Attention, Comprehension, Execution: Effects of Different Designs of Biofeedback Display

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Abstract
The rapid development of biosensors and wearable devices has led to an increasing number of quantified self applications with physiological data. However, conventional graph-style visual representations which have been commonly used for behavior monitoring and control may not be the most applicable biofeedback methods. This is because biosensor data is not intuitive and is hard to manipulate directly and precisely, especially in computer-mediated collaborative interactions. In this work, we explore four different designs, i.e., graphical, illustrative, artistic and ambient representations, by visualizing physiological data in individual settings. Following the Research through Design model, we compare these four designs in terms of their abilities to facilitate biofeedback interpretation through a within-subject controlled experiment with 24 participants. The results suggest that users' visual perception is affected by different design styles.

Author Keywords
Design; Biofeedback; Visual display; Visualization; Personal informatics; Well-being

ACM Classification Keywords
H.5.2 [Information interfaces and presentation (e.g., HCI)]: User Interfaces - *Graphical user interface (GUI), Evaluation/methodology*.

Introduction

The digital revolution of personal informatics (PI) technologies enable users nowadays to access and share their personal data in a comprehensive way. Users can easily access their own physiological data (e.g., heart rate, breathing, etc.) collected by bio-medical instruments, activity trackers or self-quantifying tools for self-management purposes. It is also possible for them to stream their data for real-time consultation and training [32]. Therefore, practical data representations are critical to the effective use of biosensor information in real-world applications such as stress management [21, 37] and affective health [29].

Current biofeedback data related PI applications on the market mainly employ conventional visualization designs such as graphs and charts to display their information [14]. Although graphical visualizations are good for statistical analysis and historical data summarization, many of the bio-data applications used for mindfulness and meditation actually focus on the moment, trying to evoke a non-judgmental sense of awareness to improve the present state of personal contentment [2, 3]. Furthermore, prior works postulate that abstract data are hard to graph out, thus introducing visual metaphors can make the information more interpretative, which, however, is rather challenging without a natural counterpart [22]. Existing research has explored multiple design alternatives on behavior data, such as tables, graphs, captions, maps, Sankey diagrams, daily lifelog views of location and physical activity data [5], as well as timeline, spark, and bouquet designs on daily Facebook interaction data [38]. However, there are still a lack of comprehensive comparisons across the different design techniques in terms of their ability to support awareness and manipulate biosensor data in individual context. We present this work as a preliminary attempt to fill this gap.

Related Work

Visualization in PI Systems

The PI system is designed to help people self-reflect by collecting their own personal information [19, 20]. A successful self-learning process is highly dependent on people's understanding of the personal information collected and shown in the PI system. Therefore, how to correctly, intuitively, and aesthetically represent these data becomes a critical problem when developing a PI system, where visualization techniques play a dominant role. Visualization research has dedicated various taxonomies for distinguishing different visual designs based on different data types [17, 26, 40], but none exist for personal tracking data. Huang et al. [10] have introduced two research fields, i.e., personal visualization and personal visual analytics, to discuss the effect of visualization and visual analytics on personal health contexts. In this paper, we propose four types of representation methods based on the above definitions and perform controlled experiments to formally compare their performances in terms of representing personal data collected from biosensors in PI systems.

Visual Designs for Biofeedback

Biofeedback is "a process which enables an individual to learn how to change physiological activity for the purposes of improving health and performance" [1]. Although underutilized [31], it is still gaining increasing popularity within the PI community [11]. Researchers have proposed novel designs for physiological information other than the existing graphical displays commercially obtainable. For example, MoodWings [21] is a butterfly-like wearable display that depicts users' stress levels by wing movements. Living-Surface [39] is an interactive wall-like shape-changing display of users' heart rate variability data. Cardiomorphologies [15] create real-time visual and sonic representations of an audience's breathing and heart rate data. Sonic Cradle [34] is a chamber of complete darkness where users shape a peaceful soundscape which reflects their respiration. Some other designs adopt more artistic styles. The Metaphone [37] is an interactive art piece that transforms users' skin response and heart rate data into colorful, evocative, perceivable visual patterns on a big canvas. These displays mainly focus on individual experiences and lack comparative evaluation of other design alternatives.

Definition
Based on previous PI systems [4, 7, 12, 13, 24, 30] designed for different purposes, we classify existing biofeedback representation techniques into four major categories: graphical, illustrative, artistic, and ambient representations. We compare these four designs in Table 1 based on five rating scales and each of these representation styles is described as follows:

Scale	G	I	A	M
Intuitive	***	**	*	*
Meditated	*	**	***	***
Specific	***	**	*	*
Holistic	*	**	***	***
Realistic	***	**	*	**
Imaginative	*	**	***	**
Descriptive	***	**	**	*
Experiential	*	**	**	***
Focal	***	**	**	*
Peripheral	*	**	**	***

Table 1: Four design styles compared along with several key factors. The number of "*"(s) indicates the rating level of the corresponding scale.

The Pip is a device that detects the electrodermal activity (EDA) variations by capturing the skin's pores on users' fingertips. It trains users to better manage their stress through biofeedback.

Graphical representation (**G**) refers to visualization designs showing the raw data or the statistical summary derived from the raw data intuitively. They are mainly used to give an overview [18] as well as detailed descriptions to help users investigate facts.

Illustrative representation (**I**) refers to the implementation of visual abstraction that are extracted from visual analogues and developed to improve the depiction of information [27, 36]. It usually reflects the feature(s) of realistic object(s) processed by people's common sense based on an abstract concept or particular situation to amplify cognition.

Artistic representation (**A**) refers to the experience oriented, imaginative, integrated expression of the biofeedback data with the intent of making art. The aim of which is to create an aesthetically pleasing experience through its art forms [35]. Usually, this representation employs visual metaphor [16] to bridge the underlying data with the artistic design.

Ambient representation (**M**) refers to a form of representation that displays the data in a visually appealing way which is attractive and tangible large scale data changes [25] by using everyday objects (meaning "non-screen" in this paper) as the media. Usually, users can easily get information from these representations without having to give it their full attention.

Design Details

Data
We estimate the users' excitement level by measuring their skin conductance based on the Pip[1], a wireless biosensor of electrodermal activities. The data are collected in real time at a rate of at least six times per second, recording information from the following four different aspects to form a multivariate time series dataset:

- Stress trends: nominal data, the value automatically calculated based on Pip's event classification algorithm.
- Previous stress trends: nominal data, the value of the most recently detected event.
- Accumulated trends: internal data, the aggregated trends over a longer period of time.
- Skin conductance: ratio data, the raw skin conductance value with continuous data.

In our experiment, we ignored the previous stress trend as we would like to inspect users' response in real time.

Visual Designs
As shown in Figure 1, we introduce four different styles to represent the above multivariate time series sensor data, which are described as follows:

Graphical representation: We employ horizon graph [9] (Figure 1(1)) to visualize the above multivariate time series data due to its space-efficiency, its precision in terms of representing the time series values, and it is also the most commonly seen graphical design among popular apps based on our survey of the top 50 PI applications' visualization. In particular, we also want to investigate whether historical records are essential to the users. Based on this design we visualize the stress trend, the accumulated trend, and the skin conductance together by three horizon graphs

[1] https://thepip.com/

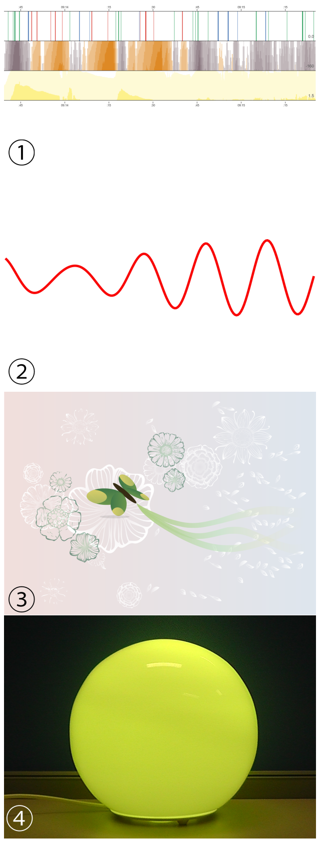

Figure 1: Visual designs of four different representations in individual context based on biofeedback data: (1) graphical, (2) illustrative, (3) artistic, and (4) ambient, respectively.

that are tightly placed in parallel on the screen. The specific values can be read when a mouse hovers over the visualization, and the initial position of the cursor depicts the present moment. During the experiment, the graph is updated in real-time, and the data is shown smoothly on the right-hand side and fades out on the left. The time window can be rescaled to a narrower interval to emphasize the current value and minimize the impact of the historical data.

Illustrative Representation: We propose several design alternatives for this style, such as gauge, Chernoff faces, and three styles of waving curves. We invite 16 students and two faculty members in art, design, and visualization to vote for their favorites. According to the results (i.e., 8 out of 18), we have chosen a dynamically waving curve (Figure 1(2)) to illustrate any changes in the data. In particular, the color of the curve encodes stress trends, with the changes from green (the most relaxed) to red (the most stressful) indicating increases in stress. The amplitude of the waving curve encodes the accumulated trend, and the frequency represents skin conductance value. In this way, a stressful emotion will result in a high frequency waving curve with a large amplitude, which is also a visual analogy of the users' electrocardiography.

Artistic Representation: We decide to use butterflies (Figure 1(3)) as the artistic representation based on a questionnaire survey. 14 participants (12 students, 2 faculty members) majoring in design or related subjects are invited to finish this questionnaire, in which six different types of design choices (i.e., fish, butterfly, cat, flower, tree, and mountain) are given. The butterfly design has the highest rating (i.e., 8 out of 14) after the survey, and such a design has also been used as a symbol of a person in both eastern [23] and western cultures [21]. Therefore, we believe using a butterfly can easily be accepted by most people. In particular, we use the color of the butterfly to represent the stress trends, the flapping frequency of the butterfly's wings to represent the accumulated trend, and the number of ribbons to represent the range of skin conductance.

As a piece of art design, we also render the butterfly in a Chinese-style ink painting by tuning its opacity and blurring the boundaries of the butterfly with flowers and petals in the background, which aims to enhance the aesthetic look.

Ambient Representation: Previous works use paper cuts [39], ink paintings [37], music [34] or projection [33] to help represent the visual effects. Among all the media with respect to expressions, we choose to use light (Figure 1(4)) as it has a large impact on the peripheral environment without too many interruptions, and users do not need to pay extra attention to the representation. We choose Philips Hue[2], a set of wireless LED bulbs which is able to illustrate over 16 million colors, to implement the ambient functionality. We have also written a program to control the bulbs to illustrate the above data based on light. In particular, we use the light colored hue to represent the stress trend, the saturation to represent the accumulated trend, and the brightness to represent the value of the skin conductance.

Study

Hypothesis

According to the stage-based model [19] given by Ian et al., we propose our hypotheses along Bloom's taxonomy of cognitive process dimensions involved in PI practices with biofeedback. Since cognitive burden is one of the reasons people abandon PI devices [6], we think that a proper design would save on users' efforts in comprehending the visual information and execution accordingly. Therefore, we hypothesize that: The effort demanded for attention allocation (***HA***), comprehension (***HB***) and execution (***HC***) is significantly different among the four visual designs. More specifically, having a simple layout, the illustrative display and the ambient display, it takes significantly less effort for people to focus their attention on relevant information than the graphical or artistic displays (***Ha***). The ambient display, with the simplest encoding, is significantly easier to comprehend than the other three designs (***Hb***). The graphical

[2] http://www2.meethue.com/

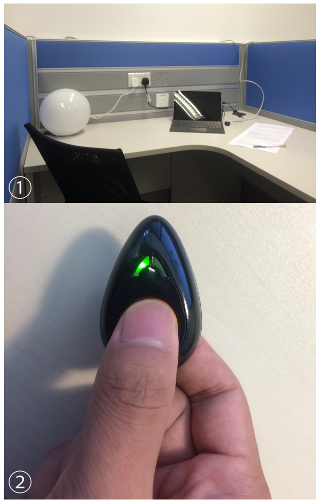

Figure 2: Experiment setup: (1) equipment arrangement in the individual mode; (2) biosensing via Pip.

display, given the nuances in its detailed visual encoding, is significantly more difficult to adjust accordingly compared to the other three representations (***Hc***).

Experiment

To test these hypotheses, we perform a within-subject controlled experiment with 24 participants (nine females; age M = 24.88, SD = 2.47) recruited from a local university. They are asked how they use and perceive different designs of biofeedback displays based on body excitement data measured by the Pip device. No one has ever heard of or used the Pip device employed in our experiment.

We arrange for two participants to arrive at the same time but sit in separate cubicles. They cannot see or communicate with each other during the experiment. One set of devices is prepared for each cubicle Figure 2 (1), including:

- a Pip (Figure 2 (2)) for taking the physiological measures;
- a lamp (with Philips Hue inside) for the ambient display in the left-hand corner of the table;
- a tablet computer (Microsoft Surface Pro 4 running 64 bit Windows 10 Pro, screen resolution is 2736×1824, CPU is Intel Core i5-6300U, RAM is 8GB) for showing the other three displays in front of the participant.

Both participants need to hold the Pip device between their thumb and index finger during the study. In the experiment, we ask participants to interpret their bodily status according to each representation and interact with the visualizations freely. When they think they have an idea of what the visualization represents, they can raise their hands to switch to the next display. Once they finish all the conditions given in a counterbalanced order, the participants are asked to use the 7-point Likert scale [8] to rate the four designs with the perceived level of effort they needed for attention allocation, information comprehension and execution.

Analysis

All possible measurements are listed in Table 2, and organized according to the hypotheses raised in cognition dimension. The repeated measures MANOVA result for "Attention" is statistically significant (Table 2 Row 1, ***HA*** accepted). The Bonferroni post-hoc pairwise comparison shows that the illustrative design ($M = 3.38$, $SD = 0.31$) requires significantly ($p < 0.01$) less effort to allocate important information on the display than the graphical design ($M = 4.58$, $SD = 0.32$). The demands of the artistic ($M = 4.08$, $SD = 0.28$) and ambient displays ($M = 3.88$, $SD = 0.31$) on the user's attention lie in the middle, but are not significantly different at either end (***Ha*** partially accepted, Figure 3). Although both use a line style of representation, the illustrative design integrates different values of the data into one element. In contrast, the details on the graphical display may sometimes overwhelm the users, as one participant commented in the interview,

> *The graphical design has so many numbers to read...each time the display changes, I have no idea which one is different, so I have to go over everything again and again (P18, male, 26).*

The differences in effort required for comprehension among the four designs are marginal (Table 2 Row 2, ***HB*** marginally accepted), and none of the pairwise differences are very significant according to the Bonferroni post-hoc pairwise comparison test (***Hb*** rejected, Figure 3). The participants' general feedback is that they feel barely any difference in their bodily status while the display is consistently changing. Therefore, it is hard for them to make the mental connection between themselves and the information shown, especially when it is too detailed as in the graphical design.

Repeated measures MANOVA suggests significant differences in the effort required for execution (Table 2 Row 3, ***HC*** accepted). Moreover, the Bonferroni post-hoc pairwise

Dimension	*Measurements*	df	*MS*	F	P	η^2	*Results of Hypotheses Testing*			
Cognition	Attention	3	6.01	4.09	0.01	0.15	***HA***	Accepted	***Ha***	P. Accepted
	Comprehension†	1.85	8.36	2.84	0.07	0.11	***HB***	M. Accepted	***Hb***	Rejected
	Execution	3	9.57	3.67	0.02	0.14	***HC***	Accepted	***Hc***	P. Accepted

Table 2: Repeated measures MANOVA results on different measurements of four visualization designs, † with Greenhouse-Geisser correction as the data violates the assumption of sphericity. *MS* represents *Mean Square*. M. means Marginally. P. means Partially.

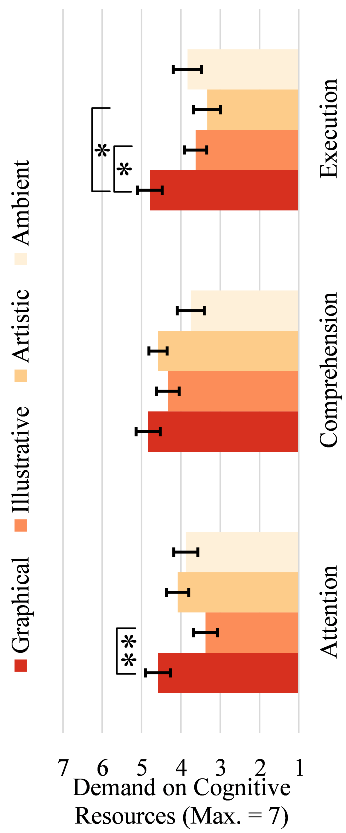

Figure 3: Comparison (with std. error) of the cognitive demand for *Attention*, *Comprehension* and *Execution* for the proposed measurements on given different designs (*: $p < 0.05$, **: $p < 0.01$)

comparison test shows that controlling the body according to the graphical design ($M = 4.79, SD = 0.31$) is significantly harder than with the illustrative ($M = 3.63$, $SD = 0.28, p < 0.05$) and artistic designs ($M = 3.33$, $SD = 0.34, p < 0.05$), but not with the ambient ($M = 3.83$, $SD = 0.36$) condition (***Hc*** partially accepted, Figure 3). Overall, the participants could eventually figure out the pattern after playing with the display and exploring different alternatives. However, some conditions are more difficult than others, as mentioned by some participants:

> *The numbers in the graphical display do not make too much sense to me, and I really cannot tell how my body is different by being given a number of 30 verses 31. Therefore, it is much more difficult to control myself to an exact number. In the end, I decided to go for the trends rather than the values (P6, female, 29).*

In summary, the effort demanded of graphical design for attention allocation and execution is significantly higher than the illustrative design, while there is no significant difference for comprehension across the four representations. The numerical readings are clear and directly reveal a participant's bodily state but they require participants' full load of attention. In comparison, the visual analogies and metaphors help participants to quickly make self-reference to the visualization, as the imaginative and experiential designs of artistic and ambient displays create a deeper impression for the participants. However, an obscure and complex visual embellishment has a negative impact on the visual expression. In general, a neat, simple design with important, properly balanced visual cues and highlighted, critical information can effectively reduce cognitive overheads.

Conclusion and Future Works

We present a comparative study on four designs of biofeedback displays, i.e., graphical, illustrative, artistic and ambient representations, in terms of their demand on cognitive resources. The results show that, in general, people prefer neat and classical designs to relieve their cognitive load and processes. Since users can share tracking data online for other people to compare and comment on in social networks [28], we will explore the process performance, emotional experiences and overall perceptions both in individual and collaborative settings in the future. We are going to explore how different types of biofeedback displays can facilitate understanding and control of one's own physical status as well as collaboration with participants about the information. In particular, we are going to conduct a within-subject experiment with participants taking part in a PI exercise in which they will learn to sense bodily excitement levels measured via the same equipment. We will keep on working on how to find the applicable biofeedback method(s) to represent physiological data.

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