A Comprehensive Study on the Aesthetics of Electricity Consumption Graphs on Appliance Level and their Triggering Potential on Human Emotions

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ABSTRACT

Sustainable energy consumption behavior in households is a decisive factor in contributing to climate protection. To provide residents comprehensible insights into their household's energy consumption data, nonintrusive load monitoring on appliance level can assist. To give consumers a simple and comprehensible overview of their consumption data, which they also find aesthetically pleasing, in this work a two-stage experimental design is used to compare the perceived aesthetic appearance of different types of electricity consumption graphs on appliance level (aggregated or time-dependent) and their triggered emotion. First, a representative survey covers the general aesthetics assessment in a 2x3 mixed factorial design. Second, an in-depth eye-tracking and facial expression investigation is used to track and quantify emotions on different electricity consumption graphs on application level and their perceived advantages and disadvantages. The main results provide comprehensive insights into the aesthetics of electricity consumption visualizations to trigger positive emotions, in particular users' preferences for simple and conventional graphs like bar charts.

KEYWORDS

Energy Data Visualization, Aesthetics, Emotions, Eye-Tracking, Facial Expression Analysis, Consumption Graphs

INTRODUCTION

Sustainable energy consumption behavior in households is a decisive factor in contributing to climate protection. However, consumers often lack knowledge regarding their energy consumption. One approach to provide them a comprehensible overview on their household's energy consumption data on appliance level is nonintrusive load monitoring. However, there is no explicit guideline as to which graph type should be used for such monitoring tools. On the one hand, electricity consumption graphs should be simple to understand, especially as consumers often try to break down energy data to single appliances. On the other hand, electricity consumption graphs should be designed in an appealing and aesthetic way to motivate consumers to use them actively. Since emotions play a key role in communication, it is essential to examine consumers' emotions on electricity consumption graphs on appliance level with the aim to provide them a positively associated tool and foster an energy efficient behavior [1].

Therefore, this paper aims at mapping the corresponding emotions to common illustrations of electricity consumption. More specifically, it is investigated how different visualizations of

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energy should be designed in order to evoke the most positive emotions among potential users.

Previous research has already investigated various forms of home energy management systems (HEMS) and energy data visualizations. The specific preferences and usage motives of consumers to use such systems can vary greatly depending on different user types and therefore need to be investigated in more detail [2]. The visualization of energy data in HEMS is critical to ensure that customers understand their personal energy use at home [3]. This data is necessary for customers to change their energy consumption behaviour to have a positive impact on the environment [2]. For a better understanding of the personal energy consumption, HEMS often use graphs to make the data more accessible. However, not all types of visualizations are equally easy to understand for all types of users [3]. Several studies have already been conducted to understand how these energy data visualizations need to be designed to increase comprehensibility.

The different types of visualization can vary from traditional, rather simple graphs to modern, artistically designed graphs. The majority of people generally like modern and artistic graphs better, but these graphs require a higher cognitive effort to read and understand. As a result, such graphs are often more difficult to interpret than graphs without additional artistic embellishments [4]. The authors Bateman et al. [5] investigated the effect of artistic components in energy visualizations on users' comprehension and recall. The results show that users like visual embellishments in graphs and find them attractive. People can even remember graphs with embellishments better after a longer period of time. However, there is no scientific evidence yet that the use of artistic embellishments in data visualization increases comprehension.

According to Quispel and Maes [6] standard visualization types such as bar charts, line charts, or pie charts promote clarity and comprehension more than unusual, divergent, or picture-like visualization types. This may be why the use of these types of visualizations is most common for presenting energy data [7]. Also, Fischer [2] has shown that consumers* prefer these more standardized graphics. In particular, pie charts are preferred to compare individual appliances, vertical bars are preferred to show time periods, and horizontal bars or line charts are favoured to view the energy consumption of different households side by side.

Instead of using visual embellishments to increase the attractiveness of visualized energy data, developers can choose to implement different colors. By using colors, both the trustworthiness of visualizations and the ability of viewers to process information cognitively can be enhanced. In doing so, the use of different colors can also increase the attractiveness of the graph. In addition, the purposeful use of colors favourably influences the viewer's cognitive processes and ultimately can affect the consumer's attitude or behaviour [8, 9].

Concerning the comprehension of energy data visualizations, developers should take into consideration the different levels of energy literacy of consumers. Whereas certain types of visualizations are easily understood by professionals, the same graphs may be too complicated to read for consumers without prior knowledge about energy-related topics [4]. The most basic level of understanding a graph means being able to read it, or more precisely, to extract relevant data from it. In order to investigate whether an individual is able to understand elementary components of a graph, simple questions can be asked in interview settings. The second level of understanding graphs is the capability to find connections in the data presented. Identifying relationships and being able to compare the components with each other requires a more in-depth understanding of the presented information. The third and deepest level of chart comprehension involves the individual's ability to understand the data shown in its entirety and to derive forecasts and future trends from the data. This level of comprehension often requires prior familiarity and knowledge about the topic at hand [10].

One possible way to gain a deeper understanding of energy charts from the viewer's perspective is to search for relationships between specific data and specific events. Consumers often use a mental model approach; they try to match the displayed data to their personal consumption, which was generated by their daily activities, with the goal to identify relationships in energy graphs. By remembering daily routines and what they have done on that specific day, they try to connect the displayed energy data to them. When consumers cannot relate energy graphs to their daily routines, the level of understanding decreases, which consequently hinders sustainable behavioural change in consumption patterns [3].

To improve the understanding of energy data visualization, several recommendations have already been made by researchers. Herrmann et al. [3] recommend not only showing disaggregated energy data, but also ignoring time in energy data visualizations. Their study findings, in which they investigated people's understanding of three distinct types of data visualizations - aggregated time series data visualization, disaggregated time series data visualization, and normalized disaggregated visualization - show that people are most accurate when commenting on normalized disaggregated visualizations. People can relate application-level energy data to their daily activities better than temporal-level energy data.

Eye-tracking studies also suggest that information can be found much faster in familiar visualization forms. Among other things, it has been found that bar charts can lead to faster retrieval of data than area or line charts under certain conditions [11].

PROBLEM AND RESEARCH NEED

The previous chapter showed in detail that data visualizations of energy data need to be carefully designed in order to enhance the comprehensiveness. Furthermore, different designs are also perceived in different ways than others in terms of attractiveness. However, studies also show that the underlying emotions that occur when looking at different graphs need to be considered. For instance, Fang, Chun and Chu [12] found through a survey that emotions play a major role in design preferences and the intention to use them. In addition to surveys, methods like the automatic facial expression analysis can also be used to determine how positively or negatively various stimulus materials are received by subjects. However, at the time of writing this paper, no single study has been identified that has used this methodology to evaluate energy visualizations. Therefore, this study examines this research gap in detail.

To address the main objective of the study, the following research question was defined:

Which emotions are triggered in users by visualizations of the electricity consumption of individual household appliances?

METHODS

In this work, a two-stage experimental design is used to compare the perceived aesthetic appearance of different types of electricity consumption graphs on application level (aggregated or time-dependent) and their triggered emotions. First, a representative survey covers the general aesthetics assessment. Second, an in-depth eye-tracking and facial expression investigation is used to track and quantify emotions on different electricity consumption graphs on application level and their perceived advantages and disadvantages. Participants were randomly assigned to one of three groups (A, B or C) with different electricity consumption graph types on appliance level. Within each group, two different levels of temporal resolution were addressed, i.e., i) aggregated weekly consumption, and ii) time series-based daily consumption. The stimuli in this 2 (temporal resolution) x 3 (graph type) nested mixed design were created from a one-day time series dataset of a multi-person household and are illustrated in Figure 1.

Figure 1. Investigated aggregated (left column) and time series-based (right column) electricity consumption graphs on appliance level

Survey participants, procedure and measures

The survey sample consists of n = 626 participants with main residence in Austria, which leads to a sample error of 3.29%. Of those surveyed, the majority were female (51.12%) between the ages of 18 and 90 (M = 48.96, SD = 16.39). 32.59% of the respondents have a school-leaving certificate or a tertiary education as the highest completed education. 21.73% have completed intermediate vocational schools, almost half of the respondents (44.89%) has completed an apprenticeship. The main participant sociodemographics are stated in Table 1.

Table 1. Participant sociodemographics

Sociodemographics	M[a]	(SD[b])	%
Gender			
Female			51.12
Male			24.24
Diverse			0.64
Age (years)	48.96	(16.39)	
Education			
Apprenticeship			44.89
Intermediate vocational school			21.73
School-leaving certificate			18.53
University degree			14.06
Other			0.80

[a] M = means, [b] SD = standard deviations, n = 626

The questionnaire was distributed in an online panel according to representative quotas with respect to age, gender and education level. Participants had to answer different a few questions on comprehension regarding both aforementioned electricity consumption graphs on appliance level. Subsequently, both electricity consumption graphs were evaluated with respect to its aesthetics.
Aesthetics were measured on a 1 = *strongly disagree* to 5 = *strongly agree* scale adopted from [13]. Three items were used to comprise the scale, e.g. “This graph has an aesthetic design” ($\alpha = 0.82$).

Eye-tracking participants and procedure

A student group of the University of Applied Sciences Burgenland recruited 50 volunteers without special background knowledge on energy topics for the eye-tracking sample. The sample consisted of 27 female and 23 male participants. The participants were on average 31 years old (± 13 years).
In addition to the general procedure, each subject was further presented with all types of consumption graphs. From each of the three different graphs, a preferred one (A, B, or C) with respect to its design had to be chosen. During the investigation, the faces of the participants were recorded and subsequently evaluated with an automatic facial expression analysis using the Facial Action Coding System (FACS). This system analyzes the movements and positions of various facial elements (so-called action units) such as eyebrows, mouth and eyes. This data provides information about the emotional state of the subjects and can be divided into positive or negative emotions [14].

The facial expression analysis was supplemented by eye-tracking, which measures the subjects’ eye movements. This data was essential to determine which facial expressions occurred with which types of graphs. For this purpose, the different graph types were defined as Areas of Interest, which allow to display detailed eye-tracking metrics for the respective area (e.g. number of fixations, time until the first fixation, etc.). Thus, it could be determined how long a graph type was viewed and how positive or negative the respective facial expression was. In addition, heat maps and shadow maps were created. In a heat map, the stimulus is color-coded to indicate where the subjects looked most often (red areas were looked at the longest, followed by yellow and then green areas). The shadow map is similar to the heat map, except that the attention-grabbing zones are marked dark [15]. The study was conducted with the eye-tracker Tobii Pro Nano in the eye-tracking laboratory of the University of Applied Sciences Burgenland. Data were collected and analyzed using the iMotions 9.0 software.

Analysis

Data analysis was done using i) a t-test to test for differences between the aesthetics of aggregated weekly consumption graphs and time series-based daily consumption graphs, ii) subsequent ANOVAs are carried out to compare aesthetics by different chart types, iii) correlations between eye-tracking metrics and measured emotions, iv) linear regression analyses with graph types and eye-tracking inputs to identify impacts on emotions, and v) further qualitative eye-tracking analyses.

RESULTS

The following section states the results of both the aesthetics survey and the in-depth eye-tracking and facial expression investigation.

Results of aesthetics survey

A paired t-test indicates significant differences between the perceived aesthetics of aggregated weekly consumption graphs (M = 4.06, SD = 0.85) and time series-based daily consumption graphs (M = 3.00, SD = 1.19), resulting in a large effect ($p < 0.001$). Subsequent ANOVAS state differences in graph types at both levels of temporal resolution. With respect to time series-based daily consumption graphs, bar charts are considered most aesthetic (M = 3.31, SD = 1.03). Significant differences to both line charts (M = 3.04, SD = 1.24, $p = 0.037$) and rose chart (M = 2.64, SD = 1.20, $p < 0.003$) are identified. On an aggregated weekly resolution, rings (M = 4.13, SD = 0.79) and bars (M = 4.12, SD = 0.77) are perceived almost equally aesthetic. They both outperform onion charts (Table 2).

Table 2. Results on aesthetics of electricity consumption graphs

Temporal resolution Graph type	M[a]	(SD[b])
Time series-based daily consumption[c]	*3.00*	*(1.19)*
Line[d,e]	3.04	(1.24)
Bar[d,f]	3.31	(1.03)
Rose[e,f]	2.64	(1.20)
Aggregated weekly consumption[c]	*4.06*	*(0.85)*
Ring[g]	4.13	(0.79)
Bar[h]	4.12	(0.77)
Onion[g,h]	3.92	(0.96)

[a] means, [b] standard deviations, [c] $p < 0.001$, [d] $p = 0.037$, [e] $p = 0.003$, [f] $p < 0.001$, [g] $p = 0.048$, [h] $p = 0.047$.

Results of eye-tracking on emotions

Table 3 illustrates the facial expressions during the examination of the energy consumption graphs in percent. The first part of the table shows the comparison of time series-based daily consumption graphs, the second part shows a comparison of the aggregated weekly consumption graphs. In the daily consumption graphs, it is clear that the negative emotions are strongest for the rose chart (9.53% of all facial expressions), followed by the bar chart (8.86%) and the line chart (7.53%). It is remarkable that the rose chart also evoked the most positive emotions at the same time, i.e. joy (8.85%).

Table 3. Facial expressions in percent when reviewing energy consumption graphs

Type	SUR	JOY	ANG	CON	DIS	FEA	SAD	NEG
Time series-based daily consumption								
Line	1.81	8.39	1.04	1.13	1.01	1.23	3.12	7.53
Bar	1.12	8.28	1.65	1.85	1.15	1.34	2.88	8.86
Rose	1.55	8.85	1.33	1.61	1.29	0.78	4.52	9.53
Aggregated weekly consumption								
Ring	3.29	11.09	1.80	2.17	1.01	1.64	2.40	9.02
Bar	2.23	9.19	1.56	4.10	1.37	2.31	2.09	11.43
Onion	2.76	8.37	3.30	5.71	1.24	2.75	4.06	17.07

SUR = surprise, JOY = joy, ANG = anger, CON = contempt, DIS = disgust, FEA = fear, SAD = sadness, NEG = negative emotions in total, values in %.

An ANOVA shows that aggregated weekly consumption graphs cause significantly more contempt than time series-based daily consumption graphs ($p = 0.018$). Further tendencies of differences between the temporal resolution of the consumption graphs are indicated with respect to anger ($p = 0.078$) and surprise ($p = 0.067$). Figure 2 further illustrates that the rose chart is higher for sadness than the other chart types. Otherwise, the emotions are mostly very similar and differ only by a few percentage points. The visualizations of the weekly consumption show a similar picture. Here it must be emphasized that the onion chart triggered the most negative facial expressions in the study (17.07%), followed by the bar chart (11.43%) and the ring chart (9.02%). The onion chart elicits the strongest negative emotions in almost all categories of negative emotions (i.e., anger, contempt, fear, sadness). Furthermore, the fewest positive emotions are triggered in this type of chart (i.e. joy). Thus, the emotion data indicate that the rose and onion charts trigger the most negative emotions in their temporal resolution levels (both daily and weekly consumption).

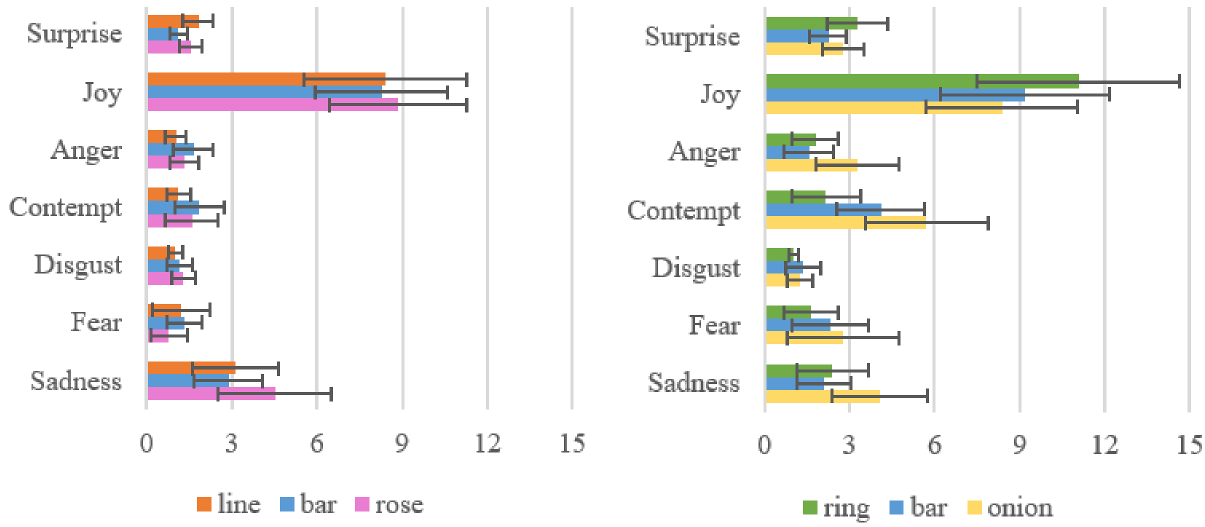

Figure 2. Facial expressions on time series-based daily consumption (left) and aggregated weekly consumption (right)

Table 4 states correlations between eye-tracking metrics and emotions. Highest correlations with respect to time series-based daily consumption graphs correspond to dwell time and disgust (r = 0.432), fixation count and disgust (r = 0.429), fixation count and anger (r = 0.250), and dwell time and anger (r = 0.227). With respect to aggregated weekly consumption graphs, notable correlations correspond to fixation count and surprise (r = 0.275) and last fixation duration and contempt (r = 0.211).

Table 4. Correlations between eye-tracking metrics and emotions

Metric	SUR	JOY	ANG	CON	DIS	FEA	SAD
Time series-based daily consumption							
FIX	0.089	0.058	0.250	0.128	0.429	-0.050	-0.017
TTFF	-0.014	0.104	-0.066	-0.072	-0.060	-0.071	-0.039
DWEL	0.092	0.028	0.227	0.087	0.432	-0.079	-0.032
DUR	0.015	-0.099	-0.037	-0.050	-0.013	-0.089	-0.041
FIRST	0.045	-0.035	-0.129	-0.081	-0.105	0.006	-0.105
LAST	-0.056	-0.087	0.006	-0.115	-0.049	-0.060	0.070
Aggregated weekly consumption							
FIX	0.275	-0.064	0.101	0.123	0.081	0.086	-0.013
TTFF	0.031	0.073	0.073	0.141	0.038	0.005	0.099
DWEL	0.161	-0.050	0.063	0.127	0.038	0.036	0.017
DUR	-0.109	0.055	-0.023	0.174	-0.047	-0.083	0.064
FIRST	-0.048	0.108	0.135	0.129	0.090	-0.021	0.128
LAST	-0.058	-0.022	-0.075	0.211	-0.085	-0.108	0.029

FIX = fixation count, TTFF = time to first fixation, DWEL = dwell time, DUR = duration of average fixations, FIRST = first fixation durations, LAST = last fixation durations, SUR = surprise, JOY = joy, ANG = anger, CON = contempt, DIS = disgust, FEA = fear, SAD = sadness.

A subsequent series regression analyses with consumption graph type and eye-tracking metrics as input parameters show that the time series-based daily consumption graph type (F = 4.53, p = 0.012) as well as the last fixation duration (F = 5.028, d = 0.027) have an impact on contempt. Furthermore, the last fixation duration has a significant impact on contempt (F = 5.048, p = 0.026) regarding to the aggregated weekly consumption graphs.

The eye-tracking data highlights the aforementioned results. In the shadow map in Figure 3, it is shown that the participants perceived all graphics, but only took a closer look at the bar chart and the line chart when selecting the preferred graph at the bottom right.

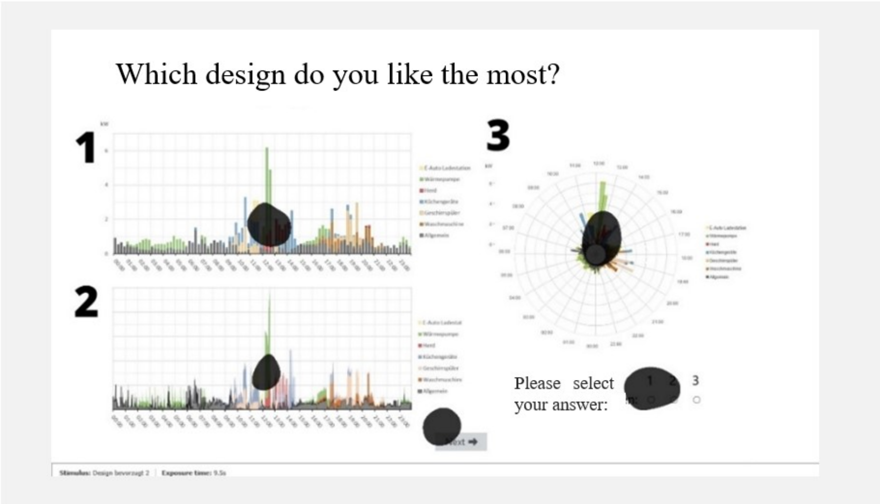

Figure 3. Shadow map of the time series-based daily consumption graphs

The aggregated weekly consumption graphs also show a similar result (Figure 4). Although all graphs were viewed in general, the decision was mostly between graph 1 and 3, in 4 out of 5 cases the decision was made for graph 1 and thus the bar chart. Graph 3 was chosen by one fifth of the test persons, only the onion chart (graph 2) was never marked as favorite. Additionally, in the heat map it can be seen that the options 2 and 3 were not often viewed and therefore were not in the closer selection when deciding for one of the graph types.

Figure 4. Heat map of the aggregated weekly consumption graphs

These results are confirmed in the qualitative interviews conducted after the study. With regard to the rose chart, the test persons mentioned in most cases that they are less familiar with this form of visualization and prefer more familiar forms of representation (bar or line graphs). One respondent said in connection with the rose chart: "I'm not a scientist, I can't understand this graphic." In contrast, bar, line, or line charts were much better accepted by the target group. "I like bar charts much more than the rose chart, which I know from various applications and reports, so I can easily understand it. The rose chart, on the other hand, I can't interpret easily, I have to find my way around once."

With regard to the bar chart in comparison to the line or area chart it was mentioned from time to time (by about one fifth of the respondents) that the latter is visually more pleasing, because too many bars next to each other are no longer appealing. In general, bars are preferred, but only if there are less than ten bars. Since in this case the total daily consumption is visually represented, the area chart makes more sense for some test persons. When asked about the energy visualizations for weekly consumption, the test persons stated that the onion chart is neither visually appealing nor easy to understand. None of the test persons stated in the interview that he/she liked the graph. One respondent stated in this context: "I don't like this kind of graphic at all, I don't know what the different rings are supposed to represent. I would not like this kind of graphic". The ring chart was judged as very good by a small part of the test persons (about one fifth preferred this kind of graph), the rest decided in direct comparison for the bar chart, because they are most familiar with it.

CONCLUSION

As a conclusion, the results of previous studies can be confirmed that participants prefer simple energy graphs, especially bar charts should be used to a greater extent. The majority of the test persons had no particular knowledge about energy topics. Therefore, it can be argued that this group of individuals would like to see simple graphs in order to familiarize themselves with the topic of energy. The results are consistent with previous study findings in which similar findings were obtained. Therefore, the development of HEMS should focus on these traditional data graph types. Graphs such as onion and wind rose graphs should be avoided, as these graph types are more likely to elicit negative emotions. As a limitation of this study, it should be taken into account that the majority of the subjects have been less engaged with the topic of energy so far, and individuals who have more experience in using HEMS or other energy platforms may have different preferences regarding chart types. This issue could be analyzed in further studies in terms of target group segmentation. Nevertheless, this study provides comprehensive insights into how to make electricity consumption graphs accessible to a broader audience.

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REFERENCES

1. Holmes, T. G., Eco-visualization: combining art and technology to reduce energy consumption, *Proceedings of the 6th ACM SIGCHI conference on Creativity & cognition,* June 2007, pp. 153-162
2. Fischer, C., Feedback on household electricity consumption: a tool for saving energy?, *Energy Efficiency* Vol. 1, No. 1, pp 79–104, 2008.

3. Herrmann, M.R., Brumby, D.P., Oreszczyn, T. and Gilbert, X.M.P., Does data visualization affect users' understanding of electricity consumption? *Building Research & Information* Vol. 46, No. 3, pp 238-250, 2017.
4. Murugesan, L. K., Hoda, R. and Salcic, Z., Design criteria for visualization of energy consumption: A systematic literature review, *Sustainable Cities and Society* Vol. 18 pp 1–12, 2015.
5. Bateman, S., Mandryk, R. L., Gutwin, C., Genest, A., McDine, D. and Brooks, C., Useful Junk? The Effects of Visual Embellishment on Comprehension and Memorability of Charts, *Proceedings of the SIGCHI conference on human factors in computing systems,* Atlanta, 2010, pp. 2573-2582.
6. Quispel, A. and Maes, A., Would you prefer pie or cupcakes? Preferences for data visualization designs of professionals and laypeople in graphic design. *Journal of Visual Languages and Computing* Vol. 25, pp 107-116, 2014.
7. Grant, W., Energy Data Visualization Requires Additional Approaches to Continue to be Relevant in a World with Greater Low-Carbon Generation, *Frontiers in Energy Research* Vol. 4, No. 33, 2016.
8. Cyr, D., Head, M. and Larios, H., Colour appeal in website design within and across cultures: A multi-method evaluation, *International journal of human-computer studies*, Vol. 68, No. 1-2, pp 1-21, 2010.
9. Bonnardel, N., Piolat, A. and Le Bigot, L., The impact of colour on Website appeal and users' cognitive processes. *Displays*, Vol. 32, No. 2, pp 69-80, 2011.
10. Friel, S. N., Curcio, Frances R. and Bright, G. W., Making Sense of Graphs: Critical Factors Influencing Comprehension and Instructional Implications, *Journal for Research in Mathematics Education* Vol. 32, No. 2, p 124, 2001.
11. Goldberg, J. and Helfman, J., Eye tracking for visualization evaluation: Reading values on linear versus radial graphs, *Information Visualization*, Vol. 10, No. 3, pp 182–195, 2011.
12. Fang, Y. M., Chun, L. and Chu, B. C., Older adults' usability and emotional reactions toward text, diagram, image, and animation interfaces for displaying health information, *Applied Sciences*, Vol. 9, No. 6, pp 1058, 2019.
13. Lavie, T., Tractinsky, N., Assessing dimensions of perceived visual aesthetics of web sites, *International Journal of Human-Computer Studies*, Vol. 60, pp 269-298, 2004.
14. Bojko, A., *Eye tracking the user experience: A practical guide to research*. Rosenfeld Media, 2013.
15. iMotions, (2017). Eye Tracking – The Complete Pocket Guide. iMotions.