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The Illusion of Control and Information Overload within a Bayesian Updating Framework*

Iluzja kontroli oraz przeciążenie informacyjne w świetle wnioskowania bayesowskiego

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Abstract:

In this paper, the hypothesis that information overload causes the illusion of control is verified with Bayesian updating. Bayesian updating is considered the rationality model of individuals' perception of their impact on the process of generating results. Here, the Bayesian model of processing information, where different priors are applied, is validated. Information overload has been operationalised by introducing uncertainty about the function and parameter values of generating results.

Keywords: overconfidence, illusion of control, information overload, Bayesian updating.

Streszczenie:

W artykule za pomocą wnioskowania bayesowskiego została zweryfikowana hipoteza mówiąca o tym, że przeciążenie informacyjne zwiększa iluzję kontroli. Wnioskowanie bayesowskie jest uważane za racjonalny model, w ramach którego jednostki oceniają swój własny wpływ na proces generujący wyniki. W artykule weryfikujemy bayesowski model przetwarzania informacji poprzez zastosowanie różnych parametrów. Przeciążenie informacyjne zostało zoperacjonalizowane poprzez wprowadzenie niepewności co do funkcji i wartości parametrów procesu generującego wyniki.

Słowa kluczowe: nadmierna pewność siebie, iluzja kontroli, przeciążenie informacyjne, wnioskowanie bayesowskie.

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1. Introduction

This paper reports on the use of Bayesian updating to understand the link between information overload and the illusion of control. The Bayesian updating process is operationalised by different priors. The illusion of control is defined as an expectancy of a personal success probability inappropriately higher than the objective probability would warrant (Langer, 1975, p. 313). It has been shown that overconfidence in the form of the illusion of control is a very strong bias among financial market professionals. This type of bias occurs more frequently with technical analysis usage (Kubińska, Czupryna, Markiewicz, Czekaj, 2018). Financial market professionals are influenced by the increasing amount of information they are confronted by, with enormous amounts of news that are not fundamental information but just a 'noise' (Black, 1986), leading to informational overload (Chewning, Harrell, 1990). Information overload occurs "when the information processing demands on an individual's time to perform interactions and internal calculations exceed the supply or capacity of time available for such processing" (Schick, Gorden, Haka, 1990, p. 199). Trading is done in an environment characterised by strong information load and it has been proved that traders exhibit an illusion of control in their investment decisions (Fenton-O'Creevy, Nicholson, Soane, Willman, 2003; Kubińska *et al.*, 2018). We hypothesise that information overload causes an illusion of control, and sought to verify this in an experimental study. We also assume Bayesian updating to be a rational decision-making model.

The illusion of control can be measured by determining the difference between the perception of one's own impact on the process of generating results and the objective influence on the results. Examining a wider range of situations with different levels of real control enables research on the illusion of control in the context of an under- or overreaction to real control. L. B. Alloy and L. Y. Abramson (1979), in their "button-light" experiment, provided such a research schema, allowing subjects to either underestimate or overestimate their real control. Subjects were tasked with finding the degree of control they had over whether or not a green light came on after a yellow "warning light" that signalled the start of a trial. They had the option of pressing or not pressing a button within three seconds of the yellow light coming on. The experimental conditions varied the percentage of the time that the green light came on after the subject pressed or did not press the button. Each subject was given 40 trials and then given a printed Judgment of Control scale, ranging from 0 to 100, and was then asked to indicate the amount of control they had over the onset of the green light. The results showed that subjects tend to underestimate their control when it is high and overestimate it when it is low. A similar experimental design was used by F. Gino, Z. Sharek and D. A. Moore (2011), who found that people underestimate their real control when they have it, but overestimate it when they do not. An experiment designed by Fenton-O'Creevy *et al.* (2003) was adopted, with index values displayed on a graph step by step. There were also additional control buttons that could influence the parameters of the index value generating process. This approach made it possible to measure the participants' activity when there are different levels of control, and to introduce informative load by introducing new parameters.

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Exact Magnitude of Change in Estimating Probabilities

The illusion of control is measured as the difference between the perception of the subject's own impact and the objective influence on the process-generating results. To formalise that measure, the following symbols are used: Actual/correct probabilities are represented by P_I^C and $P_{N\_I}^C$, and estimated/perceived probabilities are assigned to P_I^P, $P_{N\_I}^P$, respectively, for probabilities while subjects are involved (lower index *I*) and not involved (lower index *N_I*) in the process-generating outcomes. Real control is defined by the difference between correct probabilities $RC = P_I^C - P_{N\_I}^C$, while perceived control is the difference between estimated probabilities $PC = P_I^P - P_{N\_I}^P$. The illusion of control is measured by this formula[1]:

$$IOC = PC - RC.$$

The binomial distribution is obtained by assuming that the process-generating outcomes in one trial has a Bernoulli distribution and the subject was N_I times involved in that process (for example, by pressing a traffic light button like New York pedestrians), while N_{N_I} times she/he only observed outcomes but was not involved. The estimators of correct probabilities (P_I^E and $P_{N\_I}^E$) are then given by the frequencies:

$$P_I^E = \frac{N_{Up\_I}}{N_I} \text{ and } P_{N\_I}^E = \frac{N_{Up\_N\_I}}{N_{N\_I}},$$

where N_{Up_I} and $N_{Up\_N\_I}$ stand for the number of successes when the subjects were involved and not involved, respectively. Next, empirical control is given by the formula $EC = P_I^E - P_{N\_I}^E$, while the estimate of the illusion of control is $IOC^E = PC - EC$.

To analyse the exact magnitude of changes of probabilities P_I^P, $P_{N\_I}^P$ in Bayesian inference, the beta distribution, which is the conjugate prior probability distribution for the binomial distributions, must be considered (Raiffa, Schlaifer, 1961; Turner, Van Zandt, 2012). As a conjugate prior probability distribution, the beta distribution describes the initial knowledge for probability of success and is given by the following probability density function:

$$f\left(x \mid n_{Up}, n_{Down}\right) = \frac{x^{n_{Up}}\left(1-x\right)^{n_{Down}}}{B\left(n_{Up}+1, n_{Down}+1\right)},$$

where n_{Up} is the number of successes, n_{Down} is the number of failures and $B(\cdot,\cdot)$ stands for the beta function $\left(B(x, y) = \int_0^1 t^{x-1}(1-t)^{y-1}dt\right)$.

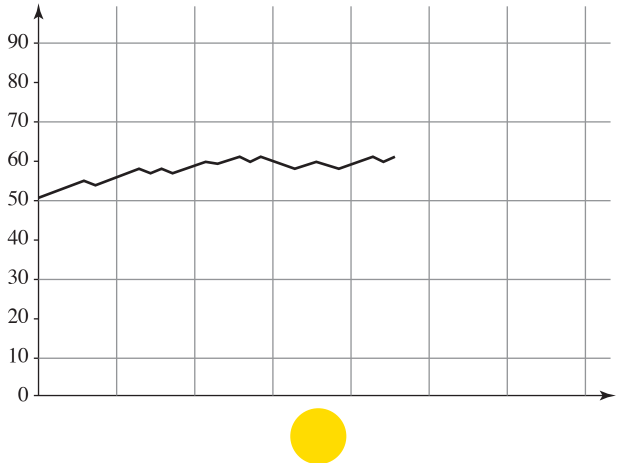
Further ideas on the illusion of control in a Bayesian updating framework can be found in Czupryna *et al* (2018), which offers an introductory example.

2. Methods

2.1. Overview

Two experiments were conducted. In both, participants could observe on a screen the simulated price movements (the prices changed stepwise). The main goal in both experiments was to cause the stock price to reach the highest level in every round by placing the cursor over the control field in the appropriate place, i.e. circles at Figure 1 or Figure 2. Participants were also informed that their actions could have no impact on the simulated prices. They were fur-

[1] This formula is applied in cases of positive or no control. But this is normalised by multiplying by -1 in the case of negative control to have the same interpretation for under- or over-estimation of one's influence on the results.



The participants observed the graph with price changes in 50 steps. The control field is the yellow circle. By placing the cursor in the control field, participants could affect the simulated stock price movements (with a one-step delay).

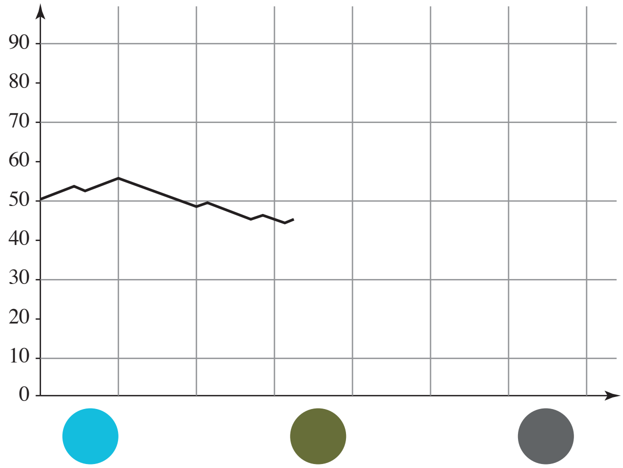
Figure 1. A Print Screen of the Simulated Price Movements in Experiment 1

Table 1. Base Probability (Control Button Released) and Steering Probability (Control Button Pressed) in Study 1

Round number	Base probability $P^C_{N\_I}$	Steering probability P^C_I
1	.50	.50
2	.75	.35
3	.25	.25
4	.50	.70
5	.25	.65
6	.75	.95
7	.50	.10
8	.25	.05
9	.75	.75

ther tasked with guessing what kind of changes would be caused if the cursor was placed over the control field. At the end of each round of those two experiments, participants were asked questions about probability levels, which were motivated by the approach used in Gino *et al.* (2011):

1. What was the base probability (no steering) of the stock price increase in a single step?
2. What was the probability of the stock price increase in a single step while steering?
3. In how many steps did you steer the probability?



The participants observed the graph with price changes in 50 steps. By pressing one of the tree control fields, participants could affect two parameters (probability and slope) of simulated stock price movements with a one-step delay. Participants did not know which button was responsible for which function.

Figure 2. A Print Screen of Simulated Price Movements within Experiment 2

Table 2. Parameters for the Rounds in Experiment 2

Round number	Base probability $P^C_{N\_I}$	Real control $RC = P^C_I - P^C_{N\_I}$
1	.50	0
2	.40	.25
3	.50	-.25
4	.35	.25
5	$P^C_{N\_1} \in (.5, .8)$	-.25
6	.45	.25

4. In how many of these steps did the stock price increase?

5. In how many steps when you did not steer did the stock price increase?

In the above questions, steering refers to the participant trying to influence the process by placing the cursor over the control field. Both experiments were programmed in Inquisit 4 Lab, Milliseconds Software (2015).

In the first experiment (referred further as Experiment 1) only non-informative priors, but different steering and non-steering probabilities, were used. There were nine rounds; the probabilities for each round are presented in Table 1. Based on the formula for real control, there was no control ($RC = 0$) in Rounds 1, 3 and 9; positive control ($RC > 0$) in Rounds 4, 5 and 6 and negative control ($RC < 0$) in Rounds 2, 7 and 8.

The second experiment (referred to further as Experiment 2) considered the variation of parameters other than probabilities, such as number of rounds and number of steering fields. This was done to increase the information load, as well as provide different levels of prior knowledge about the base probability. In Experiment 2, Experiment 1 was modified by giving additional information about the theoretical correct base and steering probabilities and the parameter of slope to be controlled in selected rounds was introduced. There were six rounds in the second experiment. The parameters of the price formation process for each round are given in Table 2. Because the base probability in the fifth round is a randomly assigned number from a uniform distribution with support at the interval (.5, .8), it is impossible to give the exact value of the steering probability in this round. The level of real control is what is being presented. In Round 1, there is no control (RC = 0), positive control (RC > 0) occurs in Rounds 2, 4, and 6; while negative control (RC < 0) occurs in Rounds 3 and 5.

In Rounds 1 and 2 of Experiment 2, the slope parameter was introduced and participants had three control fields like the print screen presented in Figure 2. Steering doubles the slope with a probability of .75 in Round 2, while there was no effect in Round 1. In rounds with three control fields, participants had the following information about possible functions:

• the control field might be responsible for the change in the probability of a price increase,

• the control field might be responsible for an increase in the absolute change (both decrease and increase) in the price observed in a single step (a change of a slope). However, this can only be effective in a certain percentage of the steps in which this control field was used,

• the control field might have no effect on the observed price movement.

Participants did not know which control field was responsible for which function.

In the first and second rounds of Experiment 2, there were three control fields, as shown in Figure 2, while in Rounds 3 through 6, participants had only one control field at their disposal, as shown in Figure 1. The goal of introducing three control fields and adding a slope parameter was to make the task more difficult and thus introduce a higher information load on the subjects' decision-making. We hypothesised that tasks that involved selecting from among three buttons requires greater cognition than a task involving just one steering button. This is similar to presenting a pattern with three dots to be recalled, which, as shown by De Neys in 2006, would be more demanding than recalling a single dot. As a consequence, the greater the number of dots, the higher the probability that information would be processed in System 1 and the lower in System 2. Thus under a higher information load (with three steering buttons instead of one), a decision-maker will be more prone to the heuristic and intuitive decision-making typical for System 1 decisions.

Since the new slope parameter and two control fields play the role of the information load, it was expected that subjects' judgments in rounds with a higher information load would be less rational (more intuitive and heuristic) and thus more biased toward the illusion of the control effect. In Round 4, the number of steps was increased to 100, to verify if the feedback would decrease the illusion of control. In Round 5, the informative prior for the base probability was given, which is one number randomly assigned with a uniform distribution from the interval (.5, .8), and in Round 6 the exact value of the base probability was given. Thus different levels of prior knowledge about base probabilities were provided, in response to the expectation

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that a higher level of prior knowledge could help subjects make more accurate judgments about probability levels and, consequently, decrease the illusion of control.

2.2. Participants

Students of the Capital Markets Major at the Cracow University of Economics during the Technical Analysis (TA) course participated in both experiments. The first experiment was carried out on a group of 51 individuals (17 women), while the second one was carried out on a group of 60 students (18 women). Both groups were made up of 3rd year students whose average age was 22. Participation was voluntary and encouraged by the researcher not associated with the TA course teacher. The same independent researcher described a study to participants and obtained informed consent for their participation. Although no monetary incentive was provided, the participants were given bonus credits.

2.3. Results

To verify the effect of changing the parameters, the *IOC* between two chosen rounds from experiment 1 and 2 was compared. An effort was made to match the cases with identical or very similar theoretical values of base and control probabilities, but with variation in other parameters, such as the number of control fields, number of steps, or providing prior information versus no information for the base probabilities.

In order to verify the differences between the *IOC* levels for different rounds, we referred to a posteriori distribution for perceived control: $PC = P_I^P - P_{N\_I}^P$ is the difference between two beta distributions. Two beta distributions were defined for each round for every subject, based on the number of steps when the stock price increased while steering and not steering and the number of steps when stock price has not increased while steering and not steering. Then F^{PC} – empirical cdf for *PC* was estimated based on 100,000 values randomly sampled from beta distributions for the steering and non-steering cases. Because of the lack of analytical distributions for the random variables being the difference of two beta distributions, an approach based on Monte Carlo simulations was adopted. The coefficient P_{IOC} measuring the probability level connected with *IOC* could then be measured by the formula:

$$P_{IOC} = F^{PC}(PC) - F^{PC}(EC).$$

To find the statistical significance, the Wilcoxon rank sum test with continuity correction was applied (due to the restricted range of values

Table 3. Comparison of P_{IOC} for Different Rounds

Case	Round A	Round B	N_1	N_2	P_{IOC} for Round A		P_{IOC} for Round B		Wilcoxon test *p* value
					M	*SD*	*M*	*SD*	
1	E2 R1	E1 R1	48	49	.25	.29	-.08	.34	.001
2	E2 R2	E1 R4	48	47	.27	.34	-.16	.38	.001
3	E2 R3	E2 R5	60	54	-.25	.38	-.05	.43	.007
4	E2 R4	E2 R6	59	59	-.22	.38	-.11	.36	.148
5	E2 R6	E1 R4	59	47	-.11	.36	-.16	.38	.434

of the *IOC* and the limited number of observations, a more general nonparametric test was used). All the calculations were done in R programming (R Core Team 2016). Comparison of the P_{IOC} for different rounds is presented in Table 3. The cases in Table 3 were created from two rounds – Round A and Round B, which were the rounds described in Table 1 within Experiment 1 (E1) or in Table 2 within Experiment 2 (E2). In Cases 1 and 2, the otherwise similar situations when Round A had three unknown control fields and Round B only one were compared. In Case 1, there are two rounds with no real control, while in Case 2, rounds with positive real control were compared. In Round A, there is additional uncertainty – only empirically increased probabilities of control and no control – that cannot be measured. In Case 3, the influence of giving prior information about the level of base probability was checked; both rounds had negative control. In Round B, subjects knew before the experiment began that $P^{P}_{N\_I}$ is a number between .5 and .8. In Round B in Case 3, there was a higher level of negative illusion control. The difference between rounds in Cases 1 and 3 are statistically significant. Case 4 compared a round with 100 steps instead of 50 with the round that provided exact prior knowledge about the base probability, but the difference was not significant. Case 5 verifies the impact of prior knowledge; within Round A, subjects were informed of the exact value of the base probability. The illusion of control level measured by P_{IOC} decreased, but the difference was not statistically significant.

3. Discussion

The results show the universality of the Bayesian approach for the analysis of the illusion of control phenomena. One of our goals was to verify if giving prior information about probability levels will influence (decrease) the illusion of control. Introducing additional information that was a relatively wide interval decreased the level of illusion of control, while providing exact information about probability levels had no effect.

Significantly greater illusion of control was observed in rounds that had additional control fields and additional steering parameters for the process. This confirmed the hypothesis that increasing informative load, by introducing the slope parameter and two control fields in the experimental design, would increase the illusion of control. This may be attributable to dual-process theories, where information is processed in two parallel underlying systems: an experiential system (System 1), devoted to intuitive thinking, and an rational system (System 2), devoted to analytical thinking (Evans, Stanovich, 2013). We stipulated that subjects operate in System 1, which forced them to make more fallacious judgments by making more intuitive, emotional decisions rather than cognitive, rational ones, but this can be explored in further studies. The influence of cognitive load on the propensity to follow the illusion of control within a Bayesian framework can also be tackled in future studies.

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