Can Biosignals be Expressive? How Visualizations Affect Impression Formation from Shared Brain Activity

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We are exploring the concept of *expressive biosignals*: leveraging wearable technologies to introduce sensed physiological data as cues for social perception. Biosignals can help us achieve a deeper understanding of each other by revealing or clarifying the psychological processes that underlie our subjective experience. We conducted an exploratory study investigating expressive biosignals, comparing the influence of a variety of brain activity visualizations on impression formation. Results revealed that while participants readily infer emotional and cognitive states from visualized brain activity, the ambiguity of the data can lead to diverse perceptions and interpretations. Participants also expressed concerns that the observation of another individual's data during interaction might be invasive or distracting. We present a set of design considerations addressing issues of interpretability, integration, and privacy of biosignals in interpersonal contexts.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; *Empirical studies in visualization*;

Additional Key Words and Phrases: biosignals; impression formation; visualization; brain activity; EEG

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1 INTRODUCTION

We typically form impressions of other people based on the visible behavioral cues that they give off—body language, facial expressions, and voice tone and pitch [3, 15, 38]. However, recent advances in technology could reveal previously *invisible* data about others that can inform our impressions. For instance, heart rate rises and falls with fluctuations in one's emotions [25], skin becomes more conductive with increases in engagement level [19, 28], and brain activity changes with different levels of cognitive processing [7, 12]. If we were able to supplement our observation of behavioral changes with access to these physiological changes that are typically invisible to the naked eye, we may be able to enhance our inferences of other people by better sensing and understanding their emotional and cognitive states. In this paper, we explore the opportunity to enrich our social perceptions through expressive biosignals: the sensing and sharing of physiological responses as new, expressive social cues.

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With the rising popularity of wearable devices, we now have the ability to sense and access our physiological states and unobtrusively introduce them into social contexts. Smart watches like the empatica Embrace are equipped with sensors that monitor signals like heart rate and electrodermal activity for stress and seizure detection [10]. Consumer-grade electroencephalogram (EEG) headsets, such as the Muse and Emotiv EPOC, can classify psychological states such as concentration or emotions [1, 6, 29]. But despite the prominence of wearable sensor technologies and their use for personal tracking, there has been little work examining the implications of *sharing* physiological data with other people. In order to transform biosignals into a new social cue, we need to better understand how people interpret and react to them, how to display them in a socially meaningful way, and what issues might emerge when considering their use in interactions.

In this research, we examine how people form impressions of each other based on visualized biosignal data. The impressions that we form are traditionally affected by visible nonverbal behaviors both consciously and unconsciously controlled [15, 38]. Research shows we readily form initial impressions from even brief observations, or "thin slices," of expressive nonverbal behaviors very quickly, in less than two minutes in some cases [3]. Moreover, research stemming from attribution theory has revealed that individuals tend to draw automatic judgments about others' personal dispositions (i.e., characterizing their internal states or traits) from observed verbal and nonverbal behaviors [14]. In our work, we investigate whether short clips of visualized EEG data might similarly provide perceivers with expressive social information with which to form impressions, and how variations in representations of the data affect the impressions that we form of others.

We contribute key design considerations, challenges, and opportunities that arise in developing an expressive biosignal system that displays a user's brain activity. We created six visualizations of brain activity and assessed participants' impressions and reactions to each in a controlled laboratory setting. Results revealed that participants associated sensed brain activity with particular emotional and cognitive states, but their interpretations of those states were strongly skewed by design features of expressive biosignal visualizations. Additionally, we gleaned concerns of privacy and cognitive load when considering the use of the visualizations for communication, depending on the level of interpretable information present. Our research reveals important insights and unresolved issues concerning the integration of displayed brain activity in social contexts, and lays the groundwork for crucial next steps in the design and deployment of expressive biosignal systems.

2 RELATED WORK

2.1 Biosignal systems in social contexts

To date, biosignals have largely been used in the context of biofeedback: the presentation of biosignals for individual monitoring, tracking, and ultimately, control [4, 41, 47, 50]. Only recently have researchers started extending biosignals to interpersonal contexts in which biosignals are shared with others, particularly as part of social interactions. Their works have begun to demonstrate that sensed data can facilitate positive social outcomes, such as increasing engagement and reducing stress, by revealing users' physiological states. For example, researchers have explored the design of biosignal systems to support self-awareness and communication between interaction partners [17, 43, 51], as well as to encourage heightened intimacy and social connection [36, 49]. In playful and entertainment settings, displaying the physiological states of players and performers has been shown to enrich interactions in both cooperative [48] and competitive [11] ways, as well as to increase engagement among spectators [8, 40]. Biosignals have also been used for work and collaboration. One illustrative study found that displaying the skin conductance, blood pressure, and respiratory rates of a worker building a K'Nex device (a toy construction system) to someone instructing the worker on how to build the device effectively reduced the stress and perceived

workload for both the worker and instructor [45]. Another recent study used brain activity to measure and provide feedback to a presenter about audience engagement levels [18]. However, though these studies provide examples of how biosignals can influence interactions in various contexts, they did not directly assess the impact of biosignals on impressions that viewers of those data formed, nor did they provide guidance on the design of these systems. The present work sought to extend these prior works by focusing on these two specific aims.

2.2 Social interpretations of biosignals

Though a handful of researchers have begun incorporating physiological data in social settings, few have addressed the ability for biosignals to serve as a useful cue for inferring others' internal traits or psychological states, and the degree to which such inferences may vary depending on the way it is presented. Leahu and Sengers note that an important direction for exploring questions around the use of biosignals for human interpretation is to understand the potential subjectivity of those interpretations [27]. Following this line of work, Howell and colleagues investigated users' subjective interpretations of biosignal displays while interacting with others. They demonstrated that the meaning of certain biosignals can be ambiguous; specifically, they observed that viewing data from a wearable display of skin conductance caused users to make various interpretations of the wearer's emotional state. The authors suggest that this interpretive uncertainty could both support and inhibit biosignals as a social cue. Users felt that the information could be used for open reflection and to show emotional engagement, but were concerned about how they would be viewed if others inferred negative emotions or a lack of engagement from the display [20].

Other types of shared physiological information appear to have less subjective, more universally associated meanings, such as the intimacy of the sound of a heartbeat [22] or the anxiety and stress indicated by elevated heart rates [34]. However, depending on the context, these meanings can still lead to different perceptions of a user [33]. In addition, these works have revealed potential issues of privacy surrounding the automatic sharing of data. Slovák and colleagues proposed that sharing heart rate information is a form of emotional self-disclosure, which people may not desire in all contexts or relationships. Moreover, given its ambiguity, the data alone could be interpreted differently than intended [42].

2.3 Impression formation and expressive behaviors

While past research has begun to reveal the impact of shared biosignals on interaction quality and outcomes, it has not directly investigated whether individuals will use biosignals as cues to form impressions about a person's traits or states. Moreover, existing systems have visualized biosignals as graphs [8, 34, 40], numbers [42, 48], icons [45], ambient lighting [43], and clothing [20, 49], providing different types of information (e.g., levels of biosignals data, changes over time) and levels of abstraction from the data (e.g., raw graphed data vs. iconic representations), but studies involving these systems have not tested how varying presentations of biosignals might differentially influence impression formation. To our knowledge, only a recent study by Hassib and colleagues has directly compared different biosignal designs [17]; however, the authors focused on supporting communication between close friends and partners, rather than discerning the first impressions made when given different biosignal visualizations.

There is strong reason to believe that individuals *will* be likely to use biosignals as cues for impression formation. Prior work has shown that observing other nonverbal expressive behaviors in someone else, such as body gestures and facial expressions, can guide inferences about their emotions, opinions, and physical and cognitive states. Research on "thin slices" of behaviors suggests that we use this information to form judgments and forecasts of others' traits when behaviors are visible for as little as 30 seconds in video clips. These behaviors can be telling of individuals' unique

personal styles [2], and thus have an important influence on how we present ourselves [9, 15] as well as form impressions of one another. Riggio and Friedman, for instance, found that people's impressions of subjects who gave spontaneous explanations were affected by frequency of certain expressive behaviors (e.g., facial expressions) and fluidity of those behaviors [38]. Similarly, Gifford and colleagues have shown that observers readily encode expressive nonverbal displays and rely on them to make inferences about personality traits [13].

Biosignals may similarly have expressive capabilities by conveying information about a user's mental states during subjective experiences. Heart rate and skin conductance, for instance, are known to be associated with changes in emotion [25, 28], and have been used by people to interpret emotional states such as stress and excitement in others and themselves, albeit with some ambiguity [20, 34, 42]. Merrill and Cheshire's recent study demonstrate that these interpretations can be drawn even from fake biosignals [34]. Further, in some cases, these interpretations can affect beliefs about traits such as trustworthiness or reliability [33]. Thus, like other expressive nonverbal cues we typically rely on, displays and representations of biosignals might be able to provide useful social information that can become a basis for forming impressions of others.

Our research aims to further our understanding of biosignals as a social cue by investigating the impressions evoked by visualizations of brain activity. Unlike heart rate and skin conductance, interpretations of brain activity in social contexts have not yet been explored. Brain activity may be capable of conveying social information as it can vary with our emotional and cognitive states [7, 12], and has shown potential for detecting the underlying processes in social interactions [5]. Additionally, per the research direction introduced by Leahu and Sengers' work [27], as detection of social experiences through brain activity advances, it is important that we understand people's subjective interpretations of brain activity. At the same time, the ambiguity of biosignal data suggested by past studies points to an important need to explore how to represent brain activity in a way that can support meaningful interpretation. To address these gaps, we ran an exploratory study to advance our understanding of the impressions evoked by sensed and shared brain activity, and to explore the effects of different visual representations of brain activity on those interpretations. Specifically, the present research addressed the following research questions:

RQ1: Will the meaning of brain activity, like other biosignals, be ambiguous to perceivers, and to what extent will perceivers be willing to use shared brain activity as a social cue to form impressions?

RQ2: How do different representations of brain activity affect impression formation?

RQ3: How do different representations of brain activity affect perceivers' evaluations of those representations for use in communication contexts?

3 SYSTEM DESCRIPTION

For this study, we built a simple expressive biosignal system using the Muse brain-sensing headset, a consumer-grade unobtrusive wearable technology with seven sensors that can measure a user's EEG waves. We developed a web application that visualized brain waves using the "relative band power" path in recorded Muse data. Brain waves differ according to frequency ranges, and have been associated with different cognitive and emotional states [7, 12, 26]. In this study, we showed three brain waves in the visualizations (delta, alpha and gamma) to cover a range of mental states.

We created six visualizations of brain activity as part of the expressive biosignal system. We designed these visualizations to explore how different presentation types would influence impression formation. Specifically, we explored visualizations that varied in the the level of interpretation from the data, as per the data representation dimension described by Hassib and colleagues' work on biosignal designs [17]. Visualizations that were more *interpreted* manipulated or added additional

Table 1. Visualized brain wave types and their associated states [21, 26]

Brain Wave	**Frequency**	**Color**	**Associated State**
Delta	1-4Hz	Green	Deep sleep
Alpha	7.5-13Hz	Blue	Relaxation and disengagement
Beta	13-30Hz	Yellow	Focused concentration and active thinking

meaning to the display of the data, while visualizations that were more *raw* presented the data closer to its raw numerical form. We also included visualizations with different information levels, based on number of brain waves present in a moment. Each of the six visualizations are described below (and can be seen in Figure 1).

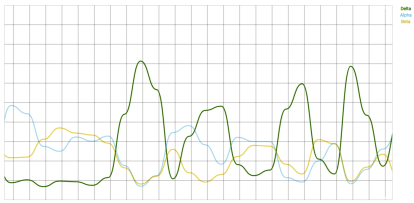
Graph. Graphs are the most common form of visualization used to display biosignals (e.g., in biofeedback); thus, we included it to provide a familiar and basic representation of physiological data. The graph streamed the different brain waves, highlighting the line with the maximum value at every second to represent the most active brain waves. We considered this visualization to be more raw because it presented the data by plotting the raw values on a graph. This visualization also showed the highest amount of information because it graphed and streamed changes in the brain activity over time.

Sliders. This visualization displayed the brain waves as a set of sliding circles. The circles represented the delta, alpha, and beta waves, and would slide left for lower activity and right for higher. This visualization was considered to be more raw because raw values were plotted on a horizontal line. However, less information was available in this visualization than in the Graph, because one could only view the values of the brain waves at a given moment and not over time.

Swirl. This interpreted visualization mapped the brain waves to the characteristics of animated swirling lines. To reflect the fact that delta waves are associated with sleepiness, when mental activity is typically slower, the speed of the lines was inversely related to the level of delta activity. Because the alpha is associated with a relaxed state, greater alpha activity resulted in smoother lines, while less activity resulted in lines that were more jagged (to suggest stress). Finally, beta was mapped to the number of lines in the visualization, with greater activity resulting in more lines to suggest the greater amount of thinking associated with high beta activity. The lines changed every second, thus one can view the activity of all three brain waves only at a given moment.

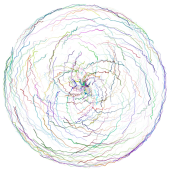
Colors. This interpreted visualization mapped the brain activity to different colors. Green and blue, which are associated with peace and calmness, were chosen for delta and alpha waves, respectively. We mapped beta waves to yellow, since yellow is a more dynamic color [30]. We displayed the colors as a radial gradient on the screen, with each gradient's opacity controlled by the value of the associated brain wave. The gradients were overlaid on top of each other; therefore, all three colors would be available at a given time, though colors with higher activity would be more visible than others. For example, if there were higher levels of delta and beta activity present, but lower alpha, the visualization would appear yellow-green due to the overlay of the green and yellow gradients.

Light. The Light was the only physical visualization we created. The Light consists of an Arduino, 2 LED lights, and a light bulb covering the system. The color of the Light would change according to the brain wave that had the highest activity at a given moment. To maintain consistency across visualizations, the color mappings were the same as those used by the Colors. This visualization shows the least amount of information, because users can only view one brain wave at a time (as only one color is shown at a time). Because the Light mapped the brain activity to different colors, like the Colors, we considered it to be a more interpreted visualization.



(a) Graph.

(b) Sliders.



(c) Swirl.

(d) Colors.

(e) Light.

(f) Emoji.

Visualization	Representation	Info Level	Display
Graph	More raw	All 3 brain waves over time	Stream of brain waves across graph, highlighting the most active brain wave/second
Sliders	More raw	All 3 brain waves at given moment	Circles representing brain waves sliding left or right depending on values of the waves
Swirl	More interpreted	All 3 brain waves at given moment	Animated swirling lines: delta for line speed, alpha for line smoothness, beta for number of lines
Colors	More interpreted	All 3 brain waves at given moment	Overlaid color gradients with changing opacity based on brain wave values
Light	More interpreted	1 brain wave at a time	Changing colors of an LED light according to most active brain wave
Emoji	More interpreted	All 3 brain waves at given moment	Changing opacity of emojis based on brain wave values: delta represented by sleeping emoji, alpha by relaxed emoji, beta by thinking emoji

(g) Description.

Fig. 1. Overview of the 6 visualizations.

Emoji. The Emoji visualization used emojis, or cartoon faces with different facial expressions, to represent the three brain waves. These emojis were created according to the definition of each brain wave, with delta represented by a sleeping emoji, alpha by a relaxed emoji, and beta by a

thinking emoji. The opacity of each would decrease and increase, respectively, with lower and higher levels of brain wave activity. The Emoji mapped brain values to images, thus we considered the visualization to be more interpreted.

4 EXPERIMENTAL DESIGN AND METHODS

In a within-subjects study, participants watched recordings of the six different visualizations that used the same source brain activity as input. Participants' self-reported ratings of the visualizations and their expressed opinions about the individual whose brain activity they viewed were used to ascertain users' evaluations, preferences, and concerns regarding the display of brain activity, as well as to investigate the impact of the visualizations' designs on impression formation.

4.1 Participants

Thirty-six participants took part in the study, which was conducted at a private university in the northeastern United States. Four participants were only able to partially complete the study; thus, we removed their data from all analyses. The remaining 32 participants included 18 females and 14 males, with ages ranging from 18 to 43 years old (M=25.94, SD=6.4). We recruited participants from the university participation pool, and compensated them with ten dollars in exchange for participating in the study. Most participants had no prior experience with brain-sensing headsets, but seven participants had worn a headset for either another research study (n=5), gaming (n=1), or for seizures (n=1).

4.2 Visualization Recordings

Prior to the study, we had recorded a user's brain activity as they wore the Muse and listened to an instrumental audio track. We chose this setup in order to provide a sufficient context for participants to simulate the subjective experience of the user. Impression formation literature has typically achieved this goal through vignettes or video clips [3]; however, we used an instrumental audio cue to ensure that the participants' judgments would not be influenced by other nonverbal cues given by the user (e.g., their voice or facial expressions). We also chose this cue in order to produce meaningful data to visualize, as past research has used music to elicit complex brain activity [37, 39]. The audio track ("Dream" by Rabpit, Deemo-version) was two minutes long, and was chosen for its evocative nature and its inclusion of a section with ambient crowd noise (to provide a minimal social prompt for impression formation). Given the research on "thin slices" of behaviors [3], we believed that two minutes would be sufficient for participants to form their impressions. All six visualizations used the same originally recorded brain activity as input.

4.3 Measures

In order to explore general reactions to the expressive biosignal system and initial impressions of the person whose brain activity they were watching (the target), we included a number of open-ended questions for participants to answer for each visualization recording. These included questions about what participants noticed in the visualization, their impression of the target, and their feelings about potentially using the visualization in a social interaction. We also included open-ended questions about their general reactions to the visualizations, including which they would prefer to use for different purposes (e.g., to provide impressions of themselves to others, form impressions of others, and predict how well they would get along with or work with someone).

In addition to the open-ended responses, we included several validated scales to assess participants' impressions of the target in each recording along specific dimensions:

Ten Item Personality Inventory/TIPI. The TIPI is a ten-item scale used to assess the "Big Five" dimensions of personality (extraversion, agreeableness, conscientiousness, emotional stability,

openness to experiences) [16]. Because participants would need to answer questions for individual visualizations six times, we chose to use this validated, short-form scale to reduce the time, redundancy, and fatigue that would otherwise be experienced with a longer personality scale.

Mind Attribution. Mind attribution refers to the inferences people draw about the mental states of others, including their emotions, intentions, and thoughts [24]. Participants completed a ten-question scale assessing the extent to which they attributed different degrees of emotion (e.g., "This person has complex feelings"), intention (e.g., "This person has goals"), and cognition (e.g., "This person can engage in a great deal of thought") to the target.

Ambiguous and Positive Impressions. We used Tanis and colleagues' six-question scale to assess the ambiguity and positivity of the impression participants formed of the target [46]. We modified the original scale by removing questions about the content of discussion, since participants did not interact with the target. We added two questions about how clearly participants could predict getting along or working well with the target. These items were included to assess whether participants felt they could use the visualizations to predict the quality of interactions in different contexts.

Finally, we include a visualization scale to assess the quality and effectiveness of each visualization. These included the amount of information the visualization presented, the clarity of the visualization and its changes in states, its intuitiveness, and its aesthetic qualities [31].

4.4 Procedure

Participants completed this study individually in a controlled laboratory setting. They took about one hour to complete the study, which involved completing experimental tasks on a computer screen. They were told that the research team had collected brain activity from people who had listened to a music clip while wearing an EEG headset, and that they would be viewing six visualization recordings of brain activity data and completing questionnaires about what they observed.

To ensure that participants understood the meaning of the brain activity, definitions of the three brain waves were accessible on-screen while they watched the visualizations. These definitions were also provided to support the impressions that participants would form. Participants completed a pretest assessing their understanding of these definitions.

Next, participants viewed six visualization recordings, one after another, presented to them individually in a random order. While participants viewed the recordings, they were able to hear the original audio that the target had listened to. With the exception of the Light, participants viewed screen recordings of the visualizations. Because the Light was physical rather than screen-based, participants were instructed to inform the experimenter when they were to view that visualization, at which point the experimenter set up the Light system next to the participant. After each recording, participants answered questions about the visualization. Once participants finished watching all of the recordings, they answered questions about their overall reactions to the visualizations. These questions are described in the previous section.

Though each visualization displayed the same recorded brain activity, we wanted to test whether participants would notice that the activity was the same. After participants watched all of the recordings and answered all of the above questions, we asked participants to answer whether they perceived that the data behind each visualization came from the same person.

Finally, at the end of the survey, participants completed demographic information, including questions about their gender, race, and age. We also asked participants whether they had any prior experience with EEG or brain-sensing headsets, and if so, to describe the nature of that experience.

4.5 Analysis

We performed analysis of the open-ended responses and survey scales using qualitative and quantitative methods.

We analyzed the open-ended responses using a grounded theory approach [44]. First, we reviewed a subset of the responses from each category of questions (e.g., impressions of the target, feelings about using visualization in an interaction) developing codes according to similarities in participants' observations and opinions. For example, for impressions, we developed codes for similarities in mentioned traits (e.g., "intellectual") versus states (e.g., "thinking"). Two raters used these codes to perform open coding independently on the same subset of responses to clarify their definitions. Then, the two raters independently coded the rest of the responses, meeting frequently to resolve differences and ensure high inter-rater reliability (overall Cohen's $\kappa = 0.74$). Finally, we performed axial coding, counting and grouping similar codes, and comparing them across visualizations to form higher-level themes.

We analyzed effects of the visualization type on the TIPI, Mind Attribution, Ambiguous/Positive Impressions, and Visualization scales using a repeated measures ANOVA, looking for distinct differences between the mean ratings of impressions and design quality. Since the brain activity was the same across all visualizations, we initially included participants' answers to whether they perceived it was the same as a between-subjects factor. However, we found no significant effects of this factor; therefore, we report the results for the full sample.

The results from both analyses were examined together during the writing process in order to refine overarching themes around participants' impressions from the different visualizations, and reactions to the expressive biosignal system. These results are discussed in the following section.

5 RESULTS AND DISCUSSION

Our results showed that participants were interested in visualizing brain activity and using visualizations for social perception and communication purposes; however, a number of concerns and challenges emerged regarding integration of these visualizations into social contexts. In this section, we discuss major themes formed in our analysis around the issues and needs to be addressed in developing expressive biosignal systems.

5.1 Perceptions of mental states and traits

Participants were generally willing to form impressions of the target when asked–only 19 of the 192 responses explicitly mentioned having difficulty or being unable to form any impression from the data. Participants usually described their impressions in terms of psychological states (112 responses) as opposed to traits (25 responses). As expected, mentioned states were typically tied to the presence of the different wave types and related to the associated states that we provided:

> *"Considering the amount of delta waves, I suggest the person was sleeping or feeling tired."* - BV-7

> *"They were somewhat scattered, moving between very relaxed (deep sleep, green) and focused thinking (yellow). They were not focused on the music or enjoying it very much."* - BV-41

Generally, users were less open to inferring stable traits than states from the visualizations. Most trait-related responses pointed out that the target is likely "an average individual." However, a few responses described him in terms of emotional stability (14), complexity of thought (12), or sociability (6):

> *"...seems to be a planner and a worrier."* - BV-75

> *"Scientific, calculating."* - BV-52

> *"They are very aloof, but when they meet others, they start to worry what the other people think of them."* - BV-65

These traits appear to have been inferred from perceptions of the target's states throughout the audio. For instance, one participant who felt that the target is "very reserved and shy and doesn't like to go out much," also noted that "when there were others talking, the person was usually in deep sleep."

5.2 Influence of design features on impressions

Despite each visualization displaying the same brain activity, participants formed diverse impressions of the target across the different visualizations (Table 2). For instance, impressions that the target was relaxed were more present in responses to the Sliders (8) than to the Swirl (2). On the other hand, participants more commonly believed the target was in thought when watching the Swirl (8) as opposed to the Sliders (0). Trait-related responses similarly differed across visualizations:

> Colors: *"[S]omeone who is relaxed and stable."* - BV-12
>
> Graph: *"A nervus [sic] wreck."* - BV-84

Table 2. Prominent states mentioned in impressions, with associated brain waves in parentheses.

Visualization	**States Mentioned**
Graph	Sleep (delta), relaxation (alpha)
Sliders	Sleep (delta), relaxation (alpha), focus (beta)
Swirl	Thinking, focus (beta)
Colors	Either sleep (delta), relaxation (alpha), thinking, or focus (beta)
Light	Moving between sleep (delta), relaxation (alpha), thinking (beta)
Emoji	Sleep (delta), relaxation (alpha)

5.2.1 Salience of changes in activity. These differences in impressions stemmed in part from the degree to which the different visualizations depicted changes in the different wave activity. In particular, interpreted visualizations, which manipulated the display of the data, affected the prominence of certain waves. For instance, though beta was actually the least active wave in the data, participants primarily noticed high beta waves in the Swirl recording. This appeared to result from the mapping of beta to the number of lines present, which was more salient than the speed of the lines (delta) or smoothness of the lines (alpha). Subsequently, participants believed that the target was concentrating and thinking heavily while listening to the audio.

> *"It was much easier to tell when the person was concentrating vs. when they were not. Other than that, it was difficult to tell when the waves were changing."* - BV-37
>
> *"Not much - the number of lines representing beta waves seemed consistently high."* - BV-43

Salience of activity in all brain waves affected impressions formed from the Light recording. Since the Light constantly changed colors based on the brain wave with the highest relative value at the time, all three waves appeared to be prominent throughout the recording. Thus, participants noted that the target experienced multiple states:

> *"Very confused person who's going in and out of deep sleep, relaxation and concentration at the same time. Maybe the person is trying to relax and almost falling asleep, but is disturbed by the noise."* - BV-69

Visualizations that mapped data to the opacity of displayed images (Colors, Emoji) made changes in brain activity less conspicuous. For the Colors, all colors mapped to different waves were technically present at different opacities, but discerning the most prominent color might have been too difficult or too subtle (e.g., "more green" versus "more yellow"). Impressions made from Colors were generally in disagreement:

> *"Person is just relaxing on a nice day and watching the world go by."* - BV-69
>
> *"Not very relaxed, always engaged and active."* - BV-60

Similarly, for the Emoji, participants had difficulty determining which emoji was more opaque:

> *"...sometimes it was hard to differentiate between which one was lit up"* - BV-75

On the other hand, more raw visualizations that allowed for side-by-side comparisons of waves (Graph, Sliders) highlighted the high activity of delta waves, leading to expected descriptions of sleepy states. However, in addition to sleepy states, participants mentioned that the target might be relaxed or focused. Given that participants did not notice meaningful alpha or beta activity, it's possible that they projected their own feelings in their impressions in these cases, such as due to the relaxing nature of the provided audio:

> *"I think they would have felt relaxed, I know I did. Even the voices acted as a sort of white noise to mellow things out even futher [sic]."* – BV-91

Results from the repeated measures ANOVA for the Mind Attribution scale support findings around salient changes in each visualization (Table 3). Visualization type had significant effects on the Emotion ($F(5, 155) = 2.50, p = 0.03$) and Cognition (with Huynh-Feldt correction, $\epsilon = 0.88; F(4.42, 135.58) = 3.20, p = 0.01$) components, as well as the overall Mind Attribution Score (with Huynh-Feldt correction, $\epsilon = 0.88; F(4.42, 136.99) = 3.00, p = 0.02$), which is the sum of the Emotion, Intention, and Cognition scores (Cronbach's α ranging from 0.68 to 0.93). More interpreted visualizations (e.g., the Light and Swirl) tended to lead to higher scores. The Swirl, which made beta waves more salient, was scored higher for cognition than other visualizations. The Light scored higher for emotion, potentially due to exposure to frequent color changes signaling changes in emotional state.

5.2.2 Visualization style and personality. Different visualization styles may have also affected participants' impressions, particularly along the personality dimension. Though participants tended not to infer stable traits in their open-ended responses, results from the repeated measures ANOVA showed significant differences across visualizations for the TIPI scale (Table 3). Participants perceived differences in the target's Extraversion (with Huynh-Feldt correction, $\epsilon = 0.82; F(4.09, 126.8) = 2.48, p = 0.05$) and Emotional Stability (with Huynh-Feldt correction, $\epsilon = 0.91; F(4.53, 140.55) = 3.88, p = 0.003$) across visualizations. An LSD post-hoc test for these traits showed that the Swirl and Sliders had the highest mean ratings for Extraversion, while the Emoji had the highest for Emotional Stability (p-values below 0.03).

Characteristics of the visualizations likely influenced participants' judgments of the target's personality. For instance, the Swirl, Sliders, and Light may have produced the highest extraversion ratings as a result of their more animated, rapidly changing visuals, as high extraversion tends to be associated with high motion activity [23]. Lines were constantly swirling, circles were moving back and forth, or distinct colors kept changing, as compared to the slow right-to-left stream of the Graph or subtle opacity changes in the Emoji or Colors:

> Sliders: *The circles were changing quickly, and one circle would go from the farthest to the right to all the way on the left within a split second.* - BV-37

Table 3. Means of measures with significant differences across visualizations, with standard deviations in parentheses. Means that do not share a superscript significantly differed at $p \leq 0.05$. Visualizations with the highest and lowest means are listed in the last two columns.

Measure	Graph	Sliders	Swirl	Colors	Light	Emoji	Highest	Lowest
TIPI (/7)								
Extraversion	3.50^{c}	$3.95^{a,b}$	4.30^{a}	$3.75^{a,b,c}$	$3.95^{a,b,c}$	$3.53^{b,c}$	Swirl	Graph
	(0.84)	(0.72)	(1.23)	(1.13)	(1.28)	(1.32)		
Emotional Stability	4.14^{b}	4.09^{b}	4.06^{b}	$4.55^{a,b}$	4.47^{b}	5.09^{a}	Emoji	Swirl
	(1.19)	(0.95)	(0.97)	(1.25)	(1.24)	(1.09)		
Mind Attribution								
Emotion (/28)	19.13^{b}	19.41^{b}	$20.06^{a,b}$	$19.81^{a,b}$	20.50^{a}	18.66^{b}	Light	Emoji
	(4.10)	(3.17)	(3.45)	(3.44)	(3.11)	(3.91)		
Cognition (/21)	$13.16^{b,c}$	12.84^{c}	14.59^{a}	$14.31^{a,b}$	$14.41^{a,b}$	$13.09^{b,c}$	Swirl	Sliders
	(3.30)	(2.69)	(2.86)	(2.65)	(2.89)	(3.46)		
Mind Attribution (/70)	45.25^{b}	46.03^{b}	48.88^{a}	$48.44^{a,b}$	48.91^{a}	45.06^{b}	Light	Emoji
	(9.73)	(7.50)	(7.63)	(7.93)	(8.17)	(9.09)		
Ambiguous/Positive Impressions (/7)								
Feelings of Connection	3.00^{c}	$3.50^{a,b}$	$3.59^{a,b}$	3.38^{c}	4.06^{a}	$3.69^{a,b,c}$	Light	Graph
	(1.41)	(1.61)	(1.24)	(1.68)	(1.63)	(1.73)		
Visualization (/5)								
Clear Changes	3.72^{a}	4.03^{a}	$2.81^{b,c}$	2.31^{c}	4.13^{a}	2.97^{b}	Light	Colors
	(0.96)	(1.00)	(1.18)	(1.23)	(0.79)	(1.36)		
Easily Understand	$3.44^{b,c}$	$3.81^{a,b}$	$2.72^{d,e}$	2.41^{e}	3.94^{a}	$3.16^{c,d}$	Light	Colors
Current State	(0.98)	(1.12)	(1.17)	(1.19)	(0.80)	(1.14)		
Aesthetically Pleasing	3.22^{b}	3.63^{b}	3.41^{b}	3.47^{b}	4.25^{a}	3.22^{a}	Light	Emoji/Graph
	(1.10)	(0.91)	(1.04)	(1.08)	(0.80)	(1.21)		
Intuitive	3.13^{b}	3.59^{a}	2.66^{c}	$2.81^{b,c}$	$3.31^{a,b}$	3.69^{a}	Emoji	Swirl
	(1.13)	(1.16)	(1.18)	(1.40)	(1.15)	(1.09)		

The high emotional stability rating for the Emoji was also likely to be influenced by the emojis provided in the visualizations. Emojis are a common representation of emotions; thus, participants may have inferred a limited range of emotions since we only showed three emojis. This may have also led to its low emotion score rating in the Mind Attribution scale.

> *"People already have preconceived ideas of what an emoji ought to represent, it would be very misleading to use only three symbols for the wide range of brain activity."* - BV-7

5.3 Visualization Preferences

5.3.1 Clarity and visual appeal. We found that participants preferred visualizations that they believed to be "clear" in terms of their comprehensibility and representation of the brain activity, as well as visually appealing. The visualization most preferred by participants was the Light, for providing impressions of themselves, forming impressions of other people, and predicting how well they would work with someone else. People believed that the color changes were easy to notice, pleasant, and soothing to view:

> *"It was really easy to know what my brain was doing and the most interesting."* - BV-98
>
> *"The LED is soft and relaxing it has a calming affect [sic] to it, I just like it a lot."* - BV-87

Participants also preferred the more raw Sliders and Graph. Seven participants chose the Sliders to provide an impression of oneself to another person, primarily for being very easy to understand. Six to eight participants chose the Graph for forming impressions of other people and predicting

interaction quality (getting along or working well with someone). Those who chose the Graph believed it was the most straightforward, familiar, and "clinical," trusting it for showing data as is:

> *"It's self-explanatory and easy to interpret."* - BV-70

> *"I always believe in graphs, they provide the data correctly."* - BV-92

Participants' preferences for visualizations were also reflected in the repeated measures ANOVA for the Visualization scale. Visualizations differed significantly in clarity of changes ($F(5, 155) = 14.64, p < 0.0005$), ease of understanding the current state ($F(5, 155) = 11.00, p < 0.0005$), and aesthetics (with Huynh-Feldt correction, $\epsilon = 0.90; F(5, 139.25) = 4.55, p = 0.001$), with an LSD post-hoc analysis showing that the Sliders, Light, and Graph were the most highly rated for clarity and understanding, and Light for aesthetics.

In addition, a third of the participants preferred the Emoji to predict positive interactions with another person. Like the Graph, participants felt familiar with the Emoji. The Emoji made emotions easily recognizable and "straightforward," which participants felt is important for predicting the quality of an interaction. The Emoji was also rated as the most intuitive from the visualization scale, where intuitiveness was significantly different between visualizations ($F(5, 155) = 4.57, p = 0.001$).

5.3.2 Perceptions of information levels on accurate understanding. Participants also desired to present and glean accurate information from the brain activity shown in the visualizations. Participants expressed varied opinions about how that information should be conveyed. Eight participants believed that it was more important for the visualization to leave room for subjective inferences or show less information, such as in the more interpreted Light or Colors:

> *"I thought that the LED light provides again a non-deterministic way of 'judging' someone without being too absolute.* - BV-69

> *"The color gradient is the most vague of all the visualizations. This would be most beneficial to me because I would not need to act a certain way, the vagueness of the colors leaves that up to interpretation."* - BV-7

On the other hand, twelve participants preferred visualizations that they perceived to have more information, such as in the more raw Graph or Slider, primarily for forming an impression of or predicting the quality of interaction with another person. These participants believed that more information would help them better understand the other person:

> Graph: *"It could show the change on how well we get together as a function of time, and you could see growth and decay of the relationship clearly."* - BV-65

> Sliders: *"This visualization seemed to give me the most information, so I feel like I would be best able to judge more information about that person's state of mind to complete a task together."* - BV-41

5.4 Concerns about Privacy

Though participants felt that the visualizations would be informative, a third of their responses mentioned concerns that they would be too revealing and intrude on privacy. Many concerned participants mentioned they would be more interested in viewing their own, rather than others' brain activity:

> *"I think it would be personally violating to see someone else's brain activity when speaking to them. I would be interested in seeing my own information because it might allow me to figure out when I'm thinking too hard and I need to relax."* - BV-91

The visualization that brought up the most concerns about privacy was the Sliders. Potentially, participants perceived that it revealed more information than they felt comfortable with. The Sliders made it easy to compare the different waves to each other and thus make assumptions about states.

> *"It might feel intrusive because it clearly provides a lot of information rather than general trends in brain activity."* - BV-41

Visualizations that provided less information appeared to garner fewer concerns about privacy. Regarding communicating with others with the Colors, one participant mentioned:

> *I would feel comfortable; there doesn't seem to be very much information associated with each color so it's not too intrusive. It's also not super clear when one color fades into another.* - BV-60

However, less information may not always be positive. For instance, participants had the least privacy concerns for the Swirl. This may have been due to the fact that the Swirl was the hardest visualization to understand, and participants mentioned it was "confusing" and "difficult" using it to gain meaningful insight about the target's mental state. The complexity of the visualization could help ensure that the brain activity is not too revealing; however, a visualization that is difficult to decipher is less likely to provide any useful information at all.

5.5 Cognitive Load

Many participants were also concerned that the visualizations would be distracting if used during social interactions. They felt that a visualization would detract from a conversation because they would focus too much on understanding it and not attending to the other person. This concern was primarily expressed for the Swirl, which people believed would take more effort to interpret because of its complexity:

> *"I feel distracted because it takes quite a lot effort to analyze and interpret the visual information of the person's brain activity."* - BV-23

The Graph and Sliders were also considered distracting. Potentially, this may be because they show a lot of information at once. Viewers would have to process changes in all three brain waves over time and compare them to each other, thus taking away from conversation. However, participants were less concerned about distraction when they imagined using the visualizations for computer-mediated communication (9 responses, as compared to 26 for face-to-face). They felt that in mediated settings, they would be able to focus on the visualization more because there is less expectation to look at the other person than in face-to-face settings, and there would be more time to consider the visualization and manage self-presentation. The Emoji, in particular, was viewed positively since emojis are often used in mediated settings.

> Graph: *"When we're online we are usually multitasking, so it would almost make sense in this case."* - BV-37
>
> Swirl: *"I think I feel better than face-to-face, because now I have time to consider the other person's reaction and adjust my reactions."* - BV-92
>
> Emoji: *"It would fit in well in online communication, because emojis are already used there"* - BV-41

5.6 Feelings of Connection

Despite concerns around privacy and cognitive load, the open-ended responses also indicated interest in expressive biosignal systems from participants. 16 of the responses noted that the visualizations would be useful for providing an "additional layer of communication" that could people understand the mental states of other users and, subsequently, better consider their own reactions

and behaviors. Generally, positivity around the system emerged while considering computer-mediated contexts, rather than face-to-face, given the limitations in existing cues that might cause communication issues:

> *"I think viewing brain activity during online chat is effective in helping me understanding the other person's reactions. It would cause less confusion or misunderstanding."* - BV-23

Certain representations of brain activity may also be more useful than others in promoting feelings of connection with others. Results from the repeated measures ANOVA ($F(5, 155) = 2.48, p = 0.03$) and LSD post-hoc analysis showed that these feelings were significantly higher for the Light visualization than others. Comments for the Light visualization in the open-ended responses similarly suggested its potential for connecting people through brain activity:

> *"Also, it may be easier to trust someone else by watching his actual brain activity. You feel like you know this person from deep heart."* - BV-77

> *"[I]t would be cool for an app that could allow couples to see what their partner is feeling over long distances."* - BV-26

This suggested connectedness may have been due to the physical and ambient presentation of the Light, as previous research has shown that ambient light can promote connectedness between remote individuals [35]. These feelings were also significantly higher than for the raw Graph, potentially due to the Graph's "clinical" appearance distancing participants from the target.

6 GENERAL DISCUSSION

On the whole, our results reveal the potential for the sensing and sharing of physiological response data to influence interpersonal judgments and perceptions. At the same time, they elucidate key challenges that must be addressed in the design and implementation of expressive biosignal systems in order for them to effectively augment or improve self-expression and communication.

6.1 RQ1: Will the meaning of brain activity, like other biosignals, be ambiguous to perceivers, and to what extent will perceivers be willing to use shared brain activity as a social cue to form impressions?

To answer RQ1, we had participants rate their impressions of an individual while viewing that individual's brain activity, which was recorded while they listened to music. Our results show that, to some degree, individuals *are* willing to rely on expressive biosignals to form impressions about others. Participants drew the strongest conclusions about another individual's cognitive or emotional states based on their displayed data, as evidenced by the results on their open-ended responses and the Mind Attribution measure. Moreover, they reserved their most significant inferences about personality to the two traits of the "Big Five" that relate most strongly to emotional states (neuroticism/emotional stability) and cognitive states (extroversion/introversion, which has been shown to be linked with levels of cognitive arousal [32]). These findings show that participants were more willing to use expressive biosignals to draw conclusions about psychological states (i.e., a person's currently experienced emotions or level of cognitive activity) than they were to infer a person's stable dispositional traits. However, at the same time, we found that the impressions that participants formed varied widely depending on the visualization. Like other biosignals [20], the meaning of brain activity was indeed ambiguous and led to multiple interpretations, particuarly as a result of different visualization design features.

6.2 RQ2: How do different representations of brain activity affect impression formation?

To answer RQ2, we compared various visualizations that were either more raw or interpreted in nature [17], yet displayed the same data. The different visualization formats significantly influenced participants' inferences. For interpreted representations, the manner in which the different brain waves were translated made certain changes more salient (e.g., noticeable beta waves-only for the Swirl, all waves for the Light). Raw representations, which allowed for more straightforward numerical comparison between waves, had more consensus in responses, suggesting that translating too far from the raw data could confuse viewers' observations of changes in the data. Additionally, independent of representation type, stylistic aspects of visualizations appeared to affect impressions based on participants' preconceptions (e.g., high motion with extroversion [23], emojis with emotions). Our work demonstrates that certain features of biosignals visualizations, such as imagery, animation, and amount of information, can produce diverse impressions even on the same data.

6.3 RQ3: How do different representations of brain acivity affect perceivers' evaluations of those representations for use in communication contexts?

In investigating RQ3, we asked participants to describe their feelings about using each visualization in face-to-face and computer-mediated communication. In their responses, participants exhibited reservations about having access to another individual's biosignals, expressing concerns about violation of privacy or distraction from an interaction. At the same time, they desired to learn and provide enough useful social information through the visualization to support an interaction. Participants' preferences for visualizations thus varied based on how clear and informative the visualizations appeared. The Swirl sparked the least amount of concern for privacy, but was also the least preferred for being too complicated and unintuitive. The more raw Sliders was highly rated for its clarity, but also elicited privacy concerns because comparisons between brain waves were so easy to make. These visualization preferences and concerns point to the need to explore the right balance and comfort levels for addressing issues related to ambiguity, privacy, and cognitive load in expressive biosignal systems used for communication.

7 DESIGN IMPLICATIONS

We present three major design considerations for the development of expressive biosignal systems, drawn from the results of our study and our plan for future work.

7.1 Designing for disambiguation

As the results of the present work demonstrate, an expressive biosignal system must account for individuals' subjective impressions from sensed data and, moreover, address the possibility that their interpretations may fail to align with the actual meaning of the data (i.e., the subjective experience or the true cognitive or emotional state of the individual whose data are being shared). Going forward, one critical question to be addressed is whether biosignals are equally ambiguous for those whose data are being sensed and those with whom the data is being shared: that is, are individuals uncertain about the meaning of both their own and others' data? If individuals indeed have some degree of insight about the connection between their current state of mental activity or emotional response and the corresponding changes in biosignal, perhaps systems that provide them with the agency to disambiguate their own biosignals will be key. The means of clarification might lie in visualization schemes that provide clearer connotations of a particular cognitive or emotional state (and the ability to choose between alternative schemes in sharing data) or the provision of

tools that link physiological responses to disambiguating context clues. In current follow-up work, we are investigating two such possibilities: kinetic typography tools that display text or speech in a style indicative of one's thought processes or state of arousal and social interaction systems that allow users to supplement sharing of biosignals with information about their current activities or states.

7.2 Designing for privacy preservation

Because expressive biosignals by their very nature involve displaying personal information that is not typically public, designing systems that preserve users' preferred level of privacy–in regard to who should have access to the data and how it should be shared–is critical. Expressive biosignal systems may require flexibility in allowing users to opt for publicly visible versus privately displayed settings depending on interaction contexts or relationships. In some contexts, the value of expressive biosignals may lie more in the self-reflection it promotes [20]–for instance, when we desire to be mindful of our own physiological responses and their impact on our behaviors. In other situations, publicly displaying data may allow for individuals to better synchronize with and understand each other. In follow-up work, we will investigate the impact and implications of personal and public biosignal displays and identify the contexts in which each is likely to be more desirable for preserving users' privacy while providing information that can help improve communication. For example, public sharing related to stress may be useful in tasks like advice giving, in order to consider the state of someone being counseled or providing advice. Indicators of cognitive processing may be useful in interviews or cooperative work, but may only be appropriate in anonymized displays to counter the potential discomfort of being exposed in a professional setting. Going forward, we will test expressive biosignal systems with different levels of translucence and customizable privacy settings during a variety of cooperative and communicative tasks.

7.3 Designing for seamless integration

We also need to consider the cognitive load that is inherent in increasing the number of expressive nonverbal cues to which one must attend during impression formation or interpersonal interactions. Brain activity, in particular, can be difficult to follow due to its inherent complexity. EEG data is already a novel and unfamiliar element in typical social situations, and having to understand the meaning of different brain waves and interpret them from visualizations may end up being more distracting than supportive. These issues may be heightened in collocated interaction, when interaction partners' attentiveness to each other is more apparent and consequential. As alluded to by a number of our study's participants, in order to reduce the cognitive processing required for interpreting physiological data, expressive biosignal systems need to present the data in a clear yet unobtrusive manner. In addition to pre-interaction training for biosignals and orientation to how they are presented, systems may need to deliver feedback at only critical moments in an interaction. For instance, biosignals could be shared early on in an interaction, when impression formation is most key, or during high levels of excitement or engagement to enhance positive feelings or interest shown at that moment. Such selective sharing schemes will reduce the disruption that might be caused by the constant display of physiological changes throughout an interaction. Future work should consider the effects of continuous, real-time feedback versus intermittent feedback on the quality of interactions.

8 LIMITATIONS

We conducted a study to explore how people form impressions of another person from different visualizations of that person's brain activity. While our findings contribute important design considerations for expressive biosignals systems, our work has some limitations. First, our study

was designed such that participants did not interact with the target, and could only form their impressions based on how the target's brain activity changed with the progression of a piece of music. This was done in order to isolate the available cues, as interacting with the target would introduce additional cues that are known to influence impressions (e.g., visible nonverbal behaviors, manner of speaking, etc. [15, 38]). As a longer-term goal, we aim to understand how to integrate expressive biosignals into communication. In designing future expressive biosignal systems, we will take into account participants' feedback about the opportunities and issues in using these systems in actual interactions. At the same time, we recognize the importance of studying the implementation of these systems in actual interactions, and plan to do so in future work.

Second, participants did not have prior knowledge about brain activity, and were only given brief definitions of different EEG waves with which to base their interpretations. While we based our study design on the methodology employed in the "thin slices" body of research, we note that the nonverbal behavioral cues we typically depend on are those we have developed familiarity with over a long term. Participants were willing to form impressions based on their understanding of how mental states might change with changes in the brain waves; however, it is possible that they would be more equipped to form impressions given a longer period to become familiar with brain activity as a potential cue. Our work supports that the data is indeed ambiguous, thus, training programs should consider providing different contexts in which brain activity can be interpreted. Future studies should investigate how much training and experience users might need to develop an appropriate understanding of the data in social settings.

Finally, the EEG data used in the present study was recorded from a user who wore the Muse headset while listening to music. We chose the Muse due to its unobtrusiveness and ease-of-use. However, as a consumer-grade headset with only seven sensors, the Muse is less accurate than research-grade headsets that have many more sensors. For the purposes of this study, we focused on how the data *visualizations* would affect impressions; thus, we felt that having great accuracy in the data was not necessary. Of course, future integration of brain activity as cues in real-world settings will require accurate and reliable data. As brain-sensing technology advances, future work should consider using consumer-grade headsets that improve in accuracy.

9 CONCLUSION

Expressive biosignals have the potential to transform the way we communicate by introducing new types of social information that could deepen our understanding of each other. However, we must consider how to seamlessly integrate physiological data into interpersonal contexts in a non-invasive yet supportive way. We conducted an empirical study that demonstrates the challenges and opportunities of using expressive biosignals for social perception. We found that while people appear willing to attribute brain activity to emotional and cognitive states, the ambiguity of the activity can lead to different impressions. Moreover, this study sheds light on several important issues concerning the level of cognitive load involved in processing unfamiliar and complex data, as well as the intrusive nature of exposing physiological information that people may not feel comfortable sharing. With these findings as a foundation, we presented a number of design considerations involved in building expressive biosignal systems that facilitate self-expression and positive social interactions.

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