

Association for Information Systems

AIS Electronic Library (AISeL)

SIGHCI 2020 Proceedings

Special Interest Group on Human-Computer
Interaction

12-12-2020

Using Digital Nudges on Analytics Dashboards to Reduce Anchoring Bias

Burak Oz

Kevin Tran-Nguyen

Constantinos K. Coursaris

Jacques Robert

Pierre-Majorique Léger

Follow this and additional works at: <https://aisel.aisnet.org/sighci2020>

This material is brought to you by the Special Interest Group on Human-Computer Interaction at AIS Electronic Library (AISeL). It has been accepted for inclusion in SIGHCI 2020 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

Using Digital Nudges on Analytics Dashboards to Reduce Anchoring Bias

Burak Oz
HEC Montréal
burak.oz@hec.ca

Jacques Robert
HEC Montréal
jacques.robert@hec.ca

Kevin Tran-Nguyen
HEC Montréal
kevin.tran-nguyen@hec.ca

Constantinos K. Coursaris
HEC Montréal
coursaris@hec.ca

Pierre-Majorique Léger
HEC Montréal
pml@hec.ca

ABSTRACT

This study investigates the effectiveness of digital nudging on reducing the anchoring bias observed in the use of supply chain management (SCM) software. A between-subjects experiment with 61 participants was conducted comparing a control group with two types of digital nudges implemented on an SCM analytics dashboard. Findings show that digital nudging can help mitigate an anchoring bias in several use conditions. Theoretical and practical contributions are discussed, which include that in addition to individual-level outcomes, digital nudging can also be applied in business environments to improve organizational-level performance.

Keywords

Digital nudging, anchoring effect, decision bias, supply chain management, ERPSim

INTRODUCTION

A cognitive bias can be defined as “systematic deviations from rational judgment” (Caraban, Karapanos, Gonçalves, and Campos, 2019, p. 2). The supply chain management (SCM) literature draws attention to the costly effects of a specific cognitive bias, the *anchoring effect*, which can be defined as making decisions under the influence of first impressions (Niranjan, Wagner, and Bode, 2011). Evidence suggests that the information systems (IS) used in the SCM practice contribute to the anchoring effect. For example, the initial forecasts from a computer application serve as anchors that influence the decision-makers (Fildes, Goodwin, Lawrence, and Nikolopoulos, 2009). This study aims to identify the conditions that increase the anchoring effect in the interactions with an IS and test the effectiveness of *digital nudging* in reducing the negative impact of this cognitive bias.

Digital nudging is “the use of user-interface design elements to guide people’s behavior in digital choice environments” (Weinmann, Schneider, and Brocke, 2016, p. 433). There is a considerable amount of research activity in the IS domain investigating the designs and impacts of digital nudges (Caraban et al., 2019; Mirsch, Lehrer, and Jung, 2017). However, the objectives of digital nudging in

the literature has been mainly limited to policy-making issues, such as energy consumption reduction, healthy consumption, environmentally conscious consumption, increased donation amounts, or increased savings (Hummel and Maedche, 2019). This study aims to extend this set of studied objectives by using digital nudging to increase employees’ decision-making performance. It also aims to bring attention to a potential solution to reduce the costly impacts of the anchoring effect in SCM. To reach these objectives, this study focuses on digital nudging in software packages used in SCM, such as enterprise resource planning (ERP) and forecasting applications. This study poses the following research questions:

RQ1. Can anchoring bias be mitigated through the use of digital nudging?

RQ2. Does digital nudging have an increased effect over time on aiding performance?

RQ3. Is the observed effect of digital nudging greater when anchoring bias is greater?

BACKGROUND AND THEORY

Cognitive Biases in Management Domains

In recent decades, supply chains have become more global, which increased the importance of adaptability to unplanned changes (Pettit, Croxton, and Fiksel, 2019). Therefore, despite the automation of many repetitive decisions, people are considered as the crucial elements of the decision-making process (Jeng, 2018). The systems’ initial forecasts are identified as systems-generated anchors for the decision-makers (Fildes et al., 2009). Such anchors contribute to the overestimation or underestimation errors in the sales forecasts of the individual levels in the chain.

Research on SCM shows that a piece of distorted information from one stage of the supply chain will impact the whole system’s performance. ‘The bullwhip effect’ is an operations management phenomenon that refers to the increased variability in the orders as one goes towards the supply side in the chain. The bullwhip effect introduces several inefficiencies to the supply chains: increased safety stock levels, overproduction, increased expediting costs, and shortages (Croson and Donohue, 2006). As an

identified source of erroneous forecast estimates, the anchoring effect is also one factor contributing to the bullwhip effect (Croson and Donohue, 2006). Therefore, any action to cope with the anchoring effect is favorable for achieving more efficient and sustainable supply chains.

The Impact of Experience and Knowledge on the Anchoring Effect

Research shows conflicting evidence regarding the impact of a person's knowledge and experience on the anchoring effect. Initially, Tversky and Kahneman (1974, p. 1129) stated that the anchoring effect is independent of the person's knowledge. In contrast, several other studies have found knowledgeable people to be less influenced by the anchoring effect (Chapman and Johnson, 1994; Wilson, Houston, Etling, and Brekke, 1996). On the other hand, Englich et al. (2006) observed the anchoring effect both on novice and expert judges in their criminal sentencing decisions. In short, the relationship between experience and the anchoring effect is still not well understood (Teovanović, 2019).

IS, such as ERP and analytics packages, form a crucial part of today's decision-making environment in supply chains. Therefore, employees are often interacting with the same IS for an extended period. In the routinized use of an IS, the initial "feature exploration" behavior evolves into a more outcome-oriented "feature exploitation" use behavior (Benlian, 2015). This argumentation can be extended to suggest that the experienced users may focus more on the design elements that are relevant to the task at hand, rather than struggling with the exploration of the IS from scratch.

Cognitive Biases and Nudging

Nudging is a type of intervention that combats or uses cognitive biases to help people make better decisions. It is defined as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler and Sunstein, 2008, p. 6). This concept is also relevant in the human-computer interaction field since digital environments provide an economic application area for nudges (Caraban et al., 2019; Mirsch et al., 2017). This paper refers to nudge applications in digital choice environments as *digital nudging* (Weinmann et al., 2016, p. 433).

Nudges change behavior by combatting cognitive biases (Mirsch et al., 2017) by fostering reflective thinking (Caraban et al., 2019). Therefore, a digital nudge that is designed appropriately according to the guidelines (Thaler and Sunstein, 2008; Weinmann et al., 2016) can be expected to reduce the negative impact of cognitive biases.

There are different mechanisms of digital nudging (Caraban et al., 2019). This study tests two of them; a social nudge and an educative nudge. A social nudge "steers an individual's choice toward a desired option by exploiting the effects of social influence between individuals"

(Kretzer and Maedche, 2018). On the other hand, an educative nudge aims to increase the users' competencies by providing them with the steps required in solving their decision-making problem (Sunstein, 2016). Both types of nudging help people in their decision-making process without telling them how to solve the problem, thus, requiring them to think critically about the solution.

In this study, we define anchoring correction as the magnitude of the change made by the decision-maker on the initial estimations provided by the IS. Therefore, a greater anchoring correction value indicates a lower anchoring effect in the decision-making process. We define experience as a two-dimensional construct formed by a user's (a) extent of domain-specific experience and (b) extent of IS-specific (i.e., similar applications) use to complete a domain-specific task. We define knowledge as the extent of a person's theoretical understanding of the task that is being done. Considering the importance of a user applying knowledge and experience on the analysis of supply chain problems, we argue that contextual knowledge and experience will reduce the extent of the anchoring effect. Integrating the earlier discussion, the following hypotheses are proposed:

H1: Prior experience has a positive impact on the extent of the anchoring correction

H2: Contextual knowledge has a positive impact on the extent of the anchoring correction

H3: Digital nudging has a positive moderating effect on the relationship between the user's prior experience and the extent of the anchoring correction, such that the relationship is stronger when nudging is present.

H4: Digital nudging has a positive moderating effect on the relationship between the user's contextual knowledge and the extent of the anchoring correction, such that the relationship is stronger when nudging is present.

Continued Use of an IS and Repeated Exposure to Nudges

Users' first interaction with an IS and their continued use behaviors should not be considered equal (De Guinea and Markus, 2009). As users interact with the IS, they become more aware of each IS function's use, and they employ this knowledge to guide their future interactions with the system (Benlian, 2015). On the other hand, repeated use brings the risk of automatic, reflexive use of the system (Ferratt, Prasad, and James Dunne, 2018). We suggest that digital nudging acts as a moderator in the continued use by promoting reflective thinking. The proposed research model is shown in Figure 1 following the hypotheses.

H5: Past anchoring correction has a positive impact on the future anchoring correction after continued IS use.

H6: Digital nudging has a positive moderating effect on the relationship between the user's past anchoring correction and the anchoring correction after continued IS use, such that the relationship is stronger when nudging is present.

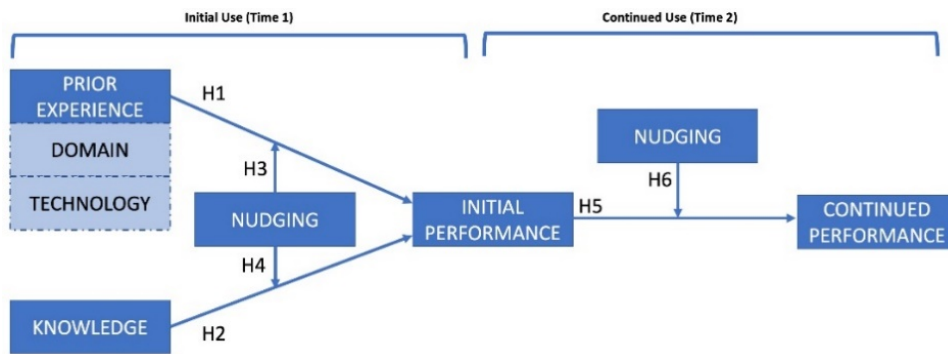


Figure 1. Proposed research model

RESEARCH METHODOLOGY

This study tested two types of digital nudges by entailing a between-subjects experimental design with three conditions: a control group (condition 1), a ‘social’ nudge (condition 2), and an educative nudge (condition 3). A convenience sample of 61 participants was recruited in this study. Participants attended the experiment through an online user experience analysis platform, and a participant’s session lasted approximately one hour. Participants received a gift card from an online retailer in the value of CA\$30 or equivalent in the currency of their country of residence. Participants provided informed consent (verbal and signed) to participate in the experiment, and the experimental protocol was approved a priori by the ethics committee of the authors’ institution.

The experimental task was adapted from Karran et al. (2018), and it involved making SCM decisions on a supply chain simulation game named ERPSim (Léger et al., 2007; Léger, 2006). In this simulation, participants analyzed a company’s previous regional transfer quantity decisions and sales data for the last ten simulated using a dashboard (see Figure 2). Based on their sales forecasts, participants are asked to enter their new regional product transfer quantities on the ERP interface. This interface presented the system’s default forecast estimates to be adjusted by the user. Participants completed this task for two consecutive rounds. Before seeing the dashboard in Figure 2, participants assigned to conditions 2 and 3 saw a digital nudging message in the form of a blog post embedded in the dashboard as a full screen overlay that covers the entire dashboard. Participants also had the option to review the nudging message by clicking on the ‘blog’ icon on the dashboard’s top right corner.

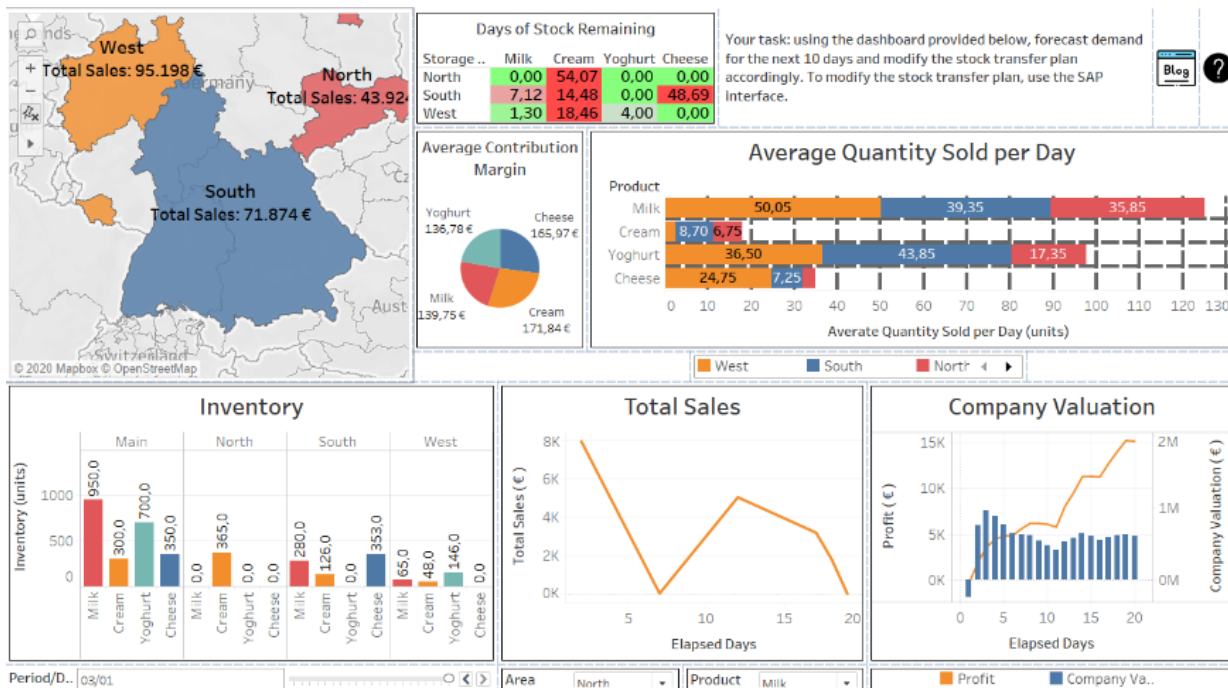


Figure 2. The dashboard used by the participants during the experiment sessions

Operationalization of the Variables

The experience level of the participants was measured with two self-reported instruments: the extent of their experience with an ERP (experience in the domain, five-level Likert scale); whether they had played the simulation game used in the experiment before (experience with the technology). The participants’ contextual knowledge was measured by the count of correct answers in a quiz consisting of seven true/false questions on economics, supply chain management, and forecasting. The measurement model also included two binary variables for the social nudge and educative nudge conditions. Both variables had a value of 0 for the control group. The anchoring effect was operationalized as a reverse measure named ‘anchoring correction.’ Considering the default transfer quantity decisions as $a_{i,j}$, the participant’s decisions to be $b_{i,j}$ and $c_{i,j}$ for the first and second tasks, respectively, anchoring correction (anc) is calculated as:

$$anc(1) = \sqrt{\sum_{i=products} \sum_{j=regions} (b_{i,j} - a_{i,j})^2} \quad (1)$$

$$anc(2) = \sqrt{\sum_{i=products} \sum_{j=regions} (c_{i,j} - b_{i,j})^2} \quad (2)$$

RESULTS

As a first step, a correlation analysis of the variables was done to verify the discriminant validity of the measurements. As expected, two experience measurements (domain and technology experience) had a correlation coefficient of 0.41. Therefore, the interaction term of these measurements was also included in the regression models.

Hypotheses Testing

To test the proposed hypotheses, two independent regression models were tested. The first model considered the participants’ ‘initial use’ of the system (simulation), and the second model focused on their ‘continued use.’ Models were estimated using a data set with 122 observations generated from the 61 participants. The results of the first model are shown in Figure 3.

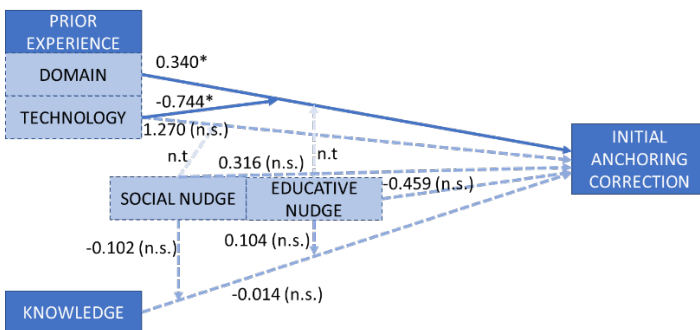


Figure 3. Analysis results of the research model at Time 1 (initial use).

*: p-value <= 0.05, n.s.: non-significant relationship, n.t.: not tested due to multicollinearity.

Dependent variable: $\ln(anc(1) + 1)$

The second model focused on the continued use part of the research model in Figure 1. Results indicate a positive relationship between ‘past anchoring correction’ (anc(1)) and ‘anchoring correction after continued IS use’ (anc(2)) (b=0.876, p<0.000). There was no statistical support for the moderating effect of nudging on that relationship.

A post hoc analysis was conducted to investigate the long-term effects of nudging. This analysis used the model in Figure 3 with ‘anchoring correction after continued IS use’ (anc(2)) as the dependent variable. Results of this analysis indicate a positive effect of domain experience on the anchoring correction (b=0.295, p<0.05), a positive effect of technology expertise on the anchoring correction (b=2.07, p<0.05), a negative interaction effect of these two experience dimensions on the anchoring correction (b=-0.964, p<0.01). Moreover, the results show a positive interaction effect of educative nudging and knowledge on the anchoring correction (b=0.428, p<0.05).

DISCUSSION AND CONCLUDING COMMENTS

In this study, an experiment was conducted to investigate the antecedents of anchoring bias that occur in interactions with an IS. Moreover, the effectiveness of digital nudges in reducing the anchoring effect’s negative impacts was also investigated. An analysis of the initial use of IS indicates that: (1) the decision-makers with higher domain experience are less likely to be influenced by the anchoring effect; (2) users may be more prone to anchoring bias when using a familiar IS tool in a different environment for the first time. This finding highlights the need for an increased focus on the potential decision biases that can occur with the automatic, habitual use of an IS, especially on the effects of habits that are developed in a different environment.

In addition to experience, our post hoc analysis indicates that an educative nudge can increase the user’s performance in continued use if the user possesses contextual knowledge about the decision they are making.

Our study suggests that managers should acknowledge the importance of identifying and understanding the risks associated with the cognitive biases that may occur in the interactions with an IS in the workplace. With this understanding, managers can initiate programs to design appropriate IS tools and digital nudging elements to mitigate these risks. According to our results, as users become more familiar with the used IS, they may become less influenced by the anchoring effect. Therefore, organizations may incorporate more hands-on training activities into their orientation programs to help the new employees have experience with the used IS even before using them in their work life.

ACKNOWLEDGMENTS

This study was financially supported by NSERC and Prompt (Grant number IRCPJ/514835-16) and ERPsims Lab at HEC Montréal.

REFERENCES

- Benlian, A. (2015). IT Feature Use over Time and its Impact on Individual Task Performance. *Journal of the Association for Information Systems*, 16(3), 144–173.
- Caraban, A., Karapanos, E., Gonçalves, D., and Campos, P. (2019). 23 Ways to Nudge: A Review of Technology-Mediated Nudging in Human-Computer Interaction. Glasgow, Scotland Uk: Association for Computing Machinery. Retrieved from <https://doi.org/10.1145/3290605.3300733>
- Chapman, G. B., and Johnson, E. J. (1994). The Limits of Anchoring. *Journal of Behavioral Decision Making*, 7(4), 223–242.
- Croson, R., and Donohue, K. (2006). Behavioral Causes of the Bullwhip Effect and the Observed Value of Inventory Information. *Management Science*, 52(3), 323–336.
- De Guinea, A. O., and Markus, M. L. (2009). Why Break the Habit of a Lifetime? Rethinking the Roles of Intention, Habit, and Emotion in Continuing Information Technology Use. *MIS Quarterly*, 33(3), 433–444.
- Englich, B., Mussweiler, T., and Strack, F. (2006). Playing Dice with Criminal Sentences: The Influence of Irrelevant Anchors on Experts' Judicial Decision Making. *Personality and Social Psychology Bulletin*, 32(2), 188–200.
- Ferratt, T. W., Prasad, J., and James Dunne, E. (2018). Fast and Slow Processes Underlying Theories of Information Technology Use. *Journal of the Association for Information Systems*, 19(1), 1–22.
- Fildes, R., Goodwin, P., Lawrence, M., and Nikolopoulos, K. (2009). Effective Forecasting and Judgmental Adjustments: An Empirical Evaluation and Strategies for Improvement in Supply-Chain Planning. *International Journal of Forecasting*, 25(1), 3–23.
- Hummel, D., and Maedche, A. (2019). How effective is nudging? A quantitative review on the effect sizes and limits of empirical nudging studies. *Journal of Behavioral and Experimental Economics*, 80, 47–58.
- Jeng, S. P. (2018). Enhancing the Creativity of Frontline Employees. *The International Journal of Logistics Management*, 29(1), 387–408.
- Karran, A., Demazure, T., Léger, P.-M., Labonte-LeMoyne, E., Sénécal, S., Fredette, M., and Babin, G. (2019). Towards a Hybrid Passive BCI for the Modulation of Sustained Attention Using EEG and fNIRS. *Frontiers in Human Neuroscience*, 13(393).
- Kretzer, M., and Maedche, A. (2018). Designing Social Nudges for Enterprise Recommendation Agents: An Investigation in the Business Intelligence Systems Context. *Journal of the Association for Information Systems*, 19(12), 4.
- Léger, P., Robert, J., Babin, G., Pellerin, R., and Wagner, B. (2007). ERPsims. *ERPsims Lab (Erpsim. Hec. ca)*, HEC Montreal, Montreal, Qc.
- Léger, P.-M. (2006). Using a Simulation Game Approach to Teach Enterprise Resource Planning Concepts. *Journal of Information Systems Education*, 17, 441–447.
- Mirsch, T., Lehrer, C., and Jung, R. (2017). Digital Nudging: Altering User Behavior in Digital Environments. *Proceedings Der 13. Internationalen Tagung Wirtschaftsinformatik (WI 2017)*, 634–648.
- Niranjan, T. T., Wagner, S. M., and Bode, C. (2011). An Alternative Theoretical Explanation and Empirical Insights into Overordering Behavior in Supply Chains. *Decision Sciences*, 42(4), 859–888.
- Pettit, T. J., Croxton, K. L., and Fiksel, J. (2019). The Evolution of Resilience in Supply Chain Management: A Retrospective on Ensuring Supply Chain Resilience. *Journal of Business Logistics*, 40(1), 56–65.
- Sunstein, C. R. (2016). People Prefer System 2 Nudges (Kind Of). *Duke Law Journal*, 66(121), 121–168.
- Teovanović, P. (2019). Individual Differences in Anchoring Effect: Evidence for the Role of Insufficient Adjustment. *Europe's Journal of Psychology*, 15(1), 8–24.
- Thaler, R. H., and Sunstein, C. R. (2008). *Nudge: Improving Decisions about Health, Wealth, and Happiness*.
- Tversky, A., and Kahneman, D. (1974). Judgment Under Uncertainty: Heuristics and Biases. *Science*, 185(4157), 1124–1131.
- Weinmann, M., Schneider, C., and Brocke, J. vom. (2016). Digital Nudging. *Business and Information Systems Engineering*, 58, 433–436.
- Wilson, T. D., Houston, C. E., Etling, K. M., and Brekke, N. (1996). A New Look at Anchoring Effects: Basic Anchoring and Its Antecedents. *Journal of Experimental Psychology*, 125(4), 387–402.