Confidence Interval	
Balloon Type	Risk Progress	Probability	SE	Lower	Upper
Low-Risk	80	99.29%	.00	.98	1.00
	90	91.96%	.03	.84	.96
	L2	9.59%	.03	.05	.18
High-Risk	80	93.44%	.02	.87	.97
	90	46.12%	.08	.31	.62
	L2	8.59%	.03	.04	.17

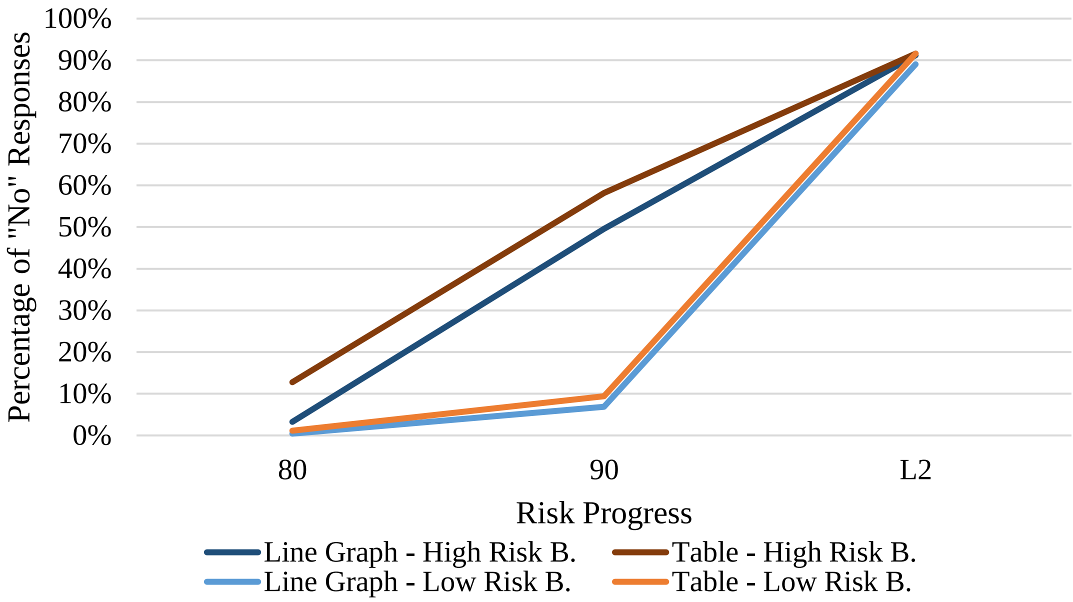


Figure 4. Line graph of Model D's predicted probabilities to respond "No"

All previous models had risk progress as a predictor, although it is also possible to test risky decisions with popping probabilities. Therefore, I also ran two logistic regressions similar to previous models with popping probabilities instead of risk progress as a predictor with the two samples. Focusing on popping probabilities instead of risk progression allowed us to test the impact of quantitative information on decision-making. Each balloon had three scenarios with the same popping probability as the other balloon. For the low-risk balloon the scenarios with 90%, L2, L1; for the high-risk balloon 70%, L2 and L1 risk progress conditions had the same popping probabilities: 10%, 33.33% and 50%, respectively (see Figure 1). Model E (Appendix L) and Model F (Table 9) are three-predictor logistic regression models fitted to the all sample (N = 228, Observations = 1368) and to the less risk averse sample (N = 189, Observations = 1134), respectively. The models predict the odds of responding with "yes" by format (Table - Line), balloon type (low-risk balloon - high-risk balloon), popping probability (10%, 33.33%, 50% as a continuous variable) and the three-way interactions of these predictors. The model fit criteria of Model F (less risk averse sample; AIC = 892.23 and BIC = 937.54) were better than Model E's (all sample; AIC = 1075.46 and BIC = 1122.45). The model fit the data slightly better in Model F ($R^2_{marg} = .47$, $R^2_{cond} = .82$) than Model E ($R^2_{marg} = .42$, $R^2_{cond} = .83$). Therefore, I will explain the results of Model F (see Table 9) and the results of logistic regression for Model E can be found in Appendix L.

Table 9. Logistic Regression Results of Model F

Predictor		Estimate	*SE*	*p*	OR	95% Confidence Interval	
						Lower	Upper
Intercept		-1.14	.23	< .0001	.32	-1.59	-.70
Format	Table - Line Graph	-29.09	.44	1.00	1.00	-.85	.85
Balloon	HR - LR	.56	.22	.01	1.76	.14	.99
Popping Probability	Popping Probability	-.18	.01	< .0001	.84	-.20	-.15
Format x Balloon	Table - Line Graph x HR - LR	.21	.43	.62	1.24	-.63	1.06
Format x Popping Probability	Table - Line Graph x Popping Probability	.02	.02	.21	1.02	-.01	.06
Balloon x Popping Probability	HR - LR x Popping Probability	-.03	.01	.07	.98	-.05	.00
Format x Balloon x Popping Probability	Table - Line Graph x HR - LR x Popping Probability	.04	.03	.20	1.04	-.02	.09

In Model F, format did not significantly predict decisions, $\chi^2(1) = 0.0000045$, $p = .99$. Balloon type, $\chi^2(1) = 6.72$, $p = .01$, and popping probability, $\chi^2(1) = 173.229$, $p < .0001$, significantly predicted risk decisions as expected. None of the two-way and the three-way interactions significantly predicted the pumping decisions. Model F predicted the probability to respond "yes" as 19% in the low-risk balloon condition, 95% CI [.13, .29], and 24% in the high-risk condition, 95% CI [.21, .41]. This pattern was unexpected, I expected that participants would report higher proportions of "yes" responses for the low-risk balloon condition would predict more "yes" answers than the high-risk balloon condition. Model F predicts the odds of responding "yes" is .84 as the popping probability increases, 95% CI [-.20, -.15]: As the balloon's popping probability increases (exponentially), participants are less likely to respond "yes" when asked whether they would pump the balloon one more time.

3.2 Risk perception

Participants were asked to rate the percentage of how risky they found pumping the balloon one more time would be. According to a point bi-serial correlation (conducted in IBM SPSS v.22), here was a negative moderate correlation between risk perception and decision making, $r_{pb} = -.63$, $p < .0001$ ($N = 3192$). This correlation result was as we expected: When risk perception was rated higher, the participants were less likely to respond with "yes" at the risk-taking question of pumping the balloon one more time (see Figure 5).

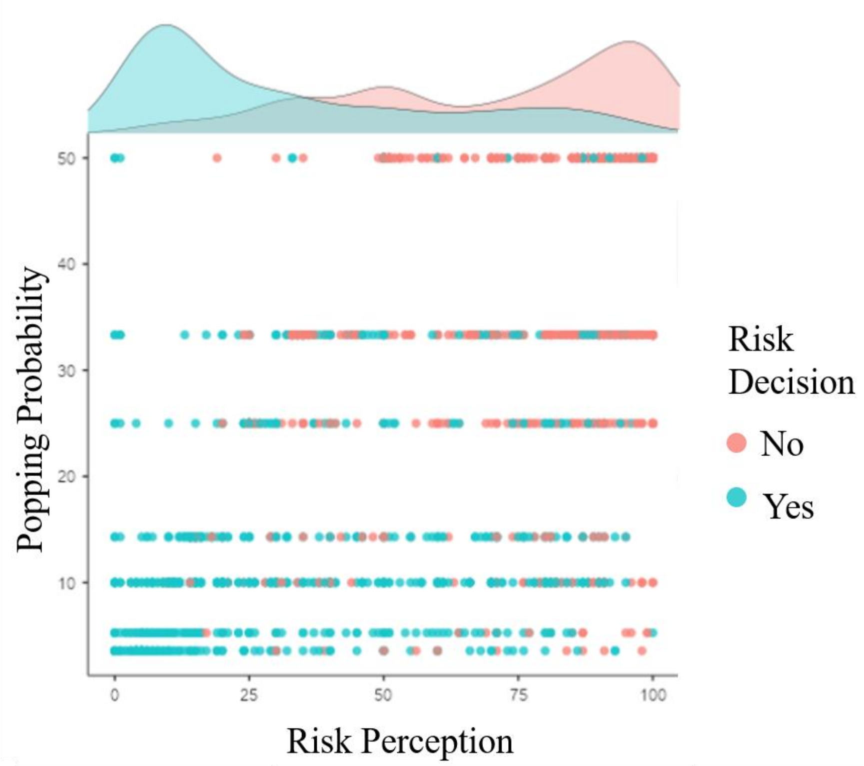


Figure 5. Scatterplot and histogram for risk decisions

I conducted two linear mixed regression models, with both the all sample and the less risk averse sample, to test whether format, balloon type and risk progress of the scenarios predicted participants' risk perception. Model G (Appendix M) had three predictors (format, balloon type and risk progress) and one covariate (DOSPERT score) and was fitted to the all sample (N = 228, Observations = 3192). Model H (Appendix N) consisted of three predictors (format, balloon type and risk progress) and was fitted to the less risk averse sample (N = 189, Observations = 1890). While Model G included all seven risk progress conditions, Model H excluded the first two risk progress conditions (50% and 60%) as participants who responded with "no" to either one of these risk progresses were excluded in the less risk averse sample. When we observe the goodness of fit statistics, Model H has better results than Model G: The model fit criteria of Model H (less risk averse sample; AIC = 1636.71 and BIC = 16421.87) were better than Model G's (all sample; AIC= 28131.77 and BIC = 28231.10). The model fit the data are similar in Model H (R^2_{marg} = .37, R^2_{cond} = .78) and Model G (R^2_{marg} = .43, R^2_{cond} = .74). Therefore, I will be reporting the mixed linear model results of Model H in detail.

In Model H, format does not significantly predict risk perception, F (1, 187) = .87, p = .35. As expected, balloon type, F (1, 1683) = 87.01, p < .0001, and risk progress, F (4, 1683) = 770.83, p < .0001, significantly predict risk perception. The regression coefficient for balloon type (B= 6.74, 95% CI [5.33, 8.16]) indicates that risk perception at the low-risk balloon condition was smaller than the high-risk balloon condition.

3.3 Strategies

After the experimental trials and the individual difference tests, participants were given a post-test survey with feedback questions. In one of the questions, participants were asked whether they used any strategies in the balloon scenarios task. I checked for patterns in the data and determined that there were four main strategies that participants used. I coded strategy feedback responses for the 228 participants I included in the analyses (see Table 10). Coding was made by looking and matching keywords. If the participant reported "not pumping the balloon after X%"; "I put myself a limit" it was coded as the limit strategy; reporting phrases such as "I used my intuition" were coded as the intuition strategy; statements such as "I looked at the elbow", "… until it increased too fast" were coded as the graphical cues strategy; and when the participants mentioned of expected values it was coded as the expected values strategy.

Table 10. Frequencies and Percentages of Participant Strategies During the Balloon Scenarios Task

Strategy	Total 168		Line Graph 77		Table 91	
	N	%	*N*	%	*N*	%
No Strategy	24	14.29%	9	11.69%	15	16.48%
Limit	56	33.33%	27	35.06%	29	31.87%
Intuition	14	8.33%	6	7.79%	8	8.79%
Graphical Cues	12	7.14%	12	15.58%	0	.00%
Expected Value	5	2.98%	2	2.60%	3	3.30%
Not Strategy / Other	57	33.93%	21	27.27%	36	39.56%

In the post-test survey question about strategies nearly half of the participants stated that they completed the task by relying on a strategy. While some stated that they behaved according to their intuition, some participants stated they put limits to the maximum pump or popping probability they would pump the balloon, used expected value calculations or relied on graphical cues (e.g. “the rising part”). The most frequently reported strategy was the limit strategy, with approximately 30-35% participants in both format groups. None of the participants in the table group stated using graphical cues; 15% of participants in the line group stated using graphical cues.

CHAPTER 4

GENERAL DISCUSSION

This study investigated the effects of information visualization format of exponentially increasing risk on decision-making. I present exponential risk probabilities either via line graphs and tables. Participants made risk-taking decisions and reported their perception of the risk in a series of balloon pumping scenarios with two balloons with different exponential risk popping while being presented with either a line graph or table showing the probabilities of the balloon popping at each pump. Contrary to my expectations, the results of all the models converged on the fact that participants' decisions and risk perceptions did not differ based on the format of exponential risk probability. This suggests that participants extracted popping probabilities in a similar manner from both line graphs and tables and responded in a more data-driven manner. We also found that participants were sensitive to the risk conveyed by balloon type and risk progression.

How people made decisions and how they perceived risk in balloon type and risk progression conditions were as expected: High-risk balloons were perceived as being riskier and were responded with fewer pumping decisions than low-risk balloons; as the risk progress advanced participants rated the risk as higher and were inclined to decide not to pump the balloon. According to information visualization literature, we know that upon viewing both tables and line graphs people can represent trends and changes of trends accurately (Zacks & Tversky, 1999; Visschers et al., 2009; Lipkus & Hollands, 1999; Meyer, Shinar & Leiser, 1997; Shamo, Meyer & Gopher,1996; Hollands & Spence,1992; Meyer et al., 1997). I wanted to investigate the interaction between format and risk progress as I expected participants might perceive risks differently and make different pumping decisions at different levels of risk progress when viewing information presented in line graphs and tables. However, none of the models showed a significant interaction between format and risk progress. Therefore, risk progress affected decision-making in the predicted direction however its effect was similar in both formats.

Risk progress conditions did not have the same risk probabilities of the balloon popping. Risk progress and risk probabilities are similar however they express different aspects of the risk. Risk progress conditions differ from each other more by visual differences as they are different percentage advancements at the x-axis for line graphs and rows for the tables. The risk probabilities in this study were given as percentages in both line graphs and tables. According to a study by Schapira et al. (2001), participants attribute "mathematical quality" to percentages (also see review by Visschers et al., 2009). Therefore, risk probabilities refer to the quantitative aspect of the risk in this study. In three risk progress scenarios, each balloon-type had equivalent risk probabilities of the balloon popping and I used them for building two similar models (Model E and Model F) with risk probabilities as a predictor instead of risk progress. Participants responded with fewer "yes" (pump) responses at the high-risk balloon than the low-risk balloon when risk progress was the predictor; while participants gave more "yes" answers at the high-risk balloon scenarios when risk probability was the predictor. The main reason we observe a change in the direction of the prediction might be due to the risk probabilities 10%, 33.33% and 50% correspond to 70%, L1 and L2 risk progress in the high-risk balloon scenarios; and 90%, L1 and L2 risk progress in the low-risk balloon scenarios. These results suggest that while the participants' decisions did not vary within the visualization format, their responses might have been affected by the order of the scenario or relative location of the risk progress in a similar in both line graphs and tables. In other words, these findings indicate that participants do not solely respond in a data-driven manner, as the risk probabilities are the same in both balloons. Therefore, participants might have depended on both quantitative and graphical information, judging the whole exponential trend in addition to the risk probability at the specific pump while making risk decisions.

We should also consider that participants' decisions could have been affected by the accumulated points. In both balloons the amount of points they would gain in each pump was the same (1 point) however, the amount of accumulated points the balloon came with each scenario was different: participants could lose more points if the balloon popped in the low-risk balloon scenarios because the balloons' pumping capacities were higher (90 pumps); the high-risk balloons had higher risks of popping but also less money to lose as their capacities were lower (30 pumps).

Model F was one of the logistic regression models that had better model fit values than the other models. The other model, Model D, was also fit to the less risk-averse sample. Model D had risk progress as one of the predictors which had three conditions: 80, 90 and L2. These conditions were put in the model with repeated contrasts, they would be compared to the subsequent condition. Risk Progress 80, 90 and L2 were conditions that were closer to the end of the risk progress: In line graphs, they were near the elbow, where the risk probabilities would start to rise very quickly; in tables, they were at the end of the rows, very near to the end, in both balloons for both visualization formats. As it can also be seen at the "yes" decision frequencies in Table 4 and Table 5, risk progresses 50% and 60% had very similar frequencies and nearly all participants responded with "yes"; 70% had slightly fewer "yes" responses but still very similar to the first two conditions; L1 (one pump before the last pump) had nearly all “no” responses. When these observations are made together with Model D, I think that risk progress 80%, 90% and L1 were the most distinctive conditions in this experiment for decision-making. While format still did not predict the decisions, balloon-type and risk probabilities significantly predicted decisions. Low-risk balloons had more pump decisions than the high-risk balloons; especially in the 90% risk progress condition which was one of the reasons why there was an interaction observed between balloon type and risk progress. Combined with the results of Model F, this finding supports that, participants are not solely relying on risk probabilities, and they might be affected by the visual order/ranking cues in both formats. The strategy statements of participants also show that some participants determined a cut-off probability to decide whether or not to pump the balloon; however, it is not known how the participants established the cut-off values.

Exponential growth bias (Cordes et al., 2019, Stango & Zinman, 2009, Wagenaar & Sagaria, 1975) and trend forecast/trend estimation studies (Lammers et al., 2020, Ebersbach & Wilkening, 2007, Mullet & Cheminat, 1995, Wagenaar & Sagaria, 1975) showed that people tend to misestimate exponential growth trends as linear or underestimate the increase rate. In most of these studies, there were correct answers and therefore errors could be calculated. This thesis study investigated how people made decisions and the scenarios did not have correct answers while the participants were not given feedback on whether or not the balloon popped. However, decision patterns and risk perception ratings in balloon type and risk progress conditions can give us an idea on how participants interpreted and read exponential growth trends in line graphs and tables. Upon viewing both tables and line graphs, participants behaved in a predicted direction, which was explained in detail in the previous paragraphs and can be seen in Figure 3 and Appendix H.

Therefore, when the whole trajectory of the exponential trends is presented, participants did not seem to underestimate the risk especially in the last scenarios. Information visualization literature has many studies comparing line graphs and tables (Meyer et al., 1997; Shamo et al., 1996). While some studies found evidence for line graphs conveying information and leading to better performance than other information visualization formats including tables; some studies reported line graphs and tables leading to similar task performances. According to a summary of findings by Jarvenpaa and Dickson (1988), line graphs were better at portraying time series data; and in some studies, graphs lead to better performance at showing trends than tables while in some there was no difference in performance. This was also the case for value reading and showing trends over time. In summary, there is not a compromise yet; perhaps this might be due to differences in tasks and information depicted in these studies are quantitatively and qualitatively different than each other. In this study, the results show consistently that participants' decisions and risk perception were not affected differently by line graphs and tables. We can infer that line graphs and tables conveyed exponential growth similarly in the balloon scenarios task. Both good performance at reading exponential growth and the lack of performance difference between tables and line graphs might be related to increased familiarity with exponential growth during the ongoing COVID19 pandemic: The sample of this study can be described as familiar with social media due to one part of the sample being recruited from the university pool and the other part of the sample was recruited from social media. Thus, it is highly probable that they saw the line graphs and tables showing the covid cases and also the infographics showing the chain of the viral spread (one person spreading the virus to 2 people).

The balloon scenario task was designed with the goal to investigate risk perception and decision making when exponentially increasing risk probabilities are presented in different visual formats. The context of the task was chosen to be BART as it is easy to explain and game-like. Due to the COVID19 Pandemic, the experiment was designed as an online survey and the behavioral characteristics of the task were not present with the addition of risk information presentation. Unlike BART, the risk decisions were not made on cumulative risk, there was no feedback to encourage learning (although the participants' decisions might have affected by the order of the scenarios) and instead of continuous decisions, the decisions were to be made on snapshot scenarios independent to each other. Since there were no consequences of the decisions (the balloons did not get actually pumped and participants did not know whether their decision would have popped the balloon), the task actually did not have "correct" responses and had higher tolerance towards risky behavior. Also, unlike BART since participants could look at the risk data as much as they wanted and were asked scenarios one by one, they might have been more inclined to make more analytical decisions. We could maybe consider this procedure as being closer to and mimicking some daily risk-taking behavior such as deciding when to get out of the door to catch the bus. These are all strengths and differences of the task developed for this thesis study, which might also be considered as limitations if the goal of the research is different. For instance, the experiment not being a behavioral design and relying on participant's self-reports while demanding to imagine scenarios that were given to them makes generalizing the findings to behavior difficult. Although, the findings are still beneficial at investigating the decision-making process at exponential risk probabilities. Another limitation that might have possibly prevented the observation of the effect of format is the lack of time limit at the task. Visschers et al. (2009) suggest that presentation format might not have an impact when participants have sufficient “time, motivation, and cognitive capacity” during the task. However, the lack of difference in decision-making and risk perception between line graphs and tables, when they are presented without a time limit can be generalized to daily life more easily as we tend to process and use visual information data without very short time limits. Lastly, I would like to note that even though I recruited part of the participants with snowballing on social media, most of the participants were highly educated and had high-risk literacy; thus, it is unclear whether participants with lower numeracy and education would perform in similar patterns. According to Visschers et al. (2009) and Schapira et al., 2001, less-educated participants tend to be more indecisive about the probability information and highly-educated participants tend to be more systematic while processing the risk information. This might lead less-educated people to rely on heuristics and be more biased in their decisions, therefore leading to different results to the question of this study.

Further research could continue to investigate the effect of other formats on decision-making for exponential trends, especially infographics. I think that comparing the effects of a visual format depicting the exponential trend and a visual infographic depicting how the exponential trend gets developed might be beneficial to understand which method leads to a better understanding of exponential growth. For instance, intervention studies on attitude towards climate change show that explaining the mechanics of climate change can improve understanding of climate change and can change participants' attitudes and beliefs towards the issue (Ranney & Clark, 2016; Clark et al., 2013). Other future research that could clarify some findings of this thesis study can be done by manipulating the point system by equating the points that can be potentially earned in both balloon types; recruiting participants of lower-education levels to generalize the findings to a larger population and to find whether there is a difference at decisions with education levels. To translate the findings of this study to behavior, a behavioral study using both BART and information visualizations could be another option for future research; as well as a one-trial only between-subjects design with this thesis study's procedure could help to control for the order effects the balloon scenario procedure had by also decreasing the number of conditions in the risk progress predictor (because many of the scenarios had similar response proportions) to make the design more simple and easier to interpret.

In conclusion, when presented with exponential risk probabilities represented with a line graph or table, highly-educated participants' risk perception and decision making are similar: As risk progression advances on the exponential growth trend and the riskiness of the balloon is higher, risk perception increases and pumping decisions decrease. I discussed the results of six logistic regression models for decision making and two linear regression models for risk perception. The results of these models were very similar while their model fit varied. I also coded strategies participants stated they used during the balloon scenario task. Some participants determining cut-off limits for the balloon scenarios suggest that participants might have made their decisions by processing both the risk at the scenario and the risk at the whole exponential trend. I argued that these results might mean that participants relied on both graphical cues and quantitative information. Perhaps lack of a time limit made participants respond to the scenarios more analytically. However, some of the findings also imply that participants used strategies relying on both quantitative risk probabilities (data-driven) and the represented location/order of that risk probability. Therefore, I suggest that line graphs and tables in this study conveyed exponential growth trends in a similar manner for participants to make similar decisions and have similar risk perceptions. In my attempt of understanding and investigating how people make decisions when encountering exponential risk information, I believe I was able to set up an online study investigating the effect of visual format on decision making with risks increasing exponentially.

APPENDIX A

ETHICS COMMITTEE APPROVAL

Evrak Tarih ve Sayısı: 12/12/2020-262

T.C.
BOĞAZİÇİ ÜNİVERSİTESİ
SOSYAL VE BEŞERİ BİLİMLER YÜKSEK LİSANS VE DOKTORA TEZLERİ ETİK İNCELEME KOMİSYONU
TOPLANTI TUTANAĞI

Toplantı Sayısı	:	10
Toplantı Tarihi	:	10/12/2020
Toplantı Saati	:	13:00
Toplantı Yeri	:	Zoom Sanal Toplantı
Bulunanlar	:	Prof. Ebru Kaya, Prof. Dr. Fatma Nevra Seggie, Dr. Öğr. Üyesi Yasemin Sohtorik İlkmen
Bulunmayanlar	:	Prof. Dr. Özlem Hesapçı Karaca

Burcu Avcı
Psikoloji

Sayın Araştırmacı,
"Impact of Risk Visualization Formats on Decision Making" başlıklı projeniz ile ilgili olarak yaptığınız SBB-EAK 2020/51 sayılı başvuru komisyonumuz tarafından 10 Aralık 2020 tarihli toplantıda incelenmiş ve uygun bulunmuştur.

Bu karar tüm üyelerin toplantıya çevrimiçi olarak katılımı ve oybirliği ile alınmıştır. COVID-19 önlemleri kapsamında kurul üyelerinden ıslak imza alınamadığı için bu onam mektubu üye ve raportör olarak Yasemin Sohtorik İlkmen tarafından bütün üyeler adına e-imzalanmıştır.

Saygılarımızla, bilgilerinizi rica ederiz

Dr. Öğr. Üyesi Yasemin
SOHTORİK İLKMEN
ÜYE

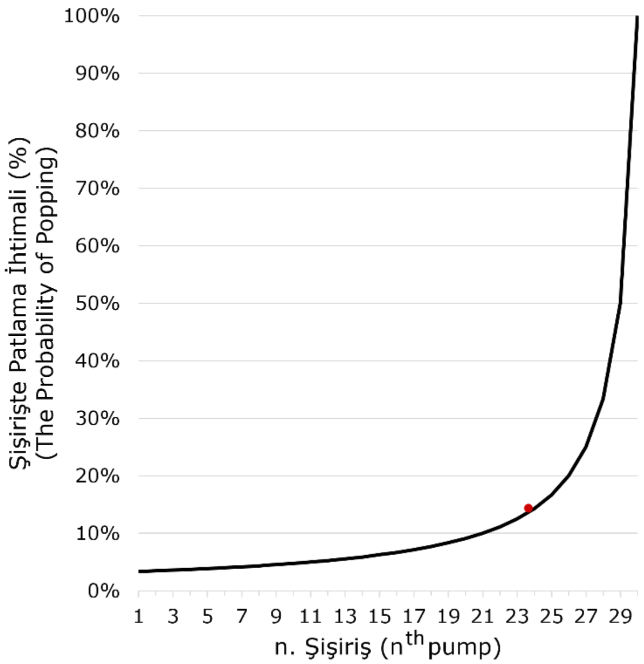
e-imzalıdır
Dr. Öğr. ÜyesiYasemin Sohtorik
İlkmen
Öğretim Üyesi
Raportör

SOBETİK 10 10/12/2020

APPENDIX B

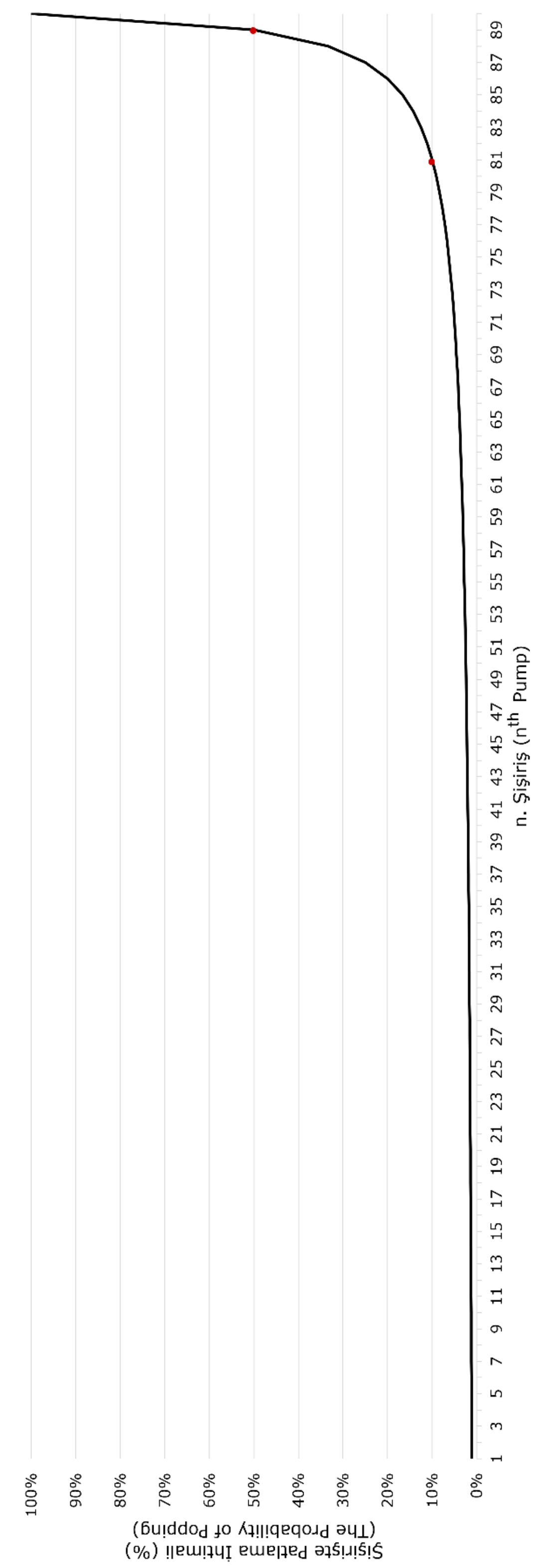
STIMULUS: LINE GRAPH OF THE HIGH-RISK BALLOON

Line Graph presented at the 90% risk progress scenario at the High-Risk Balloon condition. The table shows the probability of popping (y-axis) at each pump (x-axis) of the High-Risk Balloon.



APPENDIX C

STIMULUS: LINE GRAPH OF THE LOW-RISK BALLOON



APPENDIX D

STIMULUS: TABLE OF THE HIGH-RISK BALLOON

Table presented at the 90% risk progress scenario at the High-Risk Balloon condition. The table shows the probability of popping at each pump of the High-Risk Balloon.

(n^{th} Pump)	(The Probability of Popping)
n. Şişiriş	**Şişirişte Patlama İhtimali (%)**
1	3.33%
2	3.45%
3	3.57%
4	3.70%
5	3.85%
6	4.00%
7	4.17%
8	4.35%
9	4.55%
10	4.76%
11	5.00%
12	5.26%
13	5.56%
14	5.88%
15	6.25%
16	6.67%
17	7.14%
18	7.69%
19	8.33%
20	9.09%
21	10.00%
22	11.11%
23	12.50%
24	14.29%
25	16.67%
26	20.00%
27	25.00%
28	33.33%
29	50.00%

APPENDIX E

STIMULUS: TABLE OF THE LOW-RISK BALLOON

(n^{th} Pump) (The Probability of Popping)

n. Şişiriş	Şişirişte Patlama İhtimali (%)	n. Şişiriş	Şişirişte Patlama İhtimali (%)	n. Şişiriş	Şişirişte Patlama İhtimali (%)
1	1.11%	31	1.67%	61	3.33%
2	1.12%	32	1.69%	62	3.45%
3	1.14%	33	1.72%	63	3.57%
4	1.15%	34	1.75%	64	3.70%
5	1.16%	35	1.79%	65	3.85%
6	1.18%	36	1.82%	66	4.00%
7	1.19%	37	1.85%	67	4.17%
8	1.20%	38	1.89%	68	4.35%
9	1.22%	39	1.92%	69	4.55%
10	1.23%	40	1.96%	70	4.76%
11	1.25%	41	2.00%	71	5.00%
12	1.27%	42	2.04%	72	5.26%
13	1.28%	43	2.08%	73	5.56%
14	1.30%	44	2.13%	74	5.88%
15	1.32%	45	2.17%	75	6.25%
16	1.33%	46	2.22%	76	6.67%
17	1.35%	47	2.27%	77	7.14%
18	1.37%	48	2.33%	78	7.69%
19	1.39%	49	2.38%	79	8.33%
20	1.41%	50	2.44%	80	9.09%
21	1.43%	51	2.50%	81	10.00%
22	1.45%	52	2.56%	82	11.11%
23	1.47%	53	2.63%	83	12.50%
24	1.49%	54	2.70%	84	14.29%
25	1.52%	55	2.78%	85	16.67%
26	1.54%	56	2.86%	86	20.00%
27	1.56%	57	2.94%	87	25.00%
28	1.59%	58	3.03%	88	33.33%
29	1.61%	59	3.13%	89	50.00%
30	1.64%	60	3.23%	90	100.00%

APPENDIX F

DOSPERT-25

For each of the following statements, please indicate the likelihood that you would engage in the described activity or behavior if you were to find yourself in that situation.

1. Admitting that your tastes are different from those of a friend.
2. Going camping in the wilderness.
3. Betting a day's income at the horse races.
4. Investing 10% of your annual income in a moderate growth diversified fund.
5. Taking some questionable deductions on your income tax return.
6. Disagreeing with an authority figure on a major issue.
7. Betting a day's income at a high-stake poker game.
8. Having an affair with a married man/woman.
9. Going down a ski run that is beyond your ability.
10. Investing 5% of your annual income in a very speculative stock.
11. Going whitewater rafting at high water in the spring.
12. Betting a day's income on the outcome of a sporting event.
13. Engaging in unprotected sex.
14. Driving a car without wearing a seat belt.
15. Taking a skydiving class.
16. Riding a motorcycle without a helmet.
17. Choosing a career that you truly enjoy over a more secure one.
18. Speaking your mind about an unpopular issue in a meeting at work.
19. Sunbathing without sunscreen.

20. Bungee jumping off a tall bridge.

21. Piloting a small plane.

22. Walking home alone at night in an unsafe area of town.

23. Moving to a city far away from your extended family.

24. Starting a new career in your mid-thirties.

25. Leaving your young children alone at home while running an errand.

APPENDIX G

ADAPTIVE BERLIN NUMERACY TEST FOR EDUCATED SAMPLES

Please answer the questions that follow. Do not use a calculator but feel free to use the scratch paper for notes.

1. Out of 1,000 people in a small town 500 are members of a choir. Out of these 500 members in the choir 100 are men. Out of the 500 inhabitants that are not in the choir 300 are men. What is the probability that a randomly drawn man is a member of the choir? Please indicate the probability in percent. ______ %

2a. Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)? ______ out of 50 throws.

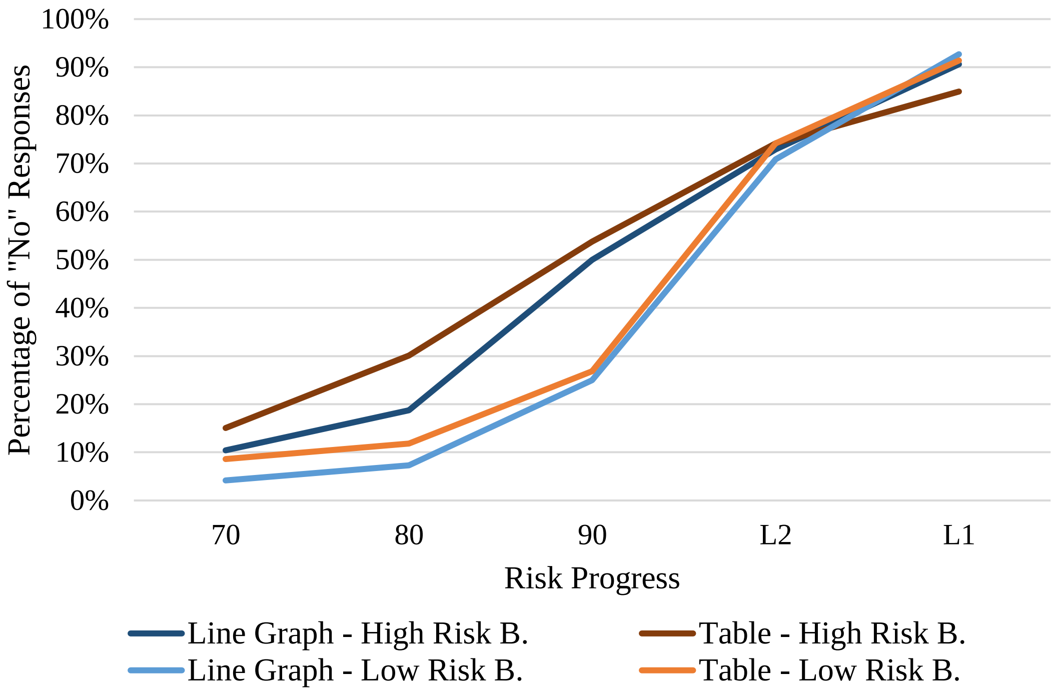
2b. Imagine we are throwing a loaded die (6 sides). The probability that the die shows a 6 is twice as high as the probability of each of the other numbers. On average, out of these 70 throws how many times would the die show the number 6? ________out of 70 throws.

3. In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red? ________

APPENDIX H

LINE GRAPH SHOWING THE PERCENTAGES OF “NO” RESPONSES IN THE

“LESS RISK AVERSE” SAMPLE



APPENDIX I

LOGISTIC REGRESSION RESULTS OF MODEL A

						95% Confidence Interval	
Predictor	Contrast	Estimate	*SE*	*p*	OR	Lower	Upper
Intercept		1.06	.22	< .0001	2.89	.63	1.49
Format	Table - Line Graph	-.39	.44	0.37	.68	-1.24	.47
Balloon	Low-Risk - High Risk	.88	.16	< .0001	2.41	.57	1.19
Risk Progress	50 - 60	.77	.33	0.02	2.15	.11	1.42
	60 - 70	1.52	.30	< .0001	4.58	.94	2.10
	70 - 80	1.08	.25	< .0001	2.94	.58	1.58
	80 - 90	2.20	.25	< .0001	9.03	1.71	2.69
	90 - L2	2.95	.26	< .0001	19.05	2.43	3.47
	L2 - L1	2.01	.33	< .0001	7.47	1.37	2.66
Affect Response		-.05	.00	< .0001	.95	-.06	-.04
DOSPERT		0.97	.30	< .0001	2.63	.38	1.56
Berlin Numeracy		-.04	.19	.83	.96	-.40	.33
Format x Balloon	Table - Line Graph x LR - HR	-.13	.32	.69	.88	-.75	.49
Format x Risk Progress	Table - Line Graph x 50 - 60	.34	.67	.61	1.41	-.96	1.65
	Table - Line Graph x 60 - 70	-.10	.59	.87	.91	-1.26	1.06
	Table - Line Graph x 70 - 80	.03	.50	.96	1.03	-.96	1.01
	Table - Line Graph x 80 - 90	-.75	.48	.12	.47	-1.70	.19
	Table - Line Graph x 90 - L2	-.03	.50	.95	.97	-1.01	.95
	Table - Line Graph x L2 - L1	.00	.65	1.00	1.00	-1.26	1.27
Balloon x Risk Progress	LR - HR x 50 - 60	-.11	.66	.87	.90	-1.41	1.19
	LR - HR x 60 - 70	-.80	.58	.17	.45	-1.94	.34
	LR - HR x 70 - 80	-.34	.50	.50	.71	-1.32	.64
	LR - HR x 80 - 90	-.75	.46	.10	.47	-1.66	.15
	LR - HR x 90 - L2	2.54	.48	< .0001	12.64	1.60	3.47
	LR - HR x L2 - L1	1.04	.62	.09	2.84	-.17	2.25
Format x Affect Response	Table - Line Graph x Affect Response	.01	.01	.19	1.01	-.01	.03
Format x DOSPERT	Table - Line Graph x DOSPERT	-.98	.60	.10	.37	-2.16	.19
Format x Balloon x Risk Progress	Table - Line Graph x LR - HR x 50 - 60	1.10	1.32	.41	3.00	-1.49	3.68
	Table - Line Graph x LR - HR x 60 - 70	-.23	1.16	.84	.79	-2.51	2.04
	Table - Line Graph x LR - HR x 70 - 80	-.16	1.00	.87	.85	-2.12	1.80
	Table - Line Graph x LR - HR x 80 - 90	.60	.92	.51	1.83	-1.21	2.42
	Table - Line Graph x LR - HR x 90 - L2	.12	.94	.90	1.12	-1.72	1.96
	Table - Line Graph x LR - HR x L2 - L1	.60	1.23	.63	1.81	-1.82	3.01

APPENDIX J

LOGISTIC REGRESSION RESULTS OF MODEL B

Predictor		Estimate	*SE*	*p*	OR	95% Confidence Interval	
						Lower	Upper
Intercept		.53	.24	.03	1.71	.06	1.01
Format	Table - Line Graph	-.41	.48	.40	.66	-1.36	.54
Balloon	HR - LR	-1.03	.20	< .0001	.36	-1.42	-.64
Risk Progress	70 - 80	1.16	.33	< .0001	3.18	.51	1.81
	80 - 90	2.50	.30	< .0001	12.14	1.91	3.08
	90 - L2	3.23	.29	< .0001	25.16	2.65	3.80
	L2 - L1	2.45	.34	< .0001	11.58	1.79	3.11
Format x Balloon	Table - Line Graph x HR - LR	.28	.39	.48	1.32	-.48	1.04
Format x Risk Progress	Table - Line Graph x 70 - 80	.07	.66	.92	1.07	-1.22	1.36
	Table - Line Graph x 80 - 90	-.97	.57	.09	.38	-2.08	.14
	Table - Line Graph x 90 - L2	-.21	.53	.69	.81	-1.25	.83
	Table - Line Graph x L2 - L1	-.69	.64	.28	.50	-1.94	.57
Balloon x Risk Progress	HR - LR x 70 - 80	.73	.65	.26	2.07	-.55	2.01
	HR - LR x 80 - 90	.32	.54	.55	1.38	-.73	1.37
	HR - LR x 90 - L2	-2.33	.49	< .0001	.10	-3.28	-1.38
	HR - LR x L2 - L1	-1.02	.60	.09	.36	-2.19	.15
Format x Balloon x Risk Progress	Table - Line Graph x HR - LR x 70 - 80	.77	1.30	.56	2.15	-1.78	3.32
	Table - Line Graph x HR - LR x 80 - 90	-.38	1.07	.72	.68	-2.48	1.72
	Table - Line Graph x HR - LR x 90 - L2	-.13	.96	.89	.87	-2.01	1.74
	Table - Line Graph x HR - LR x L2 - L1	-.67	1.19	.57	.51	-3.00	1.66

APPENDIX K

LOGISTIC REGRESSION RESULTS OF MODEL C

Predictor		Estimate	*SE*	*p*	OR	95% Confidence Interval	
						Lower	Upper
Intercept		3.27	.37	< .0001	26.32	2.54	4.00
Format		-.83	.57	.14	.44	-1.95	.28
Balloon		-2.03	.28	< .0001	.13	-2.58	-1.47
Risk Progress		-.20	.02	< .0001	.82	-.24	-.16
Format x Balloon	Table - Line Graph x HR - LR	-.08	.53	.88	.93	-1.11	.95
Format x Risk Progress	Table - Line Graph x Risk Progress	.04	.03	.23	1.04	-.03	.11
Balloon x Risk Progress	HR - LR x Risk Progress	-.05	.03	.15	.96	-.11	.02
Format x Balloon x Risk Progress	Table - Line Graph x HR - LR x Risk Progress	-.03	.06	.60	.97	-.16	.09

APPENDIX L

LOGISTIC REGRESSION RESULTS OF MODEL E

Predictor		Estimate	*SE*	*p*	OR	95% Confidence Interval	
						Lower	Upper
Intercept		-1.64	.24	< .0001	.20	-2.10	-1.17
Format	Table - Line Graph	-.21	.44	.64	.82	-1.06	.65
Balloon	HR - LR	.61	.21	< .0001	1.83	.20	1.01
Popping Probability	Popping Probability	-.17	.01	< .0001	.84	-.20	-.15
Format x Balloon	Table - Line Graph x HR - LR	.27	.41	.51	1.31	-.53	1.07
Format x Popping Probability	Table - Line Graph x Popping Probability	.01	.02	.52	1.01	-.02	.04
Balloon x Popping Probability	HR - LR x Popping Probability	-.02	.01	.08	.98	-.05	.00
Format x Balloon x Popping Probability	Table - Line Graph x HR - LR x Popping Probability	.04	.03	.17	1.04	-.02	.09

APPENDIX M

LINEAR REGRESSION RESULTS OF MODEL G

Predictor		Estimate	*SE*	95% Confidence Interval		*t*	df	*p*
				Lower	Upper			
Intercept		41.82	1.32	39.23	44.41	31.66	225.00	< .0001
Format	Table - Line Graph	-2.45	2.65	-7.64	2.73	-.93	225.00	.35
Balloon	LR - HR	-5.35	.63	-6.58	-4.11	-8.48	2938.00	< .0001
Risk Progress	50 - 60	-3.52	1.18	-5.84	-1.21	-2.98	2938.00	< .0001
	60 - 70	-8.19	1.18	-10.50	-5.87	-6.94	2938.00	< .0001
	70 - 80	-8.86	1.18	-11.17	-6.54	-7.51	2938.00	< .0001
	80 - 90	-13.16	1.18	-15.48	-10.85	-11.15	2938.00	< .0001
	90 - L2	-17.58	1.18	-19.89	-15.26	-14.89	2938.00	< .0001
	L2 - L1	-12.12	1.18	-14.44	-9.81	-10.27	2938.00	< .0001
DOSPERT		-4.02	1.84	-7.62	-.42	-2.19	225.00	.03
Format x Balloon	Table - Line Graph x LR - HR	.43	1.26	-2.04	2.90	.34	2938.00	.73
Format x Risk Progress	Table - Line Graph x 50 - 60	.68	2.36	-3.95	5.31	.29	2938.00	.77
	Table - Line Graph x 60 - 70	-1.24	2.36	-5.87	3.38	-.53	2938.00	.60
	Table - Line Graph x 70 - 80	-.01	2.36	-4.63	4.62	.00	2938.00	1.00
	Table - Line Graph x 80 - 90	.75	2.36	-3.88	5.38	.32	2938.00	.75
	Table - Line Graph x 90 - L2	-.59	2.36	-5.22	4.03	-.25	2938.00	.80
	Table - Line Graph x L2 - L1	-1.21	2.36	-5.83	3.42	-.51	2938.00	.61
Balloon x Risk Progress	LR - HR x 50 - 60	2.37	2.36	-2.26	6.99	1.00	2938.00	.32
	LR - HR x 60 - 70	4.06	2.36	-.57	8.68	1.72	2938.00	.09
	LR - HR x 70 - 80	1.88	2.36	-2.75	6.50	.79	2938.00	.43
	LR - HR x 80 - 90	-.06	2.36	-4.69	4.57	-.03	2938.00	.98
	LR - HR x 90 - L2	-14.34	2.36	-18.97	-9.71	-6.08	2938.00	.00
	LR - HR x L2 - L1	.36	2.36	-4.27	4.99	.15	2938.00	.88
Format x Balloon x Risk Progress	Table - Line Graph x LR - HR x 50 - 60	-2.68	4.72	-11.93	6.57	-.57	2938.00	.57
	Table - Line Graph x LR - HR x 60 - 70	-3.66	4.72	-12.92	5.59	-.78	2938.00	.44
	Table - Line Graph x LR - HR x 70 - 80	1.41	4.72	-7.85	10.66	.30	2938.00	.77
	Table - Line Graph x LR - HR x 80 - 90	2.07	4.72	-7.19	11.32	.44	2938.00	.66
	Table - Line Graph x LR - HR x 90 - L2	-.25	4.72	-9.50	9.00	-.05	2938.00	.96
	Table - Line Graph x LR - HR x L2 - L1	-1.16	4.72	-10.42	8.09	-.25	2938.00	.81

APPENDIX N

LINEAR REGRESSION RESULTS OF MODEL H

Predictor		Estimate	*SE*	95% Confidence Interval		*t*	df	*p*
				Lower	Upper			
Intercept		49.00	1.60	45.86	52.14	30.59	187.00	< .0001
Format	Table - Line Graph	-2.99	3.20	-9.27	3.29	-.93	187.00	.35
Balloon	HR - LR	6.74	.72	5.33	8.16	9.33	1683.00	< .0001
Risk Progress	70 - 80	-8.81	1.14	-11.05	-6.57	-7.70	1683.00	< .0001
	80 - 90	-13.91	1.14	-16.15	-11.67	-12.17	1683.00	< .0001
	90 - L2	-18.62	1.14	-20.86	-16.38	-16.29	1683.00	< .0001
	L2 - L1	-12.92	1.14	-15.16	-10.68	-11.30	1683.00	< .0001
Format x Balloon	Table - Line Graph x HR - LR	-2.26	1.45	-5.09	.57	-1.56	1683.00	.12
Format x Risk Progress	Table - Line Graph x 70 - 80	.46	2.29	-4.02	4.94	.20	1683.00	.84
	Table - Line Graph x 80 - 90	1.99	2.29	-2.49	6.47	.87	1683.00	.38
	Table - Line Graph x 90 - L2	-.99	2.29	-5.47	3.49	-.43	1683.00	.67
	Table - Line Graph x L2 - L1	-1.01	2.29	-5.49	3.47	-.44	1683.00	.66
Balloon x Risk Progress	HR - LR x 70 - 80	-1.71	2.29	-6.19	2.77	-.75	1683.00	.45
	HR - LR x 80 - 90	-.59	2.29	-5.07	3.89	-.26	1683.00	.80
	HR - LR x 90 - L2	14.91	2.29	10.43	19.39	6.52	1683.00	< .0001
	HR - LR x L2 - L1	-.71	2.29	-5.19	3.77	-.31	1683.00	.76
Format x Balloon x Risk Progress	Table - Line Graph x HR - LR x 70 - 80	.22	4.57	-8.74	9.18	.05	1683.00	.96
	Table - Line Graph x HR - LR x 80 - 90	-4.54	4.57	-13.50	4.42	-.99	1683.00	.32
	Table - Line Graph x HR - LR x 90 - L2	-1.02	4.57	-9.98	7.94	-.22	1683.00	.82
	Table - Line Graph x HR - LR x L2 - L1	1.65	4.57	-7.31	10.61	.36	1683.00	.72

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