Graphical Displays in Eco-Feedback: A Cognitive Approach

Rebecca Ford[1,*] and Beth Karlin[2,*]

[1] Centre for Sustainability, University of Otago,
PO Box 56, Dunedin, 9054, New Zealand
rebecca.ford@otago.ac.nz
[2] School of Social Ecology, University of California, Irvine,
202 Social Ecology I, Irvine, California, 92697-7075
bkarlin@uci.edu
[*] Both authors contributed equally to this work.

Abstract. Psychological research indicates that the provision of feedback is a key element in reinforcing and/or changing behavior, and whilst results from empirical studies on eco-feedback are positive, variation in findings suggests that its effectiveness may depend on both what information is provided and how it is presented. The design of graphical displays is an important component, but past display research has been primarily qualitative and exploratory. This paper introduces and tests a cognitive model of visual information processing applied to eco-feedback to evaluate differences in interpretation and preference between images. Participants were shown images that varied by number of data points as well as display features and were asked to interpret the images and report on image usability. Findings support the cognitive model, suggesting that eco-feedback displays appear to be more successful when they: (1) contain fewer data points; (2) employ data chunking; and/or (3) include pictures.

Keywords: Eco-feedback; Graphical Display; Information Overload; Psychology; User Interface.

1 Introduction

As electricity infrastructure moves towards smart grid systems, smart meters with the ability to measure and deliver energy use data in real-time are being installed across Europe and North America [1]. Coinciding with this new potential, research surrounding eco-feedback is becoming more salient in the HCI literature [2]. Eco-feedback has been defined as “technology that provides feedback on individual or group behaviors with a goal of reducing environmental impact” [2 p1999]. When applied to home electricity use, eco-feedback provides users with greater understanding and control over their energy use by making it more visible, and enabling links to be made between actions and impacts [3]. As such, feedback is being increasingly promoted as an effective and cost-efficient behavior change strategy for energy reductions compared to other intervention strategies [3], [4].

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Over 100 studies on the use of residential energy feedback have been conducted since the 1970s; reviews of this literature suggest that effective feedback is frequent, clear and simple, comparative, appliance-specific, interactive and technology-driven [5], [6]. Although savings do seem to increase as these factors are incorporated, the range of savings varies dramatically across studies [3]. Some variation may be attributed to differences in samples and methodology, but it is also likely that this variation is due to differences in *how* eco-feedback is presented to users.

There has been limited work to date investigating responses to different eco-feedback displays; most studies analyze the effectiveness of a single type of feedback [7]. Further, the effectiveness of eco-feedback in field studies tends to be measured by observed reductions in energy consumption with little attention given to the interpretation or perceived usability of eco-feedback displays. [8]. Given the variation in effects across studies, investigating the design features within eco-feedback displays and their effects on interpretation and usability could help understand what constitute a "good display" [7]. Although eco-feedback research in HCI has largely focused on the design process and the production of eco-feedback artifacts, drawing on psychological theory has great potential for leveraging key mechanisms to improve displays and maximize effectiveness [2], [9].

One of the most commonly reported visualization designs used in residential energy feedback is the bar chart, which show viewers a breakdown of their historic total-energy consumption [3], with the increasing abundance of smart meters enabling the provision of daily and/or hourly data [1]. With the growing capacity to provide feedback disaggregated by appliance as well [10], the quantity of available information could increase to millions of data points per year.

Although technological improvements enable this quantity of energy data to be collected and processed, it is ultimately up to the consumer to use (or not use) this data to change their behaviour. Therefore, it is important to understand some of the key attributes that govern the way users respond to information provided by eco-feedback, as this may impact potential energy savings induced by the data.

This paper presents the results of an online experimental study investigating the effect of visual display elements on user response to eco-feedback, using a theoretically grounded cognitive approach to information processing. The following sections introduce a cognitive model of information processing, apply this model to eco-feedback, and make suggestions for both improved design and further study of eco-feedback displays based on study findings.

2 Literature Review

Quantitative information, like that provided by eco-feedback, can be presented in many visual display formats, including graphs, charts, maps, and diagrams [11]. A good display should be unambiguous, with its meaning and interpretation immediately obvious; lack of clarity in interpretation can decrease the effectiveness of the message [11]. Understanding the psychology of visual information processing can aid in identifying attributes of visual displays that may assist or impede interpretation.

A basic cognitive model of visual information processing includes three elements: perception, short-term memory, and long-term memory [12]. Perception organizes the image into logical parts, short-term memory holds specific information in mind, and long-term memory provides connections to previously stored information to make sense of the image. Therefore visualization design should take into consideration image legibility, the quantity of information to be assimilated, and the ability to integrate past experience.

2.1 Cognitive Model of Visual Processing

The amount of information presented and the visual attention required to process this information is closely tied to image interpretability. As the information content of a display increases, so does performance, up to a certain point. Beyond this point, people find it hard to identify relevant information, and their decision accuracy is reduced. This occurs when the Information Processing Requirements (IPR) of the data exceed the Information Processing Capacity (IPC) of the individual [13].

Theories of visual attention have been grouped into three categories: object-based, discrimination-based, and space-based [14]. Object-based theories, the most prevalent of the three, refer to the number of objects that can be stored in the short-term memory simultaneously [14]. The span of this immediate memory is thought to be somewhere between four and seven groups [11], [15]. Similarly, the span of absolute judgment, which refers to the "limit to the accuracy with which we can identify absolutely the magnitude of a uni-dimensional stimulus variable" [15] has also been found to hover around seven items.

Discrimination-based theories refer to that the number of distinctions, or discriminations, that can be processed in the visualization. Miller [15] claimed that the seven-item limitation might be increased by breaking information into either multiple dimensions or sequences of smaller chunks of information (data chunking). Examples include phone numbers and credit card numbers, which are generally chunked, or split, into smaller groups of numbers for easier memorization and recall.

Space-based theories refer to the spatial area from which an individual can pick up information. Eriksen & Hoffman [16] propose that attention can only focus on and fully process information from a particular area of visual space. Therefore, the ability to see several things at once may be limited not only by the number of data points but also by the spatial area use to display them.

2.2 Interpretation of Visual Information

Drawing from the resources of short-term memory, the interpretation of visual information involves connecting the perceived images and/or data to previous information about the topic being presented. Viewers derive meaning from a visualization based on their reasons for using the information and their background knowledge about the information presented [17]. This background knowledge includes organized groupings of information stored in long-term memory called schemata. People have schemata about events, objects, actions, and concepts, and use them to decrease processing requirements of new information, by making links between existing schemata and new information assimilated to short-term memory.

The use of pictures can assist the viewer in making these links. Text information is remembered better when presented in conjunction with pictures [18]. Pictures serve up to five functions in text processing: decoration, representation, organization, interpretation, and transformation [19]. Decoration serves to increase interest in the text through making it more attractive. Representation serves to reinforce the text by overlapping the same idea in image form. Organization serves to add structure to the text or connect various textual passages. Interpretation serves to help aid in the understanding of complex or vague text. And transformation serves to enhance memorability of text by translating it into a picture form that is easier to remember. Decoration and representation are not predicted to improve cognitive processing, but organization, interpretation, and transformation should all lead to increases.

3 Current Study

A cognitive model of visual processing illustrates how significantly the design of eco-feedback displays can affect users' subsequent ability to perceive and interpret the energy information depicted; "an effective display must be easily encoded and comprehended by the visual-information processing system" [11 p192]. As such, the study presented in this paper has three goals. The first goal is to test the hypothesis that perceived ease of use and interpretability of eco-feedback displays will decrease when the number of data points provided to users exceeds the users IPC of around 7. The second goal is to test the hypothesis that perceptual assistance in the form of data chunking should attenuate the hypothesized decrease in perceived ease of use and interpretability for large data sets, but not for small ones. The third goal is to investigate the use of perceptual assistance in the form of pictures in eco-feedback displays. Although pictures can help people perceive and interpret information, they also add to the total quantity of data; suggesting that pictures may improve ease of use and interpretability, so long as the number of data points remain below the users' IPC.

3.1 Participants and Procedure

Data were gathered through an online survey in June 2012. 1470 US residents were recruited using Amazon Mechanical Turk for a 10-15 minute survey and were paid $0.31 for completion. Those who completed the survey in less than 5 minutes or answered a trick question incorrectly were removed, leaving 1103 responses. The final sample was 47% male and 78% white with an average age of 31 and income of $52,940. 46% were homeowners and the average home occupancy was 2.9.

3.2 Measures

Participants were randomly shown either one of the four images illustrated in Figure 1 or one of the four images illustrated in Figure 2. The images in Figure 1 show energy use by time over either a week (7 data) or a month (31 data points), and perceptual assistance is provided in the form of data chunking (e.g., different colored bars for weekdays and weekends). The images in Figure 2 show energy use by appliance; the cost to run either 5 or 10 appliances for a week is depicted, and perceptual assistance is provided through the addition of pictures illustrating this cost.

To assess perceived ease of use of the images, the four-item UPscale "ease of use" subscale [20] was used. Table 1 shows mean scores, standard deviations, and reliability of the scale for both the use by time and use by appliance image groups. To assess actual interpretability of the images, participants were asked a series of questions to measure their ability to read the data, read between the data, and read beyond the data [21]. The resulting variable, *interpretation*, represents the proportion of questions that the participant answered correctly. Table 2 shows mean scores, standard deviations and example questions for both images. Numeracy levels were calculated using three questions [22] and variations in interpretation due to levels of numeracy were removed before reporting.

Table 1: Means, standard deviations, and reliability for the UPscale "ease of use" subscale [20]

	Use by time images	Use by appliance images
Ease of use	M=3.97, SD=0.855, α=0.847	M=4.20, SD=0.687, α=0.820
• I think the image is difficult to understand. • A person would need to learn a lot in order to understand this image. • I feel very confident interpreting the information in this image. • I am able to get the information I need easily.		

Note: responses are scored on a Likert scale from "strongly agree" to "strongly disagree"

Table 2: Means and standard deviations for questions used to assess actual interpretation

	Use by time images	Use by appliance images
Interpretation	M=0.73, SD=0.145	M=0.85, SD=0.253
Read the data Example:	M=0.98, SD=0.113 During which time period did the household user more than $1.00 of electricity?	M=0.89, SD=0.277 Which of these appliances cost the most money to run last week?
Read between data Example:	M=0.92, SD=0.211 What is the difference in energy used between Friday 16th March and Saturday 17th March?	M=0.88, SD=0.283 What is the difference in cost between the PC and the fridge?
Read beyond data Example:	M=0.28, SD=0.315 During which part of the week is more energy used?	M=0.79, SD=0.341 If last week is typical, how much will the fridge cost to run a year?

Note: all questions are multiple choice with four possible responses

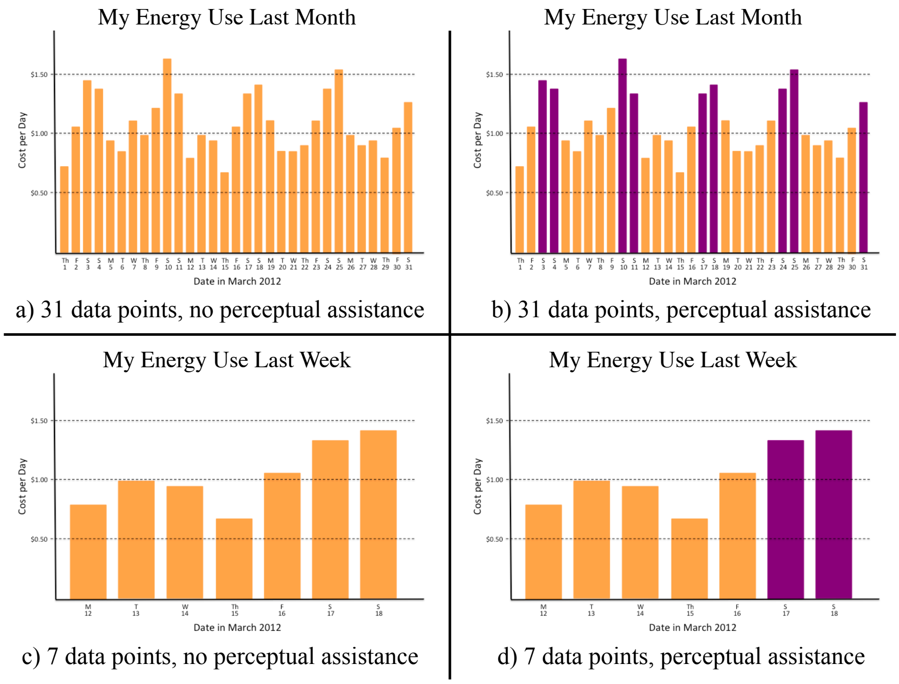

Figure 1: Images showing energy use by time

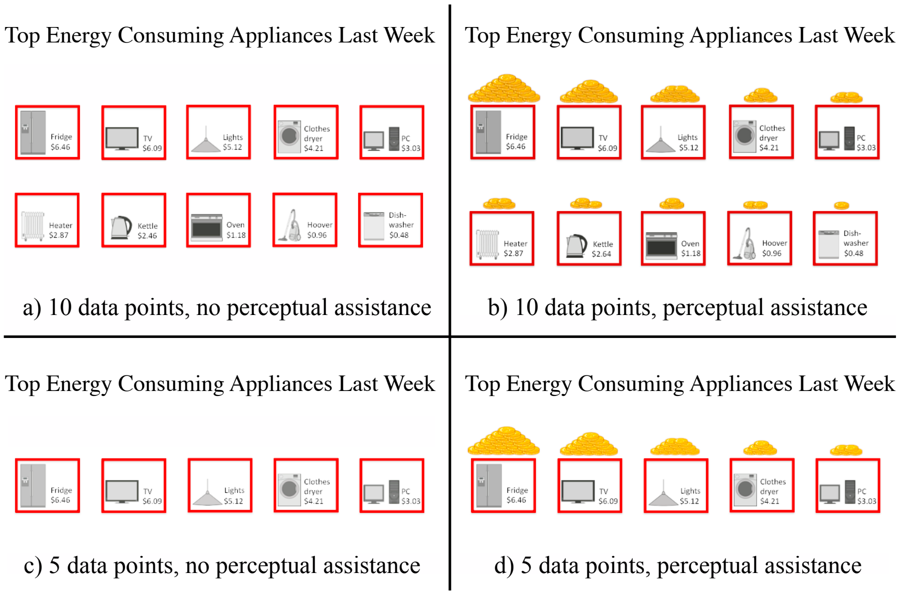

Figure 2: Images showing energy use by appliance

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3.3 Results

Use by Time Visualizations. A two-way analysis of variance (ANOVA) for ease of use yielded a main effect for information density, $F(1,572)=8.321$, $p=.004$, such that ease of use was higher for the weekly (M=3.07, SD=.768) than for the monthly use graph (M=3.86, SD=.926). Perceptual assistance was not significant, $F(1, 572)=1.704$, $p=.192$, nor was the interaction effect $F(1, 572)=.203$, $p=.652$.

A two-way ANOVA for interpretability yielded a main effect for information density, $F(1,572)=16.676$, $p<.001$, such that the accuracy of interpretation was higher for the monthly (M=.753, SD=.146) than for the weekly use graph (M=.703, SD=.140). The main effect of perceptual assistance was not significant, $F(1, 572)=.014$, $p=.908$. The interaction effect was marginally significant, $F(1, 572)=3.250$, $p=.072$. Post hoc analyses using Tukey's HSD indicated that those who received perceptual assistance interpreted the monthly energy use image more accurately than those who did not. However, those who saw the weekly energy use graph *without* perceptual assistance did better than those with perceptual assistance.

These findings, shown in Figure 3, indicate that monthly energy use graphs are perceived as less easy to use but result in more accurate interpretation of the data. Perceptual assistance was found to have no impact on ease of use, but did positively impact interpretability for larger data sets.

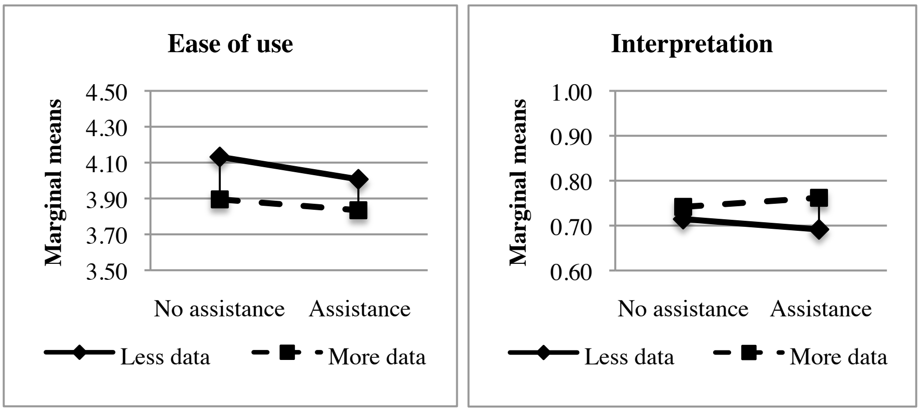

Figure 3: Perceived ease of use and actual interpretability of use by time images

Use by Appliance Visualizations. A two-way ANOVA for ease of use yielded a main effect for perceptual assistance, $F(1,523)=6.311$, $p=.012$, such that ease of use was higher for those with assistance (M=4.27, SD=.619) than for those without (M=4.11, SD=.750). Information density and interaction effects were not significant; $F(1, 523)=1.844$, $p=.175$ and $F(1, 523)=1.714$, $p=.191$ respectively.

A two-way ANOVA for interpretability yielded a main effect for information density, $F(1,523)=63.995$, $p<.001$ and perceptual assistance, $F(1,523)=97.413$, $p<.001$, such that interpretability was higher for people who saw more appliances (M=.918, SD=.144) than those who saw fewer (M=.786, SD=.316), and for those who received perceptual assistance (M=.935, SD=.119) than those who did not (M=.758, SD=.324). The interaction effect was also significant $F(1, 523)=60.320$, $p<.001$. Post hoc analyses using Tukey's HSD indicated that people who saw fewer appliance *with* perceptual assistance more accurately interpreted the visualization than those *without*. Perceptual assistance did not change interpretability of the larger data set, and no significant differences existed between the two data sets *with* perceptual assistance.

These findings, shown in Figure 4, indicate that visualizations containing fewer appliances are perceived to be easier to use, but are in fact harder to interpret *unless* perceptual assistance is also provided. When perceptual assistance is provided there is no difference in interpretability between images with 5 appliances and 10 appliances.

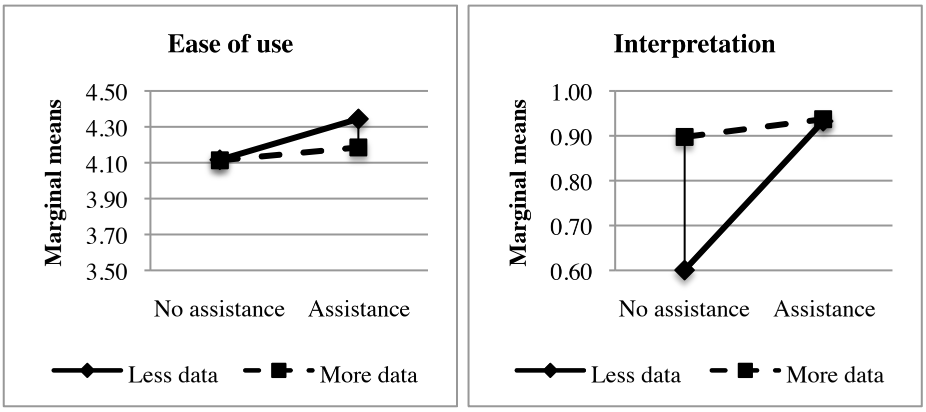

Figure 4: Perceived ease of use and actual interpretability of use by appliance images

4 Discussion

This paper set out to test the effect of information density and perceptual assistance on perceived ease of use and interpretability of eco-feedback displays. The first hypothesis was that that both ease of use and interpretability will decrease when the number of data points provided to users exceeds the users' Information Processing Capacity (IPC) of around 7. These results support the hypothesis for ease of use when comparing monthly energy use graphs (31 data points) to weekly energy use graphs (7 data points). However, analysis of both image sets indicate that this hypothesis does not hold for interpretation; as the number of data points increases there is a corresponding *increase* in ability to accurately interpret the information.

The second goal was to test the effect of perceptual assistance provided by data chunking. The results presented here support the hypothesis that data chunking increases the interpretability of visualizations of large data sets but not small ones; in fact, data chunking reduced the interpretability of the smaller data set (weekly energy use graph). However, there is no evidence in this study that data chunking increases perceived ease of use for either large or small data sets.

The third goal was to investigate the effect of perceptual assistance provided by the inclusion of pictures. Results show that the addition of pictures increase perceived ease of use, more so for smaller data sets than larger ones (though not significantly).

They also significantly increased interpretability for smaller data sets but not larger ones. This suggests that the additional amount of data provided to users by adding pictures is effective, but only when the total amount of data is below the users Information Processing Capacity (IPC).

4.1 Implications for Eco-Feedback Displays

The results suggest support for a cognitive model of visual information processing, and have several implications on the design and study of eco-feedback displays. As larger data sets with increasing granularity in terms of both time and end use (i.e. appliances) become available to consumers, small changes in the way in which this data is presented may significantly impact its subsequent interpretation and use.

When providing use by time data, practitioners may be more successful designing displays that implement data chunking to help viewers make discriminations within the data set. Although this does not alter user perceptions, it does result in a more accurate interpretation and understanding of energy consumption. When providing appliance specific feedback, the use of pictures to assist data interpretation may be beneficial for both ease of use and interpretability.

The results also suggest that displays should be designed to suit specific goals; images perceived as easier to use are not necessarily the same as those enabling the most accurate interpretation. If the intention is to increase understanding about energy use, a display that leads to greatest levels of interpretation is preferable. However, as feedback relies on continued user engagement on a voluntary basis, displays perceived as easier to use may be more successful than those imparting the most accurate knowledge. Further work investigating these hypotheses on actual behaviour change and continued engagement over time is recommended.

4.2 Conclusion

As eco-feedback continues to grow in popularity, so will the importance of designing displays that are legible, pleasing, and interpretable to users. Although this study builds upon decades of basic cognitive research, its application in HCI and in eco-feedback is novel and vitally important. This approach is both theoretically grounded and empirical in nature, providing replicable insights for future design.

Results suggest that both ease of use and interpretability of displays are linked to the capacity limits of the short-term memory, and to the mechanisms by which the visualization prompts links between short-term memory and existing schemata. Eco-feedback displays appear to be more successful when they: (1) contain fewer data points; (2) employ data chunking; and/or (3) include pictures.

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References

1. Darby, S.: Smart metering: what potential for householder engagement? Building Research & Information, 38(5), 442--457 (2010)
2. Froehlich, J., Findlater, L. Landay, J.: The Design of Eco-Feedback Technology. In: Proc. CHI'10. pp. 1999--2008. ACM Press (2010)
3. Ehrhardt-Martinez, K., Donnelly, K. A., Laitner, J. A.: Advanced metering initiatives and residential feedback programs: a meta-review for household electricity-saving opportunities. Technical report, ACEEE (2010)
4. Allcott, H., Mullainathan, S.: Behavior and Energy Policy. Science, 327, 1204--1205 (2010)
5. EPRI Residential Electricity Use Feedback: A Research Synthesis and Economic Framework. Technical report, EPRI (2009)
6. Fischer, C.: Feedback on household electricity consumption: a tool for saving energy? Energy Efficiency, 1, 79--104 (2008)
7. Fitzpatrick, G., Smith, G.: Technology-Enabled Feedback on Domestic Energy Consumption: Articulating a set of design concerns. Pervasive Computing, 8, 37--44 (2009)
8. Pierce, J., Fan, C., Lomas, D., Marcu, G., Paulos, E.: Some consideration on the (in)effectiveness of residential energy feedback systems. In: Proc DIS '10. pp. 244--247 . ACM Press (2010)
9. Strengers, Y.: Designing Eco-Feedback Systems for Everyday Life. Proc CHI'11. pp. 2135--2144. ACM Press (2011)
10. Froehlich, J., Larson, E., Gupta, S., Cohn, G., Reynolds, M. S., Patel, S. N.: Disaggregated End-Use Energy Sensing for the Smart Grid. Pervasive Computing, 10, 28--39 (2011)
11. Kosslyn, S. M.: Understanding charts and graphs. Applied Cognitive Psychology, 3, 185--225 (1989)
12. Spoehr, K.T., & Lehmkuhle, S.W.: Visual Information Processing. W.H. Freeman, San Francisco (1982)
13. Eppler, M. J., Mengis, J.: The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines. Information Society, 20, 325--344 (2004)
14. Duncan, J.: Selective attention and the organization of visual information. Journal of Experimental Psychology: General, 3, 501--517 (1984).
15. Miller, G. A.: The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information. The Psychological Review, 63, 81--97 (1956)
16. Eriksen, C. W. Hoffman, J. E.: The extent of processing of noise elements during selective encoding from visual displays. Perception & Psychophysics, 14, 155--160 (1973)
17. Redish, J. C.: Reading to learn to do. IEEE Transactions on Professional Communication, 32, 289--0293 (1989)
18. Levie, W. H., Lentz, R.: Effects of text illustrations: A review of research. Education Community Technology Journal, 30, 195-–232 (1982)
19. Levin, J. R.: On functions of pictures in prose. In Pirozzolo, F. J., Wittrock, M. C. (eds.), Neuropsychological and Cognitive Processes in Reading, Academic Press, New York, 203--228 (1981)
20. Karlin, B., Ford, R. The Usability Perception Scale (UPscale): A measure for evaluating feedback displays. In: Proc HCII’13. Springer (2013)
21. Galesic, M., Garcia-Retamero, R.: Graph literacy: A Cross-Cultural Comparison. Medical Decision Making: An International Journal of the Society for Medical Decision Making 31, 444--457 (2011)
22. Schwartz, L. M., Woloshin, S., Black, W. C., Welch, H. G.: The role of numeracy in understanding the benefit of screening mammography. Annals of Internal Medicine, 127 966--972 (1997)

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