

# Behavioural levers to enhance data visualisation.

Jose Vila<sup>1</sup> and Jose L. Cervera-Ferri<sup>2</sup>

1. DevStat chair at University of Valencia. University of Valencia, ERI-CES and IDAL.

2. DevStat

## Abstract

*This paper presents different experiments implemented by the authors, which helps understand critical behavioural insights conditioning the effectivity of visualisation methods. Specifically, the paper surveys recent research on the behavioural patterns in the processing of simple statistical data in different visual formats (Arribas, Comeig, Urbano and Vila 2014; Gomez, Martinez-Moles and Vila 2016; Vila and Gomez 2016) and the impact of gamification (Attanasi, Cervera, Hernandez and Vila 2014) in the understanding and utilisation of quantitative information. The surveyed papers apply different experimental methods (economic experiments, eye tracking techniques, gamification, etc.).*

## 1. Introduction

One of the key implementation areas of the modernisation of official statistics, as recalled in the European Statistical System Vision 2020, is the improvement of dissemination and communication of official statistics, including data visualisation (Cervera-Ferri et al, 2016). Data visualisation aims to aid expert and non-expert users in exploring, understanding, and analysing data through iterative visual exploration. With the development of user-friendly and powerful IT tools for data visualisation and the boom in big data analytics, data visualisation is spreading in a variety of applications, including official statistics. However, besides the technical aspects of preparing data visualisations, it is important to recall that it is not free of human cognitive biases and decision-heuristics. The specific way in which statistical information is presented may have a relevant impact in how the human brain processes the information. Visualisation conditions both the perception process and the decision-making of the users of the information. In this context, visualisation methods can be understood as implicit nudges, in the sense of Thaler and Sunstein (2008). Section 2 surveys four behavioural-economic experimental experiments implemented by the authors, which helps to understand critical behavioural insights conditioning the effectivity of visualisation methods. Section 3 presents a brief discussion and implications of these studies to enhance visualisation from a behavioural viewpoint, especially for official statistics producers.

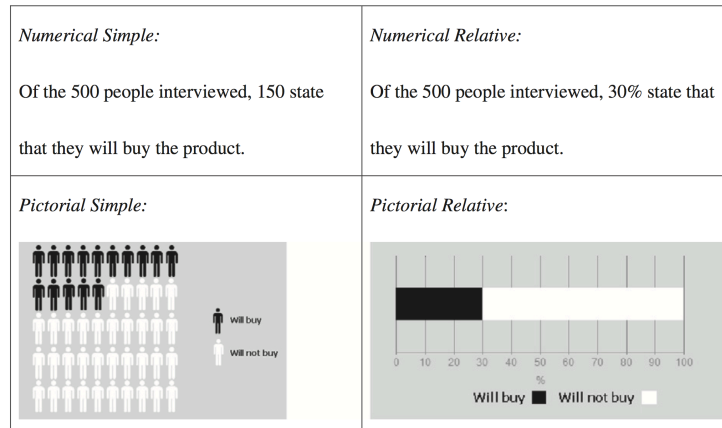
## 2. Review papers

### *2.1. Statistical formats to optimize evidence-based decision making: A behavioral approach*

Arribas, Comeig, Urbano and Vila (2014) assess the impact of alternative dissemination formats in the presentation of quantitative data on both the optimality of decision-making and the time required to perform the decision-making process. An economic

experiment provides the data for this study. The experiment presents statistical information in simple frequencies and relative frequencies using numerical and pictorial representations in the context of different informational environments, as shown in Figure 1.

Figure 1. Example of the statistical formats



The key findings are that statistical information presented in terms of relative frequency formats (both the numerical and pictorial relative formats) give rise to more accurate decision-making than data presented in terms of simple numerical frequencies. When time is the relevant variable, numerical formats lead to a faster interpretation than pictorial ones.

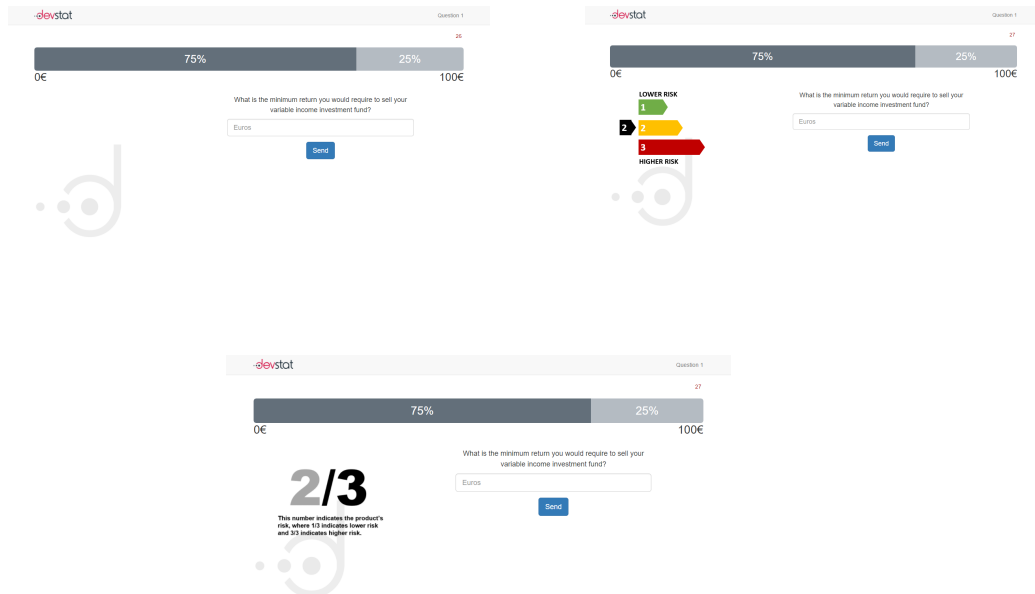
## 2.2. Spanish regulation for labelling of financial products: a behavioral-experimental analysis.

Gomez, Martinez-Moles and Vila (2016) assess the impact of the Spanish Ministry of Economy and Competitiveness' (Board of Executives (BOE) Order ECC/2316/2015. Economy and Competitiveness Ministry, Spain, 2015) new regulation for financial product labelling. They design and conduct an economic experiment where subjects make risky investment decisions under three different treatments (Figure 2): a control group where subjects have only objective information about the key features of the products they must select and two treatment groups introducing visual labels resembling the labels required under the new Spanish regulation.

The results of the experiment, analysed within the framework of rank-dependent utility theory (Wakker, 2010), shown that visual labels do not change the utility function of the subjects, but they do significantly affect the subjects' weighting functions. The introduction of numerical and color-coded labels significantly increases the concavity of the weighting functions and increases pessimism and risk-aversion in cases where the probability of obtaining the best outcome is high. Labels widen the difference between real subjects' behaviour and that of the perfectly rational agents described by expected utility theory. Consequently, these empirical findings raise doubts as to whether the new regulation actually achieves its objectives. The regulation seeks to empower retail investors by enhancing their understanding of financial products. Introducing the visual labels, however, seemingly increases the differences between actual risk levels and the decision weights applied by subjects when making decisions. Moreover, labels increase

investors' pessimism and risk-aversion when the best outcome is likely and fail to alter investors' risk-aversion when the worst outcome is likely.

Figure 2. Framings applied to present the information of a risky event

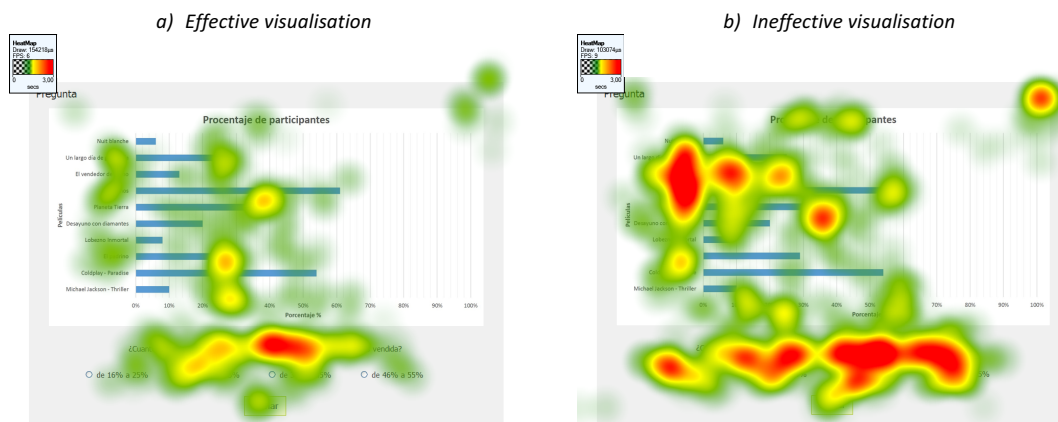


### 2.3. Extracting business information from graphs: An eye tracking experiment.

Although data visualization through basic statistical graphs is a common practice to support evidence-driven business decision making, Vila and Gomez (2016) show that the extraction of relevant information from such graphs may become a difficult task even in very simple situations. This paper applies the methodology of experimental economics to the analysis of graph reading and processing to extract underlying information. Specifically, they design and implement a behavioural-economic experiment whose baseline treatment includes graphical and numerical information. The experiment applies eye-tracking technology to uncover subtle cognitive processing stages that are otherwise difficult to observe in visualization evaluation studies.

The experiment presented information in a bar graph and asked the participant to answer a question related to the information in the graph. There was an economic incentive for right answer. The main result of the paper is the identification of two different visualisation patterns, linked to the level of understanding of the information and the effectivity in decision-making: visualization patterns of the 43.3% of subjects who answer the question properly (for short, effective visualization patterns) and of 56.7% who are not able to provide the right answer (for short, ineffective visualization patterns). The key feature distinguishing both patterns is that subjects responding the question properly focused their attention in a small subset of relevant and informative parts of the graph, whereas the others spare their attention in a wider set of areas, some of them completely irrelevant to answer the proposed question, as shown in the heat maps of Figure 3.

Figure 3. Heat maps showing the effective and ineffective visualisation patterns. Colour represent the eyes fixation time at each point of the graph, from light green (shortest fixation time) to intense red (longest fixation time).



The results of the experiment provide an empirical foundation for two key guidelines to improve chart presentation. Firstly, the experiment shows that those subjects who are not able to answer the question properly seem to have difficulties to discriminate relevant from irrelevant elements. The application of graphical framings that (1) stress the key pieces of information of the chart (for instance, the top of each bar) and (2) avoid highlighting other elements in the graph that provide no information and could distract the subjects during the scanning process could be useful to increase the effectiveness of data visualization.

#### 2.4. Can expertise close the experience-description gap?

In a framework of Prospect Theory (Kahneman and Tversky, 1979), Attanasi, Cervera, Hernandez and Vila (2014) designed and implemented a behavioural-economic experiment to estimate the weighting function. Following Abdellaoui, L'Haridon and Paraschiv (2011), subjects disclose their willingness to pay for a prospect (lotteries) under two alternative treatments. In the first one, named as "description treatment", the information of the lottery is presented in an explicit and objective way, providing the numeric value of the possible outcome and their actual probabilities. In second treatment, named as "gamified treatment", subjects are not provided with explicit information on outcomes and probabilities and are invited to play a game where they can observe a sample of outcomes of realisations of the lotteries. The experiment was replicated twice: once with an expert groups including participants with a high statistical background (staff of Eurostat, National Statistical Offices, etc.) and a second time with a non-expert groups including participants with no quantitative background. This experimental design provided with four alternative estimations of the weighting function, as shown in Figure 4.

Figure 4. Estimation of the weighting function for the non-expert and expert groups.

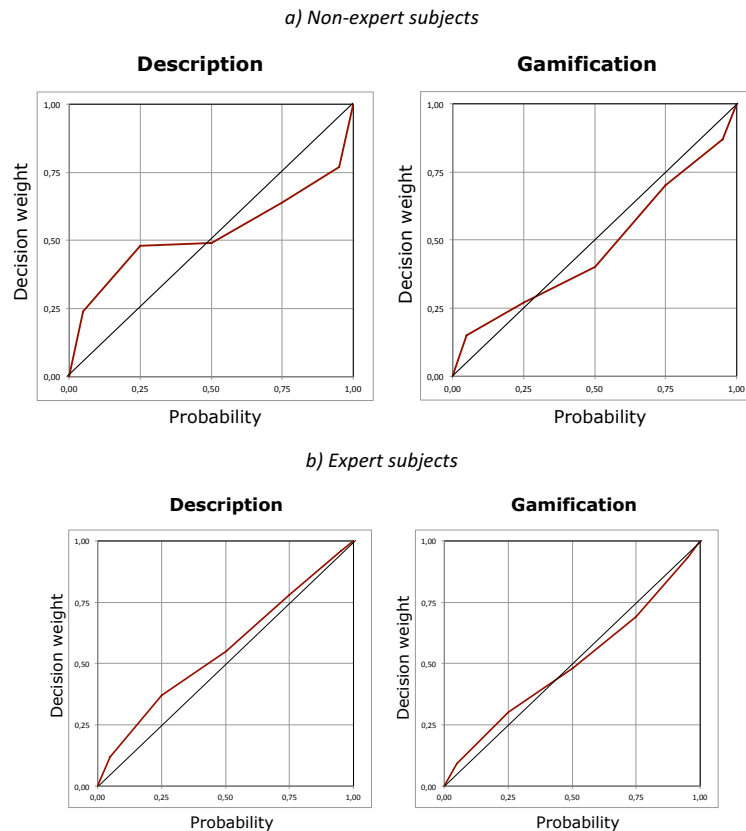


Figure 4 shows that, for non-expert users, gamification enhances the understanding of the information and improves its use for decision-making. However, for expert users, gamification does not enhance understanding and can be even misleading. In other words, the experiment shows that, gamification can reduce cognitive biases in the process of statistical information in specific segments of users.

### 3. Conclusions

The four behavioural-economic experiments reviewed in this paper show that the role of visualisation goes far beyond than just make clearer the quantitative information. Visualisation is also able to activate cognitive levers and condition decision heuristics. Since visualisation impacts the understanding of information and is able to nudge decision-making in an automatic and unconscious way (i. e. through System 1 of reasoning, as defined in Kahneman, 2011), behavioural economic experiments provide with an effective tool to analyse the impact of alternative visualisation formats and to define the optimal visualisation technique in each decision context and for each user persona. Until now, the application of this behavioural-economic experimental methods to improve data dissemination, and specifically data visualisation for statistical dissemination, is scarce.

In particular, the fundamental role of official statistics in the provision of evidence for policy design and evaluation implies that better understanding is needed, through the research on cognitive aspects, of the impact of data visualisation on (1) the awareness about existing statistical information (2) the understanding of complex issues (data

literacy) by policy-makers (3) the effective use of statistics in the design and evaluation of policy instruments.

In the case of business registers and business statistics, the following research avenues can be suggested:

- Impact of visualisation on the identification by analysts of trends in the business sector (e.g. emergence of economic activities, value-chain linkages between sectors);
- Impact of geographic visualisation of the business activity for the design of local development policies (e.g. business clusters, Smart Specialisation strategies, local employment policies);
- Impact of visualisation of business statistics and registers on business managers to identify opportunities (e.g. location of establishments, design of supply routes);
- Impact of visualisation by job-searchers (students, unemployed, prospective entrepreneurs) of business statistics and registers for the personal strategy for job search and skill acquisition.

In summary, there is a critical research gap to be filled and its innovation potential to be levered for dissemination and official statistics and visualisation of information to improve decision-making in both policy-making and business development.

#### References:

Abdellaoui, M., L'Haridon, O., & Paraschiv, C. (2011). Experienced vs. described uncertainty: Do we need two prospect theory specifications?. *Management Science*, 57(10), 1879-1895.

Arribas, I., Comeig, I., Urbano, A., and Vila, J. (2014). Statistical formats to optimize evidence-based decision making: A behavioral approach. *Journal of Business Research*, 67(5), 790-794.

Attanasi, G., Cervera, J., Hernandez, P., and Vila, J. (2014). Can expertise close the experience-description gap?. ERICES working paper.

Cervera,-Ferri, J.L., De Jonge, E., V. Kasperuniene, V. Dinculescu, P. Votta (2016). ESS Visualisation Workshop – Valencia 2016. Summary and conclusions.  
[http://ec.europa.eu/eurostat/cros/system/files/technical\\_workshop\\_report\\_valencia2016\\_final3006.pdf\\_en](http://ec.europa.eu/eurostat/cros/system/files/technical_workshop_report_valencia2016_final3006.pdf_en)

Gómez, Y., Martínez-Molés, V., and Vila, J. (2016). Spanish regulation for labelling of financial products: a behavioral-experimental analysis. *Economia Politica*, 33(3), 355-378.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the econometric society*, 263-291.

Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan.

Thaler, Richard H.; Sunstein, Cass R. (2008). *Nudge: Improving Decisions about Health, Wealth, and Happiness*. Yale University Press.

Vila, J., & Gomez, Y. (2016). Extracting business information from graphs: An eye tracking experiment. *Journal of Business Research*, 69(5), 1741-1746.

Wakker, P. P. (2010). *Prospect theory: For risk and ambiguity*. Cambridge university press.