Decision-Making under Uncertainty: How the Amount of Presented Uncertainty Influences User Behavior

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ABSTRACT

In everyday life, people regularly make decisions based on uncertain data, e.g., when using a navigation device or looking at the weather forecast. In our work, we compare four representations that communicate different amounts of uncertainty information to the user. We compared them in a study by publishing a web-based game on Facebook. In total, 44 users played 991 turns. We analyzed the turns by logging game metrics such as the gain per turn and included a survey element. The results show that abundance of uncertainty information leads to taking unnecessary risks. However, representations with *aggregated detailed uncertainty* provide a good trade-off between being understandable by the players and encouraging medium risks with high gains. Absence of uncertainty information reduces the risk taking and leads to more won turns, but with the lowest money gain.

Author Keywords

Decision-making; risk; representations; uncertainty.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

INTRODUCTION & BACKGROUND

Weather forecasts are based on simulation, which is a powerful technique used to investigate the behavior of complex systems [4]. However, simulations usually produce uncertain results. For weather forecasting, 70% of the public prefers to have information about the uncertainty of the forecast [6].

Uncertainty visualizations for experts, such as glyph visualizations [8, 13], are well explored. Additionally, new versions of standard representations such as box plots [9], bar charts [1], and line charts [11] have been investigated with experts and laymen. The results show that qualitative information [12] as well as quantitative information [5] can be misleading for laymen. The influence of uncertainty information on decision-making is also widely discussed in related literature.

Figure 1. Facebook game called "Farm Smart" as study environment.

Several surveys and user studies showed that people make better decisions with uncertainty information [3, 7, 10].

Although the topic of uncertainty visualization and decision-making has been widely studied, there is still no common consensus about which uncertainty visualization to use in which context. Another unanswered question concerns the right level of detail when displaying uncertain information as details add cognitive costs.

Our work is based on previous research of Greis et al. [2] who compared twelve representations for uncertain data in an online survey. They identified four representations that show different amounts of uncertainty information and compared them in a small controlled study. We incorporated these four representations here to conduct an in-the-wild study. The novelty lies in using a Facebook game for visualization research (see Figure 1). This allows us to analyze players' risk taking depending on the amount of presented uncertainty under natural conditions. We also provide details about the game mechanics and data analysis.

The contribution of our paper is **two-fold**. *First*, we present a Facebook game deployment as an in-the-wild study with logged analytics and surveys for HCI and visualization research. *Second*, we provide an analysis of the effects of presenting different amounts of uncertainty information on decision-making and risk taking.

METHOD

In the turn-based Facebook game "Farm Smart", the player buys, plants, and harvests crops in order to earn money. Each

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crop has its own requirements regarding precipitation. In addition, each crop is characterized by a ripening time between one and three days. In order to successfully grow crops, the precipitation threshold has to be met throughout the whole ripening time.

The selection of promising crops is supported by a weather forecast, which can be opened by clicking on a button. It shows the forecasted precipitation. After planting as much crops as desired, the player can go to the next day by clicking a button. The actual weather (displayed in the upper left corner of the screen) and specific field icons indicate whether the planted seeds survived or withered.

Ten days (i.e. turns) correspond to one game. The representation of the weather forecast does not change during one game. Each player can play up to four games, one with each of the four representations and is randomly assigned to one of the 24 permutations of representations at the first start of "Farm Smart". To recruit players, we shared the game link on Facebook and advertised in online gaming communities.

Requirements and Prices of Crops

The seed costs, sales prices, ripening times, and weather requirements of crops were specified in a way that a wide range of possible decisions is offered to the player in the majority of the weather situations. Furthermore, the player is motivated to equally consider more demanding crops, as higher requirements or ripening times are rewarded with a higher gain when selling the crops. The rewards for the overall game were chosen to achieve pareto-optimal rewards.

Weather Calculation

The weather throughout the game is based on the real measured values of a meteorological station[1] in a German city. The values cover a continuous period of 62 days between spring and summer of 2001.Every game starts at a specific day within that period that is chosen uniformly at random from the first 49 days to ensure having enough forecasts to cover the next ten days.

A weather forecast in "Farm Smart" corresponds to a set of three modified Gaussian distributions. For a day d the forecast for the n-th day ($n \in \{1, 2, 3\}$) is constructed as follows:

1. The expected value μ' of the Gaussian distribution is calculated by offsetting the real value of the day $d + n$ by a factor $n \cdot \alpha \cdot X$ with $\alpha > 0$ and a sample $X \sim \mathcal{N}(0, 1)$. This corresponds to the assumption that the magnitude of the inaccuracy in weather forecasts is approximately normally distributed and increases linearly with the temporal distance to the predicted event.

2. The standard deviation of the Gaussian distribution is chosen as $n \cdot \sigma$ with $\sigma \in \mathbb{R}_0^+$. This corresponds to a horizontal compression of the distribution's graph and represents the linearly increasing uncertainty within temporal distant weather forecasts. It follows the Gaussian distribution $\mathcal{N}(\mu', n \cdot \sigma)$. After pre-testing, the parameters α and σ were chosen as $\alpha = 0.8$ und $\sigma = 1.0$.

[1]Source: Deutscher Wetterdienst `http://www.dwd.de`

	Survey Question (*After each game*) Agreement = Agree, Strongly Agree	Percentage (%) of Agreement			
		REP1	REP2	REP3	REP4
1	I was familiar with the presentation	59.1	**66.7**	61.9	47.6
2	The representation was easy to understand	54.6	**66.7**	**66.7**	38.1
3	The representation was visually appealing	22.7	**58.3**	33.3	38.1
4	The representation supported me in making a decision	31.8	54.2	**57.1**	28.6

Table 1. Percentage of agreeing players in the survey. *Green* shows the highest values. *Red* shows the lowest values.

Representations

To compare the influence that different amounts of uncertainty have on players' behavior, we implemented the four different representations identified in [2] using HighCharts[2].

(REP1) Text: It shows the expected value, which gives no information at all about the uncertainty (see Figure 2a).

(REP2) Line chart: It also shows the expected value, but adds quantiles, which were chosen as the 0.05 and the 0.95 quantile (see Figure 2b).

(REP3) Bar chart: It visualizes the sum of probabilities within a certain range (see Figure 2c). For the bar colors, we used the HCL color space to achieve optimal differentiability and provoke equally intense perceptions.

(REP4) Probability distribution function: It displays the underlying distributions in full detail in a probability distribution function graph (see Figure 2d).

Each representation shows an *increased amount* of uncertainty information: REP1 shows no information, REP2 shows aggregated uncertainty information, REP3 shows aggregated detailed information, and REP4 shows all details.

Data Collection

We collected *two* types of data: (1) *survey* - personal data and subjective feedback about the representations and (2) *logged analytics* - calculated metrics during the game play. We saved all game parameters such as accumulated money, representation type, weather forecasts, and the actual weather. To track the number of times a player opened the weather forecast, we counted the number of clicks on the associated button. After finishing a game, we asked the player to judge the representations using a *five-point Likert scale* (see Table 1).

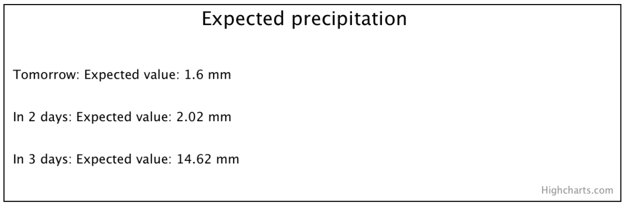
RESULTS

We analyzed the data of 44 players who played 98 games composed of 991 turns (on average 2.23 games per player, $SD = 1.27$). In these games, the weather forecast was opened at least once. The average number of played turns per representation is 247.75 ($SD = 34.13$). Players who played less than four games experienced only a subset of the representations.

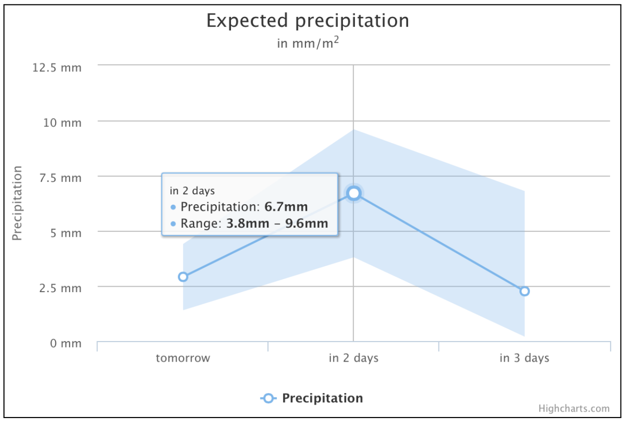
Survey

The online survey was fully answered 88 times after completing a game by 38 players in total (29 male, 9 female). The answers per representation were grouped into *three* categories: (1) *agree* (includes agree and strongly agree), (2)

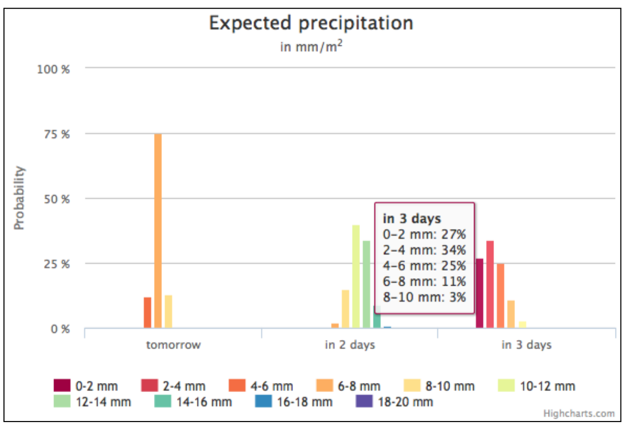
[2]`http://www.highcharts.com`



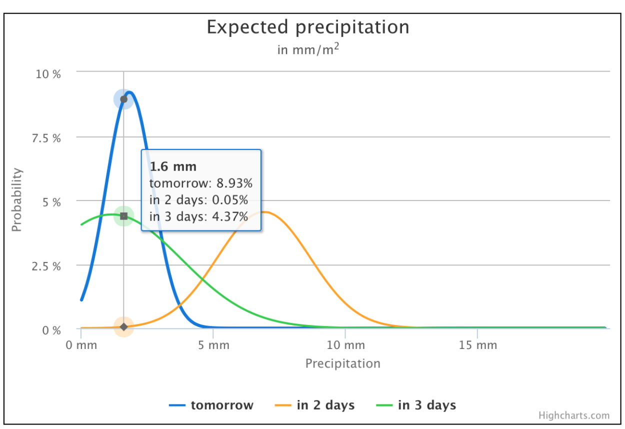
(a) REP1 - Text



(b) REP2 - Line chart



(c) REP3 - Bar chart



(d) REP4 - Probability distribution function

Figure 2. The four representations each display weather forecasts with a different amount of uncertainty information.

REP	METRIC 1 Average weighted risk from all turns		METRIC 2 % of turns ending with winning/losing		METRIC 3 Average money gained / lost from all turns	
	Mean	SD	Win	Lose	+ve (Gain)	-ve (Loss)
Group 1: Representations Without Uncertainty Aggregation						
REP1	12.8	24.9	**24.1%**	47.4%	435.3	173.7
REP4	**20.3**	33.4	15.8%	49.0%	**612.4**	161.2
Group 1: Representations With Uncertainty Aggregation						
REP2	**18.7**	31.5	17.7%	54.4%	448.1	130.2
REP3	17.3	29.1	**23.5%**	49.8%	**772.2**	170.3

Table 2. Overview of analytics collected during the game plays. Dark shades show the highest value. Light shades show the lowest value within a group. Red shows the highest value for loss.

neutral and (3) *disagree* (includes disagree and strongly disagree). The *agreements* are summarized in Table 1. They show that REP2 and REP3 (*aggregated uncertainty information*) were preferred by the players. In contrast, REP4 (*detailed uncertainty information*) was their least favorite.

Logged Analytics

We present below a set of *three* metrics to explore the following questions: (1) How did the representations affect risk taking? and (2) How did the representations affect the decision-making? The results are summarized in Table 2.

Effect on risk taking: We defined a metric called *"mean weighted risk"* (**Metric 1**). It indicates the average *risk per turn* the players were willing to take during all turns. The *risk per turn* accounts for planting various crops with diverse risks. The *risk per plant* is the integral of the probability distribution function for the weather forecast up to the critical value for the plant's requirement. Players took the most risky decisions using REP4 and the most conservative decisions using REP1.

Effect on decision-making: The game has an "achieve as much as you can" style with no preset winning target. Thus, a *good decision* results in winning money by the end of a turn. We defined *two* metrics for winning. The first is *"percentage of won turns"* (**Metric 2**). A won turn ends by positive money gain, regardless of the amount. The second is *"mean positive money gain"* (**Metric 3**). It is the winning magnitude by averaging positive money gain in all turns. The players won the highest number of turns using REP1. However, they won the highest amount of money using REP3.

DISCUSSION

We focus in this section on discussing the effect of the representations on: (1) risk taking and (2) assisting the players in decision-making to maximize their gains during the game. We categorize the representations using into *two groups*: (1) Representations without uncertainty aggregation (*REP1 and REP4*) and (2) Representations with uncertainty aggregation (*REP2 and REP3*). Next, we compare the best representation from each group.

Group 1 - Without uncertainty aggregation: The players took the highest risks using REP4 which represents the highest level of details about uncertainty. The result is a degradation in the performance as indicated by a higher percentage of lost turns. The risky decisions could be attributed to the impaired understanding of the abundant details in the presented information. This is supported by the survey showing it was perceived as the most complex representation. On the other hand, it is plausible that players who truly understood the representation were able to perform exceptionally well with it. This can be seen in the positive money gain through the turns where REP4 ranked as the second highest. Similarly, the players had the least uncertainty information using REP1 and took the lowest risks possible. The result is the highest percentage of winning turns but with the lowest amount of gained money and the highest amount of lost money. In a nutshell, REP1 lead to the higher winning percentage of turns while REP4 lead to higher money gain.

Group 2 - With uncertainty aggregation: Both representations are showing aggregated uncertainty information. The players took similar risks using both representations. This is also supported by the survey as both representations were favored and understood best although players subjectively preferred the visual appearance of REP2. Nevertheless, using REP3 resulted in winning more turns with a noticeable increase in the amount of gained money while using REP2 resulted in the highest number of lost turns. In a nutshell, REP3 resulted in a higher percentage of winning turns and gained money.

The combined analysis of both groups using the winning metrics is in favor of **REP3**. Using *Metric 2*, REP3 has a noticeably higher percentage of winning turns compared to REP4 and a similar one to REP1. However, the amount of gained money (*Metric 3*) using REP3 is noticeably the highest. Corresponding to the findings of Greis et al. [2], we found that showing aggregated uncertainty as in REP2 is not optimal. However, in contrast to their findings, REP4 did not perform best. We attribute this result to our larger sample size and the recruitment process over Facebook. Analyzing the wins, losses and the money gained/lost provided us with deeper insights on the risk taking behaviour of players.

CONCLUSION

The *objective* of this paper was to understand the effect of the presented amount of uncertainty on risk taking and decision-making. We embedded four distinct representations (identified from [2]) in a Facebook game.

Players do not favor *representations with no uncertainty* as they tend to value the availability of the extra uncertainty information. However, these representations are a “Low risk, Low reward” option as they maintain high winning rates but with low won amounts. Nevertheless, abundance of uncertainty information does not result in better decisions as illustrated by *representations with detailed uncertainty*. The degraded understandability was associated with higher rate of unjustified risky decisions and losses. However, they are a “High risk, high reward” option as they are also associated with highest winning amounts when understood correctly. On the other hand, *representations with aggregated uncertainty* are perceived as the most helpful and understandable. Yet, they encourage taking incalculable risks without considering the depth of missing information. Finally, *representations with aggregated detailed uncertainty* offer a good compromise between understandability, encouraging educated risks, and achieving plausible winning scenarios with high gains.

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