Cognitive load model in the context of decision-making

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1 Introduction

In an era characterized by data abundance and escalating complexity, the ability to make timely and informed decisions has become a critical factor for organizational success. Yet, between the poles of intuitive action based on complete information and the paralysis that can result from informational gaps, decision-makers often find themselves navigating uncertain terrain. The intricate web of interdependencies between data sources, systems, tasks, and even user roles adds further challenge to this landscape. To manage such complexity, techniques like Dependency and Structure Modelling (DSM) have been employed to visualize and analyze relationships within systems. However, when these dependencies manifest in real-time decision environments, their impact must also be addressed at the interface level. Nowhere is this more evident than in the domain of Business Intelligence (BI) and Analytics, where self-service platforms promise to democratize access to data while also raising new challenges: How can interfaces guide users through uncertainty without overwhelming them? What visual or interactive elements foster not just exploration, but actionable understanding? And how can design support the transition from information retrieval to confident, context-aware decision-making?

As organizations continue to invest in self-service BI tools, the effectiveness of these systems hinges not only on the data they expose, but on the manner in which that data is presented, navigated, and interpreted. Against this backdrop, examining the design of GUIs as cognitive and communicative artifacts is not merely a question of usability. It is a question of strategic enablement. Tversky and Kahneman (1974) discovered systematic biases in human decision-making processes that have both a negative and positive impact on decision-making. For an intuitive quick decision, the bias system is the basis and main assistant, while with a deeper consideration of the factors influencing the decision, biases often have a negative impact by limiting and distorting the analytical process. In this article we propose a model of the dependence of cognitive load on biases with the aim of subsequently quantifying the impact of biases and determining debiasing. We justify the need to include visualization in this model for reducing cognitive load by redistributing cognitive resources. The next modification of the model will allow for a detailed analysis and evaluate the degree of influence of various types of data visualization on debiasing and reducing cognitive load. Human cognitive resources are scarce: limited working memory, limited ability to carry out complex algorithms, or lack of readily-accessible knowledge. In this regard, the issue of reducing cognitive load, or rather redistribution of cognitive resources for processing huge amounts of information in the decision-making process is relevant. Excessive cognitive load leads to the fact that our brain makes decisions based on a subjective system of biases and without accounting many important factors, the analysis of which is necessary for making the right decision. A new research direction "visualization psychology" considers more cognitive aspects in visualization decision-making models that provide significant assistance in the decision-making process and contribute reducing cognitive load (Szafir et al., 2023). To improve visualization research in the context of decision-making, it is crucial to understand the impact of biases on visual attention and system thinking.

This paper investigates how graphical user interfaces support decision-making capabilities across the continuum between full knowledge and information seeking. Its anchor is to analyze the degree of influence of biases on the thinking system in decision-making and to consider the cognitive load model taking into account the influence of biases, and identify opportunities of debiasing and redistribution of cognitive resources using visualization.

2 Review of decision-theoretic models

We considered different decision-theory models (Gabaix, 2019), which are used for description behavioral inattention. It also can be used to discuss the psychology of attention. In these models, attention is understood as the effort expended by a so-called thinking system to analyze some factor in the decision-making process.

Attention is parameterized by a value m:

- $m = 0$ corresponds to zero attention - hence, to a very behavioral model in which the agent relies on a very crude “default” perception of the world

- $m = 1$ to full attention - hence, to the traditional rational model

$0<m<1$ characterize the degree of attention to factors, i.e. the agent’s subjective model of the world.

Most models are variants or generalizations of the model

$$\bar{a}(x) = mx + (1 - m)x^{d}$$

where x is a true value, drawn from a Gaussian distribution $N(x^{d},\ \sigma_x^2),$ where x^{d} is the default value (the prior mean) and variance σ_x^2.

This model describes the average action which the agent takes (a basic example of prior-anchoring and adjustment toward perceived signals in a model with Gaussian noise).

The generalizations of the inattention models (as in Gabaix and Laibson, 2006; Chetty et al., 2009; DellaVigna, 2009; Gabaix, 2014) represent in view

$$u(a, x, m) = u(a, m_1 x_1 + (1 - m_1)x_1^d, \dots, m_n x_n + (1 - m_n)x_n^d)$$

where $m_i \in [0,1]$ is the attention to variable x_i, and where x_i^d is the "default value" for variable i – it is the value that spontaneously comes to mind with no thinking. We do a lot of things and routine actions automatically using System 1 (brushing teeth, washing, using cutlery, driving a car and many more). For example, when learning to drive a car under certain conditions, we perform the necessary actions (turn the steering wheel in case of an obstacle or press the brake pedal for stopping at a red traffic light). So, we can state that if at the beginning of the learning process System 2 is actively used, then after a certain number of actions performed System 1 will automatically issue a basic solution x_i^d.

This is as if x_i is replaced by the subjectively perceived x_i^s:

$$x_i^s := m_i x_i + (1 - m_i)x_i^d$$

When m_i= 0, the agent "does not think about x_i", i.e. replaces x_i by $x_i^s = x_i^d$.

When m_i= 1, she perceives the true value ($x_i^s = x_i$).

When 0 < m_i< 1, she perceives partially the true value, though not fully

Human decision-making depends from the combination of many factors and the characteristic of the situation and bases on the following Systems Thinking [Stanovich (1999) and Kahneman (2003)]:

- System 1 is an intuitive, fast, largely unconscious, and parallel system

- System 2 is a deliberative, slow, relatively conscious, and serial system.

When System 1 is operating, the attention coefficient for a given variable x_i is 0 (m_i=0) under System 2, m_i>0.

At the same time, System 1 unconsciously monitors many variables and decides, which of them is to be provided to System 2 for more detailed analysis (i.e., whether they should satisfy m_i>0).

In working System 2, the human body uses more energy than for work of System 1. For example, it is more difficult for a tired person to make logically decisions that require additional energy expenditure for the work of his System 2 than for a person who is rested and full of strength and energy. Thus, cognitive load implies additional energy expenditure of the human body and, accordingly, its reduction is one of the tasks of cognitive science.

Decision making by system 1 is maximally conditioned by the human's system of biases (such as previous experience, anchoring, confirmation bias, etc.), while the attention coefficient for certain factors is 0. In turn, System 2 also uses biases in decision-making, but to a much lesser extent. Because both systems rely to varying degrees on biases in their operation, we propose to include a bias component in the inattention model.

3 Results

Based on the analysis of attention systems and models, we propose to consider the attention component depending on the degree of influence of biases

$$m = \frac{100 - \beta}{100 + \beta}$$

where β – degree of influence of biases (%) $\beta \in [0; 100\%]$.

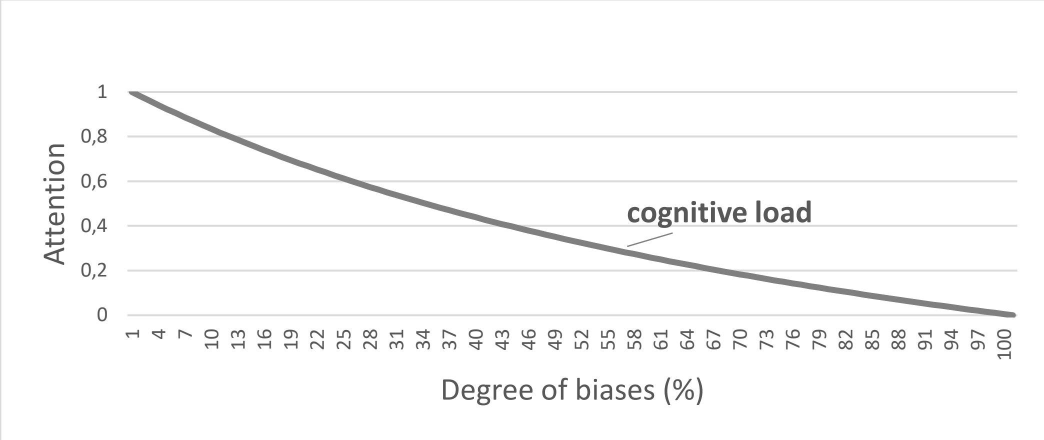

Figure 1. Dependence of attention on the degree of biases.

The derivative of function m characterizes the productivity of System 2

$$m' = \frac{-200}{(100 + \beta)^2}$$

Its value at each point is negative, which indicates a decrease in the productivity of System 2 with an increase in the degree of influence of biases (Figure 2).

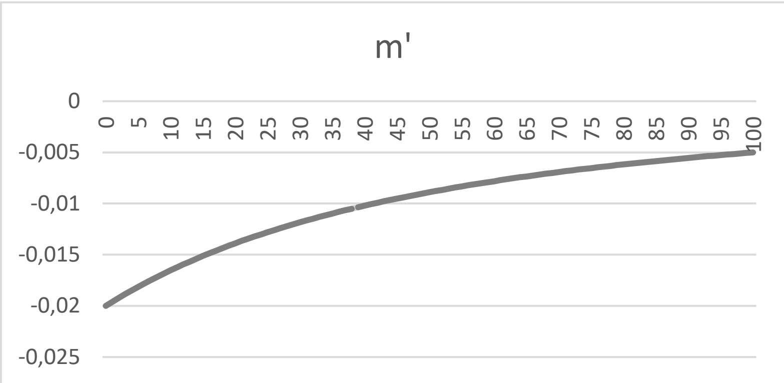

Figure 2. Productivity of System 2.

Kahneman (Kahneman, 2011) states that most decisions stem from intuitive thinking (system 1) rather than rational and calculated thinking (System 2). Making decision using fast System 1 is appropriate when we do not have enough time for analyzing all factors. Slow System 2 requires more time and thinking effort for decision-making.

If System 1 has already decided, then System 2 will not launch even if there is time for an informed decision. As a result, many important factors missed and the decision made is not optimal. In our opinion, it is important to use System 2 in the decision-making, because the result will be a meaningful and logically correct decision with an analysis of all influencing factors and consequences. In this regard, the main task is to activate the analytical process. Thus, special activators need to launch the analytical thinking in the decision-making process and visualization is one of them.

Visualization is one of the levers for attracting attention of our brain and influences on the visual attention. As a result, System 2 activates and meaningful decision-making will occur with a higher attention and a lower degree of influence of biases. In turn, in the decision-making visualization helps to facilitate and accelerate the perception and analysis of various factors x_i, i.e. it promotes lower energy expenditure for the thinking process.

We suppose that the dependence of attention on the degree of influence of biases when using visualization will have the following view

$$m^* = \frac{100 - \beta}{100 + \beta^2}$$

where β – degree of influence of biases (%) $\beta \in [0; 100\%]$.

We suggest that the area between m and m* represents the amount of cognitive load that can potentially be reduced by using visualization i.e. the degree of influence of visualization on cognitive load (Figure 3). On the other hand, this area reflects the potential for debiasing due to visualization.

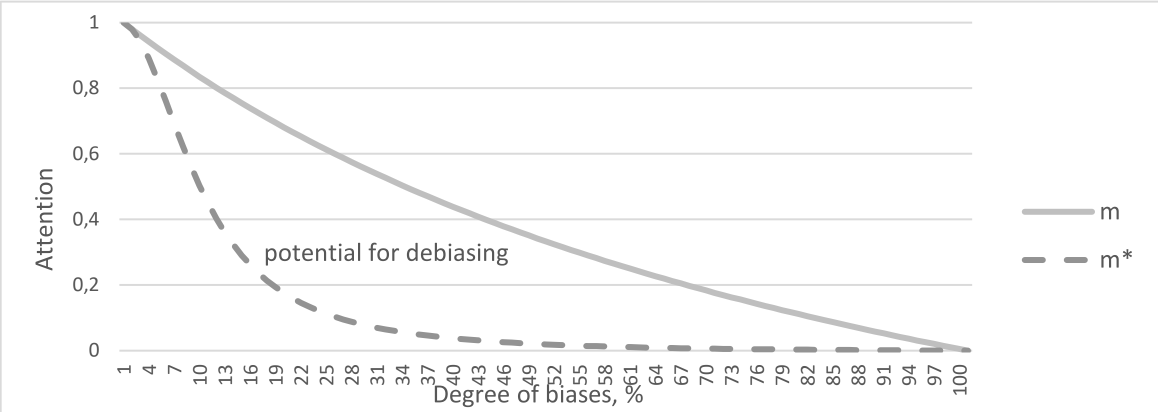

Figure 3. Influence of visualization on the cognitive load.

In our opinion, using visualization helps to increase the productivity of System 2, due to the redistribution of cognitive resources and reduce the cognitive load and the degree of influence of biases.

4 Conclusion

We reviewed a generalized decision-making model and suggested studying cognitive load as a function of the relationship between the attention component and the degree of biases. Our analysis of cognitive load using visualizations in decision-making showed a reduction in cognitive strain due to decreased energy expenditure in cognitive processing and a redistribution of mental resources, along with a reduction in the influence of cognitive biases. Since excessive cognitive load, driven by the need to process large volumes of information, imposes additional energetic demands on the thinking system, there is a clear need to identify mechanisms that enable more efficient cognitive resource allocation. Existing methods for measuring attention (Gabaix, 2019) allow quantification of the degree of bias in the decision-making process and support the evaluation of debiasing efforts. However, the cognitive load model currently lacks a structured representation of interdependencies between attention, bias, visualization, and information complexity. To address this, we propose incorporating Dependency and Structure Modelling (DSM) as a methodological framework to map and analyze these interrelationships. DSM offers a systematic approach to visualize cognitive dependencies and may help to identify leverage points where visualization techniques most effectively reduce load and bias. In future research, it would therefore be advisable to enhance the cognitive load model by integrating both visualization and DSM perspectives, enabling a more structured analysis of debiasing mechanisms across different types of data visualizations and their measurable impact on cognitive effort.

References

Chetty R., Looney A., Kroft K., 2009. Salience and taxation: theory and evidence. The American Economic Review 99 (4), 1145–1177.

Douglas P., 1976. "The Cobb-Douglas Production Function Once Again: Its History, Its Testing, and Some New Empirical Values". Journal of Political Economy. 84(5): 903–916.

DellaVigna S., 2009. Psychology and economics: evidence from the field. Journal of Economic Literature 47 (2), 315–372.

Gabaix X., 2019. Behavioral inattention Handbook of Behavioral Economics - Foundations and Applications, pp. 261-343.

Gabaix X., Laibson D., 2006. Shrouded attributes, consumer myopia, and information suppression in competitive markets. The Quarterly Journal of Economics 121 (2), 505–540

Gabaix X., 2014. A sparsity-based model of bounded rationality. The Quarterly Journal of Economics 129 (4), 1661–1710.

George J.F., Duffy K., Ahuja M., 2000. Countering the anchoring and adjustment bias with decision support systems Decision Support Systems 29 (2000), pp. 195–206

Kahneman D., 2003. Maps of bounded rationality: psychology for behavioral economics. The American Economic Review 93 (5), 1449–1475.

Kahneman D., 2011. Thinking Fast and Slow. Farrar, Straus and Giroux, New York.

Stanovich K. E., 1999. Who Is Rational?: Studies of Individual Differences in Reasoning. Psychology Press.

Szafir D.A., Borgo R., Chen M., Edwards D. J., Fisher B., Padilla L., 2023 Visualization Psychology, Springer Nature Switzerland AG.

Tversky A., Kahneman D., 1974. Judgment under uncertainty: heuristics and biases, Science 185 (1974), pp. 1124-1131

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