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RESEARCH ARTICLE

Physiological Responses to Movies Predict Marital Satisfaction

YUICHI ISHIKAWA[1], NAO KOBAYASHI[1], ROBERTO LEGASPI[1], KAE NAKAJIMA[2], AND YASUSHI NARUSE[2]

[1]KDDI Research Inc., Fujimino-shi, Saitama 356-8502, Japan

[2]Center for Information and Neural Networks (CiNet), National Institute of Information and Communications Technology, Kobe-shi, Hyougo 651-2492, Japan

Corresponding author: Yuichi Ishikawa (ishikawa_yuichi@yahoo.co.jp)

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ABSTRACT People perceive psychological characteristics (PCs), such as the personality and values of a marriage partner, as extremely important factors in partner selection. Due to its importance, considerable work has investigated the relationship between couples' PCs and their marital satisfaction, and their findings have been adopted by matchmaking services. However, these studies and services have determined the PCs using self-report questionnaires, in which the resulting measurements have limited amount of information and various biases, and thus, have limited predictive utility for marital satisfaction. Given this, we examined the predictive utility of brain and cardiac responses, which are known to correlate with PCs, providing information that are very different in nature and quality from what a questionnaire measures and present fewer biases. We collected the EEG and ECG data of 51 married couples while they watched a set of preselected movies and examined the association between their physiological measurements and marital satisfaction. Performing regression analyses, we confirmed that the brain and cardiac responses to the movies have significant predictive utility for marital satisfaction. When we used these physiological responses to one of the movies in the models, the prediction error for male and female marital satisfaction was reduced by an average of 19.0% and 10.1% in terms of RMSE, respectively, compared to baseline models that used only the questionnaire measurements of psychological characteristics.

INDEX TERMS Brain, electrocardiography (ECG), electroencephalography (EEG), marriage, matchmaking, partner selection, personality.

I. INTRODUCTION

One aspect that is vital to our well-being is the healthy relationship we have with others, among whom are our marriage partners. People generally believe that who they marry determines whether or not they can live a happy married life and thus spend considerable effort on selecting a suitable marriage partner. Among various factors considered in partner selection, such as age, appearance, and social and financial status, multiple studies report that both males and females see psychological characteristics, such as personality and values of a partner, as the most important factors across cultures (e.g., China [1], Germany [2], Japan [3], [4], Serbia [5], and the U.S. [1], [6]). Because of its importance, many studies have been conducted, mainly in the field of psychology, on the relationship between couples' psychological characteristics and their marital satisfaction [7], [8], [9], [10], [11], [12], [13], [14], [15]. These studies have found that the personality traits of two individuals, such as extraversion and emotional stability, have significant correlation with marital satisfaction [7], [8], [9], and [10]. They also found that the more similar a couple's personalities and values are, the higher their marital satisfaction is [11], [12], [13], [14], [15]. Leveraging these findings, several matchmaking services

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today determine users' personalities and values, based on which they select and recommend potential partners for each user.

In the above studies and services, it has been a common practice to regard personalities and values as consisting of multiple dimensions, and measure each dimension with the use of self-report questionnaires. To determine personality, for instance, many existing studies have used the Big Five trait model [16] that regards personality as consisting of five dimensions: *Extraversion* (*Ex*), *Neuroticism* (*Ne*; opposite of *Emotional Stability*), *Agreeableness* (*Ag*), *Conscientiousness* (*Co*), and *Openness* (*Op*).

However, there are limitations to this approach in terms of the amount of information and the reliability of its measurements. For the amount of information, to avoid cognitively overloading respondents, the questionnaires consist of a limited number of items, which in turn restricts the scope of the questionnaire in terms of the psychological characteristics they can determine. In addition, answers to individual items are aggregated into scores for a small number of dimensions, which reduces the amount of information coming from the item-by-item responses. Furthermore, because the score of each dimension is calculated by summing the answers to an n-point Likert scale or binary scale (yes/no), it is discrete rather than continuous, i.e., its granularity is coarse. As for the reliability, questionnaire surveys in general are exposed to the risk of various biases. When it comes to matchmaking in particular, there is the risk of social-desirability bias in which respondents consciously or unconsciously try to make themselves look good. When the answers are biased in such a way, the measurements deviate from the true psychological characteristics. Given these limitations, we consider that questionnaire measurements have suboptimal predictive utility for marital satisfaction.

In light of the above, we examine the utility of a couple's physiological responses to stimuli for predicting their marital satisfaction. Specifically, we focus on their brain and cardiac responses to audiovisual stimuli. Existing studies demonstrated that these two physiological responses to stimuli reflect psychological characteristics. For example, Harvey and Hirschmann [17] reported that heart rate responses to adverse visual stimuli (slide presentations of people who died violently) were significantly associated with *Ex* and *Ne* (e.g., those who have lower *Ex* and higher *Ne* showed initial accelerated heart beats). Multiple studies have also found that when positive or rewarding stimuli (e.g., photos of puppies and cakes) are presented, activity levels in the brain regions related to reward system are positively associated with *Ex* [18], [19], [20], [21], [22], [23]. Based on these studies, we consider that physiological responses to audiovisual stimuli, which reflect an individual's psychological characteristics, would also have predictive utility for marital satisfaction. In addition, we consider that they would provide additional predictive information that cannot be obtained from using questionnaires as they contain both time- and frequency-domain information. Furthermore, because physiological responses arise unconsciously, they tend to suffer less from bias compared to questionnaire-derived information. Given these, we expect that using physiological responses to stimuli would improve the accuracy of predicting marital satisfaction and, hence, enable matchmaking services to find potential couples who are more likely to lead a happy married life.

Our main research question (RQ) in this study is as follows:

RQ1 In predicting couples' marital satisfaction, do brain and cardiac responses to audiovisual stimuli have predictive utility that is independent of the questionnaire measurements of their psychological characteristics?

To measure the brain and cardiac responses, we use electroencephalography (EEG) and electrocardiography (ECG), respectively.

Among various ways to measure brain responses, such as positron emission tomography (PET), single photon emission computed tomography (SPECT), functional magnetic resonance imaging (fMRI), near infrared spectroscopy (NIRS), and magnetoencephalography (MEG), we selected EEG for the following reasons. First, unlike PET and SPECT, which require subjects to be administered a radioactive compound, EEG can measure brain responses in a non-invasive way. A subject just needs to wear a headgear with multiple electrodes attached to the scalp. Second, it costs much less than PET, SPECT, and fMRI, which come with a large piece of equipment that costs significantly much more than the EEG headgear. They also require subjects to visit a facility that has such equipment, lie in it, and stay still during the scan procedure, imposing much inconvenience on them. Lastly, in recent years, several companies are commercializing wearable devices with EEG (e.g., headphones [24] and VR headsets [25]). Such trend, which we have not seen for NIRS and MEG as much as for EEG, would make EEG more common and less costly. Given these features, we envision our findings derived from EEG measurements have greater potential to be adopted in the field than the others.

As the audiovisual stimuli, we used full-length movies. Generally, full-length movies consist of various story lines and, thus, are more likely to elicit diversity of individual differences in emotional experience and corresponding physiological responses compared to having short contents [26]. Therefore, we consider that brain and cardiac responses to full-length movies would reflect broader aspects of psychological characteristics, hence they are more suitable to predict marital satisfaction.

Assuming that the answer to RQ1 is yes, we set the sub-RQs, RQ2 and RQ3, as follows.

RQ2 Is gender difference a factor in the predictive utility of brain and cardiac responses to movies?

Pennebaker and Roberts [27], [28] argue that males compared to females rely more on perceiving internal body state (known as interoception), such as heartbeat and respiratory resistance, as information sources on emotions because males have greater interoceptive senses (e.g., more accurate at detecting heart rate than females). Based on [27] and [28], we consider the association between the emotional experience and the cardiac responses from watching movies would be stronger in males than in females. This would create the predictive utility of cardiac responses (as well as the predictive utility of brain responses relative to the cardiac responses) that differs across gender. We examine this by RQ2.

RQ3 Do similarities in a couple's physiological responses to a movie have significant predictive utility?

Existing studies report that similarities in brain and cardiac activities between two persons are associated with various qualities of human relationships [29], [30], [31], [32], [33], [34], [35], including marital relationship [36], [37]. However, none of them have incorporated control variables such as individual-level physiological activities or similarities of psychological characteristics determined by questionnaires in their analyses. Therefore, the effect of the similarities in physiological activities might have been confounded with the effects of these variables. We address this by RQ3.

To address RQ1∼3, we recruited married couples and had them watch full-length movies while collecting their EEG and ECG data. By administering self-report questionnaires, we also collected their personality traits, sense of values, and marital satisfaction. Using these data, we built multiple linear regression models to predict their marital satisfaction using different sets of independent variables and performed model comparisons.

Our key contributions are summarized as follows. 1) We examined the utility of couples' physiological responses to movies measured by EEG and ECG for predicting their marital satisfaction, which has not previously been studied or reported in the existing literature, and confirmed that these physiological responses have predictive utility that is independent of questionnaire-based measurements of their psychological characteristics. 2) We also discussed the practical and theoretical implications of our results, clarifying how the results benefit matchmaking services and how they compare with existing knowledge on the association between physiological activity and human relationships.

II. RELATED WORK

Thus far, many studies have investigated the association between physiological signals collected from two (or more) persons and their human relationships. One research category focused on interpersonal physiological synchrony. Using EEG, Kinreich et al. [30] examined the similarity between the temporal neural fluctuations of two persons (neural synchrony; NS) while they were interacting socially and found that the NS observed in romantic couples was significantly stronger than that between strangers. Azhari et al. [33] and Bevilacqua et al. [32] examined the NS present in other kinds of human relationships. The former examined the NS between mothers and children when they watched animated videos together and found that the strength of their NS was negatively correlated with the parenting stress of the mother. The latter examined the NS between a teacher and students in classes using EEG and confirmed that the students who perceived social closeness to the teacher showed stronger NS with the teacher.

While these studies examined synchrony in the brain activities, cardiac synchrony has also been studied [31], [34], [35], [36]. Among such studies, one conducted by Levenson et al. [36] is closely related to our study in the sense that they also investigated married couples. They measured the extent to which the couples' heart rates varied together while the couples discussed a source of conflict in their married life. The result showed that the couples' cardiac synchrony accounted for 60% of the variance in self-reported marital satisfaction.

These studies suggest that physiological synchrony of two persons are significantly associated with the perceived quality of their human relationship (e.g., marital satisfaction). However, they only examined physiological signals during social interactions. To leverage their findings for predicting human relationship quality, two persons in question need to have interaction. This is impractical for matchmaking services because they typically have thousands of users and thus cannot arrange to have every pair of their users interact with each other to find potential couples.

Parkinson et al. [29] and Li et al. [37] conducted experiments without such limitation. They had individual participants watch short video clips alone without interacting with other participants during an fMRI scan. They recruited participants who are directly or indirectly connected in a social networking service (SNS) [29] and married couples [37], and demonstrated that similarities of brain activities between the participants were positively correlated with closeness in SNS [29] and marital satisfaction [37]. The similarities in brain activities might be attributed to prior interactions the participants had (e.g., daily conversations, habitual patterns developed with each other) to some extent. However, as the adage says "birds of a feather flock together," we consider that their similarities in psychological characteristics by nature could make their relationship close and satisfiable, and these similarities in psychological characteristics would have been reflected to the similarities in brain activities when they were watching the video clips.

Following [29] and [37], we also adopted a setting where participants had no social interaction while watching the movies. However, there are several major differences between [29] and [37] and our study. The first is that we used EEG whereas they used fMRI. While measurements by EEG cost much less than fMRI, its spatial resolution is significantly inferior to that of fMRI. Because EEG electrodes measure electrical activity at the scalp, it is difficult to determine whether the signal arose near the surface or from a deeper region of the brain. Given this limitation of EEG, it is uncertain whether EEG data that are collected when subjects are not socially interacting are also associated with human relationships.

Second, [29] and [37] examined similarities in brain activity without controlling the effect of individuals' brain activities. Some psychological studies on the relationship between personality similarities and marital happiness argue that not controlling for individual personalities leads to overestimating the effect of personality similarities [7], [8], [38], [39]. We speculate this might hold true for similarities of brain activities. Therefore, different from [29] and [37], we incorporated in the analysis not only similarities of EEG measurements but also features of an individual subject's EEG measurements.

Lastly, [29] and [37] did not control the participants' psychological characteristics determined by questionnaires, let alone the similarities of the questionnaire measurements. There is a wealth of literature demonstrating that similarities in the psychological characteristics have a significant effect on their human relationships (e.g., [11], [15]). Given this, we examined whether the association between the brain response similarities and human relationships persists even when we control the effect of similarities in psychological characteristics determined by questionnaires.

III. METHOD

A. PARTICIPANT RECRUITMENT AND DATA COLLECTION

We recruited 51 Japanese heterosexual married couples with normal hearing and vision (mean age: males-38.2, females-37.3). We asked them to come to our experiment facility where they watched three full-length movies in total while being monitored with EEG and ECG devices. Each movie was presented on different days to avoid cognitive overload and physical exhaustion. We also administered questionnaires to assess the participants' personality, values, and marital satisfaction after they watched the first movie. The data collection was conducted after gaining the approval of the Ethics Committee of our organization. All participants were fully informed in advance of the contents of the experiment and the experiment was conducted only after obtaining the consent of the participants.

1) QUESTIONNAIRE SURVEY

Table 1 shows the questionnaires and statistics of the survey. For personality and values, we used the Big Five (BF) [16] and Schwartz's Basic Values (SBV) [40], respectively. The SBV is based on the idea that human basic values can be reduced to 10 distinct dimensions. It is widely applied to international surveys of individual values such as the World Values Survey.[1] Among multiple scales for personality and values, we selected the BF and SBV because of their wider acceptance in the scientific community. We used the questionnaires developed by Namikawa et al. [41] and Schwartz [42] to determine the BF and the SBV, respectively.

To determine marital satisfaction, we used the Quality Marriage Index (QMI) [43]. Other than the QMI, there are several other self-report tools to evaluate marital satisfaction, e.g., [44], [45], [46], [47], and [48]. We selected the QMI not only because its Japanese version is available, but also it has only six items, which is smaller and requires less time to answer than the others. A meta-analysis study [49] confirmed an average strong reliability of the QMI.

2) MOVIES (stimuli)

Table 2 lists the movies presented to the participants. We endeavored to select movies through which physiological responses would have predictive utility for marital satisfaction. We assumed that movies with large variance of impression among participants would elicit large inter-participant variance in physiological responses and such movies would have greater predictive utility compared to movies with small variance. Based on this assumption, we first selected 30 popular movies whose box-office earnings in Japan were more than one billion yen. We did not consider unpopular movies because we deem the unpopular movies would be more likely to induce a similar impression (i.e., boring) among the participants. We asked the participants before the experiment if they had watched the 30 movies before and their overall impression (0-had never seen it before, 1-very boring, 2-boring, 3-neutral, 4-interesting, or 5-very interesting; 1-5 are for those who had seen the movie before).

We then selected the movies with large impression score variance among the participants (we calculated the variance excluding 0). We did not have any assumptions on how the movie viewing experience would affect the results. Therefore, we grouped the movies into three classes based on the number of participants who had seen the movie and picked the movie with the largest variance of impression scores from each group: few - TGT, some - JSW, and many - TTR.

3) EEG AND ECG MEASUREMENT

Fig. 1 shows the experimental room and the device we used. Due to the limited capacity of the experiment facility, we divided the participants into several groups and conducted the physiological measurements for each group on different days. Participants put on the device with the support of a staff and watched a movie projected onto a 200-inch movie screen as shown in the figure. While both husband and wife were in the same group (i.e., watched the same movie at the same time), we arranged their seats such that they sat apart and instructed them not to interact with each other (e.g., not to establish eye contact).

We used the device developed by Yokota et al. [50] with seven electrodes (a∼g in the figure): two for EEG (a, e), one for ECG (b), two for electrooculogram (EOG; c, d; the reading was used to remove the noise caused by eye movements and blinking from the EEG reading), and two for reference (f) and ground (g). We placed (a) and (e) at positions Fz and Oz according to the 10-20 international electrode placement system [51] to measure brain responses related to auditory and visual perception, respectively. Note that the actual position of (b) was lower than the position

[1] https://www.worldvaluessurvey.org/wvs.jsp

TABLE 1. Questionnaires and statistics of the survey.

Construct	Scale	Questionnaire	# of items	Response scale	Dimensions	Male				Female			
						Mean	SD	Min	Max	Mean	SD	Min	Max
Personality	Big Five (BF)	[41]	29	5-point Likert	Openness	18.7	3.06	11.0	24.0	17.0	3.07	10.0	23.0
					Conscientiousness	20.7	4.43	13.0	29.0	23.0	3.36	14.0	30.0
					Extraversion	13.5	4.04	6.0	24.0	14.1	3.34	6.0	22.0
					Agreeableness	16.4	2.09	12.0	22.0	16.7	1.83	13.0	21.0
					Neuroticism	14.2	2.66	8.0	21.0	14.3	2.93	7.0	22.0
Values	Schwartz's Basic Values (SBV)	[42]	21	6-point Likert	Self-direction	4.14	0.89	2.00	6.00	4.12	0.80	2.50	6.00
					Power	3.19	0.97	1.00	5.50	3.07	0.85	1.00	5.00
					Universalism	4.20	0.71	2.67	5.67	4.32	0.62	3.33	5.67
					Achievement	4.04	1.07	1.50	6.00	3.97	0.94	2.00	6.00
					Security	4.01	0.94	1.00	6.00	4.32	0.82	3.00	6.00
					Stimulation	3.61	1.11	1.50	6.00	3.37	0.83	1.50	5.50
					Conformity	3.58	1.04	1.00	6.00	3.60	0.73	2.50	6.00
					Tradition	3.85	0.75	2.00	5.50	3.71	0.67	2.00	5.00
					Hedonism	4.17	0.89	2.50	6.00	4.57	0.86	2.50	6.00
					Benevolence	3.85	0.88	1.00	5.50	3.65	0.71	2.00	5.00
Marital satisfaction	Quality Marriage Index (QMI)	[43]	6	4-point Likert	QMI	21.3	3.00	13.0	24.0	20.9	2.50	16.0	24.0

TABLE 2. Movies.

ID	Title	Ratio*1	Rating		Genre*2	Length	IMDb ID
			Average	Variance			
TTR	My Neighbor TOTORO	89.2%	3.12	0.70	Animation, Family	86m	tt0096283
TGT	The Gentle Twelve	49.0%	2.60	1.04	Comedy	116m	tt0104330
JSW	Jurassic World	74.5%	2.68	0.93	Action, Adventure, Sci-Fi	124m	tt0369610

*1 The ratio of the participants who had seen the movie before the experiment. *2 We referred to IMDb for genres.

shown in the figure (the lower left clavicle; closer to the heart position) to measure cardiac activities accurately. The device measured electric potential at a sampling rate of 500Hz from all electrodes. All the devices received the CPU time from the same computer via Bluetooth in microseconds precision and recorded the electric potential following the CPU time [50].

B. FEATURE EXTRACTION FROM PHYSIOLOGICAL MEASUREMENTS

From the EEG and ECG measurements, we extracted the features corresponding to an individual's physiological responses, as well as those representing similarities between spouses. Below we describe how we extracted these features.

1) EEG FEATURES

As of the current, many researchers have examined using EEG brain responses to naturalistic audiovisual stimuli such as TV advertisements [52], [53], [54], TV shows [55], [56], and movie trailers [57], [58], [59]. These studies used power within individual frequency bands, i.e., δ (1)-4 Hz), θ (4-8 Hz), α (8-12 Hz), β (12-30 Hz), and γ (30-40 Hz), and confirmed their significant associations with subjects' perception of stimuli. Since we also used the same type of audiovisual stimuli, we followed their approach. That is, we calculated the power values within the individual frequency bands and used their statistics (e.g., mean, min, max) as an individual's EEG features.

In addition to these features derived from individual frequency bands, we also used features that are calculated from powers across multiple frequency bands. For this type of features, we referred to Shestyuk et al. [56], who examined power decrease in α and concomitant increase in θ ($S1$) and power increase in θ and γ ($S2$). They confirmed that these were significant predictors of the extent to which the subjects were attracted by the TV shows (e.g., the number of tweets related to the TV shows). We considered that $S1$ and $S2$ would also have predictive utility for marital satisfaction because the extent to which each individual is attracted by particular audiovisual stimuli would reflect the individual's psychological characteristics according to existing literature (e.g., [60]).

To extract the features from individuals' EEG signals, we first preprocessed the signals to remove noise (refer to Appendix A for the preprocessing). We then divided the EEG signals into one-second segments, applied short-time Fourier transformation to each segment, and calculated for

FIGURE 1. **Measurement room (left; permitted by the participants for use) and device.**

each segment the power of individual frequency bands. Afterwards, we z-standardized the powers per participant, from which we calculated $S1_t = \alpha_{t-1} - \alpha_t + \theta_t - \theta_{t-1}$ and $S2_t = \theta_t - \theta_{t-1} + \gamma_t - \gamma_{t-1}$. We averaged $S1$ and $S2$ as well as powers of individual frequency bands per minute for smoothing. Finally, for each of them, we calculated the mean, max, min, and standard deviation (SD) for the whole movie and used them as individual participants' EEG features for the movie. In total, we extracted $7(\delta, \theta, \alpha, \beta, \gamma, S1, S2) \times 4$(mean, max, min, sd) $\times$ 2(Fz, Oz) = 56 features for each participant per movie.

For the features that represent the similarities between the couples' EEG signals, we used the Single-trial Phase Locking Value (PLV) computed between spouses. The PLV is a metric that quantifies similarities of phase differences between a pair of time series and has been used in studies of neural synchrony (e.g., [61]). The PLV is formulated as

$$\mathrm{PLV} = \left| \frac{\sum_{n=1}^{N} \exp(j(\psi_1[n] - \psi_2[n]))}{N} \right|, \tag{1}$$

where $\psi_1[n]$ and $\psi_2[n]$ denote instantaneous phases of a husband and wife's EEG signal at sampling point n, and N is the number of valid sampling points in the whole movie. We used the Hilbert transform [62] to compute $\psi[n]$. The PLV ranges from 0 to 1 and approaches 1 when the phase difference between the spouses is constant. To calculate the PLV, we applied to the preprocessed EEG signals finite impulse response (FIR) bandpass filters of the individual frequency bands (3300th), i.e., δ, θ, α, and β. We then computed the PLV for the individual frequency bands, as well as for the whole frequency bandwidth (1)-40 Hz), and used them as couples' similarity features for th movie. In total, we extracted $5(\delta, \theta, \alpha, \beta, \mathrm{All}) \times 2(\mathrm{Fz}, \mathrm{Oz}) = 10$ features for each couple per movie.

2) ECG FEATURES

We extracted from the ECG measurements the features related to heart rate (HR) and heart rate variability (HRV). Much work has been done to examine the associations between HR and HRV features and various psychological constructs such as emotions [63], [64] and personalities [65]. We referred to these studies for extracting the features of ECG from individual participants. These include both time- and frequency-domain features (eight features in total): for the time domain, we used the mean, min, and max of HR, standard deviation of all normal-to-normal (NN) intervals (SDNN), and the root mean square of successive differences between NN intervals (RMSSD); and for the frequency-domain, we used the powers of the low-frequency band (0.04 −0.15 Hz; LF) and high-frequency band (0.15 −0.4 Hz; HF), and the ratio of LF-to-HF power (LF/HF). For the details of each feature, we referred to [66]. To extract these features, we applied a bandpass filter (10 −48 Hz) to the ECG data for noise removal and then detected R-peaks to compute the NN intervals, from which we calculated the time- and frequency-domain features. We used the following python toolboxes for the feature extraction: BioSPPy [67] for the preprocessing and r-peak detection (we used the algorithm proposed by Hamilton [68]), and pyHRV [69] for the feature calculation.

For similarities of cardiac responses between spouses, we calculated the cross-correlation coefficients (CCC) of couples' NN intervals as in the existing studies on cardiac synchrony [70], [71], [72], [73]. According to Bizzego et al. [70], CCC "quantifies the presence of common patterns in the NN intervals series"(p.4). It "measures the extent to which the two physiological signals co-vary, while also allows a non-perfect alignment between the two time series through a lag parameter to account for anticipations or delays of the physiological response of one member with respect to the other" (p.4). Following [70], we computed the CCC with multiple lags from −10 s to 10 s with intervals of 1 s and used the maximum value as the feature.

C. REGRESSION ANALYSES

Table 3 shows the regression models and how we compared the models to address the RQs. Except for M_{Base}, all the models were built for each movie.

TABLE 3. Regression models and model comparisons.

Independent variables	# of vars.	M_{Base}	$M_{\mathrm{ECG+EEG}}$	M_{EEG}		M_{ECG}	
				$-\mathrm{sim}$	$+\mathrm{sim}$	$-\mathrm{sim}$	$+\mathrm{sim}$
Age	3	✓	✓	✓	✓	✓	✓
Personality (BF) and values (SBV)	*	✓	✓	✓	✓	✓	✓
Individual's EEG features	112		✓	✓	✓		
Couple's EEG similarity (PLV)	10		✓		✓		
Individual's ECG features	16		✓			✓	✓
Couple's ECG similarity (CCC)	1		✓				✓

* For the number of variables of BF, and SBV, refer to the main text

RQ		Compared models
RQ1	Do brain and cardiac responses to a movie have predictive utility for marital satisfaction that is independent of questionnaire measurements of psychological characteristics?	M_{Base} vs. $M_{\mathrm{ECG+EEG}}$ M_{Base} vs. M_{EEG} M_{Base} vs. M_{ECG}
RQ2	Is gender difference a factor in the predictive utility of brain and cardiac responses to movies?	M_{EEG} vs. M_{ECG} (compared in males and females separately)
RQ3	Do couples' similarities in physiological responses to the same movie have predictive utility?	$M_{\mathrm{EEG-sim}}$ vs. $M_{\mathrm{EEG+sim}}$ $M_{\mathrm{ECG-sim}}$ vs. $M_{\mathrm{ECG+sim}}$

$M_{\mathrm{EEG}}/M_{\mathrm{ECG}}$ denotes the better model of $M_{\mathrm{EEG+sim}}/M_{\mathrm{ECG+sim}}$ and $M_{\mathrm{EEG-sim}}/M_{\mathrm{ECG-sim}}$

Although we had a limited number of samples ($n = 51$couples $\times 2 = 102$), we still decided to build models to predict marital satisfaction (i.e., QMI) that are separate for males and females. This is because we assumed that brain and cardiac responses would contribute to the prediction differently between males and females. We based our assumption on the studies by Pennebaker and Roberts [27], [28] discussed in section I.

Other than building the models separately, another approach to take into account this gender difference would be to build models common to males and females and incorporate in these models interaction terms between gender and the EEG and ECG features. However, doing so makes the models complicated and less interpretable. We prioritized the interpretability in the analyses while evaluating model fit using metrics that are penalized based on the number of independent variables, i.e., the adjusted R^2 ($Adj.R^2$), the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), so as to account for the overfitting risk.

1) INDEPENDENT VARIABLES

We explain in the following the independent variables used in the models. Note that we used the same variables in both models on male and female though we built them separately.

a: AGE

We differentiated the age of male and female and took as well their age difference (male − female). We incorporated these variables to control their effect on marital satisfaction. Several studies (e.g., [74], [75]) report that marital satisfaction and age difference between spouses are significantly negatively correlated and males tend to have higher marital satisfaction with females younger than them for reproductive reasons.

b: BF AND SBV

We used the scores of males and females for each BF and SBV dimension ($(5 + 10) \times 2 = 30$ variables). For similarity between spouses, we used two sets of variables. One is the similarity in each dimension (male - female; $5+10 = 15$ variables). The other is the similarity of the whole profile of the BF and SBV. There are multiple metrics for the latter similarity that have been used in existing studies [38], [76]. Referring to these studies, we quantified the latter similarity by three different metrics: 1) cosine similarity and Euclidean distance, 2) similarities of shape (Pearson correlation between a couple's scores), mean (absolute difference between husband and wife's mean scores across all the dimensions), and variance (absolute difference between husband and wife's variances of dimension scores), and 3) intraclass correlation coefficients (ICC). Note that we computed 1-3 for the BF and SBV separately and thus the number of variables of 1, 2 and 3 are four, six, and two for each couple, respectively. Because 1-3 are correlated with each other, we put each of them separately in M_{Base}, building three M_{Base} models for males and females, i.e., M_{Base}-1, -2, and -3. We then compared these models to identify the best similarity metric. All the models that used the BF and SBV variables used the best metric identified here.

c: EEG AND ECG FEATURES

We used the features discussed in section III-B as independent variables. In the male and female models, we incorporated individual's features of both male and female (i.e., EEG: $56 \times 2 = 112$ features, ECG: $8 \times 2 = 16$ features) and couple's similarity features (i.e., EEG: 10 features, ECG: 1 feature).

2) BUILDING AND COMPARING THE REGRESSION MODELS

Because the number of independent variables was large relative to the sample size, we first conducted Least Absolute Shrinkage and Selection Operator (LASSO) [77] regression to select the independent variables to be used for linear regression. First, we fine-tuned the LASSO parameter λ, which controls the strength of the imposed regularization based on the number of selected variables. Over a set of λ values, we sought the value that output the most accurate prediction (i.e., minimum mean squared error between the actual and predicted QMI scores) performing five-fold cross-validation (CV) multiple times. Second, we conducted the LASSO regression again using the value of λ determined in the previous step and selected variables for which the regression coefficients were not zero. However, it is possible that doing the first and second steps only once would inadvertently select variables that have no significant predictive utility. We followed the approach taken by Sakata et al. [78] to mitigate such risk, i.e., we repeated the first and second steps 30 times splitting data differently for the CV in the first step and selected the variables whose coefficients were not zero in more than four trials. We then performed the linear regression using the selected variables.

To compare the models, we used metrics that can account for overfitting. We used the adjusted R^2 ($Adj.R^2$), the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). We used both the AIC and the BIC to assess the reliability of the results. While both of them estimate the relative amount of information lost from the true process that generates the data (hence, the lower, the better), neither of them determines which model is closer to the true model. However, they do indicate which model is *more likely* to be closer to the true model. Therefore, following [79], "if a model results in a lower value than other models according to both the AIC and the BIC, the result is more reliable than the results obtained using either the AIC or the BIC" (p.340).

Using the AIC and BIC, we also examined the significance of the difference between the two models. Specifically, we calculated the relative likelihood (RL) and posterior odd (PO) by the AIC and BIC, respectively. Both of them range from 0 to 1 and are formulated as follows:

$$RL(M_1, M_2) = \exp\left(\frac{\mathrm{AIC}(M_1) - \mathrm{AIC}(M_2)}{2}\right), \tag{2}$$

$$PO(M_1, M_2) = \exp\left(\frac{\mathrm{BIC}(M_1) - \mathrm{BIC}(M_2)}{2}\right), \tag{3}$$

where $\mathrm{AIC}(M)$ and $\mathrm{BIC}(M)$ are the AIC and BIC of M, respectively, and $\mathrm{AIC}(M_1) < \mathrm{AIC}(M_2)$ and $\mathrm{BIC}(M_1) < \mathrm{BIC}(M_2)$. Both $RL(M_1, M_2)$ and $PO(M_1, M_2)$ are interpreted as the relative likelihood that M_2 is closer to the true model than M_1. Therefore, the lower the RL and PO, the greater the likelihood that M_1 is closer to the true model. On the other hand, RL/PO=1 means that the likelihood of M_1 being closer to the true model is equal to that of M_2 being closer to the true model.

TABLE 4. Regression analysis results of M_{Base}.

		M_{Base} 1	2	3
Male	AIC ↓	**120.8**	121.4	120.9
	BIC ↓	**136.3**	136.9	140.2
	Adj. R^2 ↑	0.468	0.462	**0.484**
Female	AIC ↓	134.8	133.6	**129.2**
	BIC ↓	146.4	145.2	**140.8**
	Adj. R^2 ↑	0.277	0.294	**0.352**

- Bold fonts denote the best results among 1-3
- We used the models boxed with thick lines as M_{Base} in the subsequent evaluations

Prediction Accuracy Evaluation: In addition to comparing the model fit using all samples, we also compared the models' prediction accuracy. This was done to address RQ1 and see how the models are generalizable to new users that are not in the training samples.

We evaluated prediction accuracy by performing five-fold CV. That is, we randomly divided the participants into five groups and used four of them (i.e., 80% of the participants) for training the models and the rest for testing. We repeated this five times changing the group for testing and predicted the QMI scores for all the participants. Each model used the independent variables selected by LASSO. Because how we divided the participants in the CV affects the results, we conducted the CV for twice dividing the participants differently (CV1 and CV2).

To assess the prediction accuracy, we used the following metrics:

- MAE: mean absolute error
- RMSE: root mean square error
- MAPE: mean absolute percentage error
- Spearman correlation: Spearman's rank correlation between actual and predicted QMI scores

For MAE, we tested statistical significance of the difference between M_{Base} and the other models by paired-samples t-test.

IV. RESULTS

For simplicity, we show the model fit and prediction accuracy metrics in this section. The lists of selected variables and their partial coefficients can be found in Appendix B.

A. RQ1: DO PHYSIOLOGICAL RESPONSES TO A MOVIE HAVE PREDICTIVE UTILITY FOR MARITAL SATISFACTION THAT IS INDEPENDENT OF QUESTIONNAIRE MEASUREMENTS OF PSYCHOLOGICAL CHARACTERISTICS?

First, we evaluated the three models of M_{Base} that use different metrics for the similarities of couples' BF and SBV (i.e., 1-3 discussed in section III-C1). In all the models, the similarities of BF and SBV were selected as predictors of marital satisfaction though we incorporated individuals' BF and SBV in the models to avoid overestimating the effect of the similarities (refer to Table 10 in Appendix B for detail). This indicates that the similarities of BF and SBV have predictive utility independent of individuals' BF and SBV.

Table 4 shows the model fit metrics of M_{Base}. In the table, ↓ means the lower the better, and ↑ means the higher the better. The three male models are not significantly different. While M_{Base}-1 is best in terms of the AIC and BIC, the difference in the AIC from the other two is marginal. In addition, the best in terms of $Adj.R^2$ is M_{Base}-3, which uses the ICC as the similarity metric. On the other hand, for the female models, M_{Base}-3 is the best model in terms of all three metrics. Based on these results, we decided to use the ICC to assess the similarities of the BF and SBV in all the models. In the following, we refer to M_{Base}-3 as M_{Base} for simplicity.

We then compared the M_{Base} and the five types of models that used physiological measurements, i.e., $M_{\text{ECG+EEG}}$, $M_{\text{ECG-sim/+sim}}$, and $M_{\text{EEG-sim/+sim}}$. Table 5 shows the results. For $M_{\text{EEG-sim/+sim}}$ and $M_{\text{ECG-sim/+sim}}$, we compared −sim and +sim models (a model without and with couple's physiological similarity, respectively; see Table 3), in each condition and show the better of the two in the table. For example, the result of M_{EEG} in TTR-male shows the result of $M_{\text{EEG+sim}}$, which outperformed $M_{\text{EEG-sim}}$ in all three metrics. In the following, we refer to the model that is better between −sim and +sim as M_{EEG} and M_{ECG} for simplicity.

In comparison to M_{Base}, $M_{\text{ECG+EEG}}$ resulted in better fitting to the data in all the metrics across gender and all the three movies. According to the RL and PO, the likelihood of M_{Base} being closer to the true model than $M_{\text{ECG+EEG}}$ is only .148 at most. In addition, both or either EEG and/or ECG features resulted in significant predictors for marital satisfaction in all $M_{\text{ECG+EEG}}$ models (refer to Table 11 in Appendix B for detail). These results suggest that physiological responses to a movie measured by EEG and ECG together have predictive utility that is independent of questionnaire measurements of psychological characteristics. In other words, the physiological responses to a movie improve the prediction of marital satisfaction when they are used in addition to the questionnaire measurements of psychological characteristics.

Similarly, M_{EEG} also resulted in better fitting compared to M_{Base} in all the metrics across the movies for both males and females. While the difference between M_{Base} and M_{EEG} in JSW-female is relatively small ($PO(M_{\text{EEG}}, M_{\text{Base}}) = .278$) compared to the other conditions, M_{EEG} outperforms M_{Base} in all three metrics as in the other conditions. The results indicate that brain responses to a movie measured by EEG have predictive utility for marital satisfaction that is independent of the questionnaire measurements of psychological characteristics.

According to the results of M_{ECG}, however, whether or not cardiac responses have predictive utility is dependent on gender and movies. For males, the ECG measurements have significant predictive utility in two out of three movies (TTR and TGT), whereas, for females, it is only TTR in which the ECG measurements have significant predictive utility.

1) DIFFERENCE OF MOVIES IN PREDICTIVE UTILITY OF BRAIN AND CARDIAC RESPONSES

It is notable that the physiological responses to different movies have significantly different degrees of predictive utility. Comparing male $M_{\text{ECG+EEG}}$ models across movies, the best and worst models in terms of model fitting are the models of TTR and JSW, respectively, and their difference is significant ($RL(\text{TTR, JSW}) < .001$ and $PO(\text{TTR, JSW}) < .001$). Similarly, there are big differences between the best and the worst for both M_{EEG} and M_{ECG}. Such difference among movies is also observed for females. It should be also noted that the best models for males and females are derived from different movies (e.g., $M_{\text{ECG+EEG}}$: male-TTR, female-TGT). These results suggest that movie selection is quite important for predicting marital satisfaction, and movies should be selected separately for predicting male and female marital satisfaction.

On another note, we do not see any association between previous viewing experience of a movie and its predictive utility. According to the results of $M_{\text{ECG+EEG}}$, the degree of predictive utility is TTR > TGT > JSW and TGT > TTR > JSW for males and females, respectively, while the number of participants who had seen the movie before is TTR > JSW > TGT for both males and females.

2) PREDICTION ACCURACY

Table 6 shows prediction accuracy of the models. Overall, the results accord with the model fit results. While $M_{\text{ECG+EEG}}$-JSW-female in condition 1 and $M_{\text{ECG+EEG}}$-TGT-male in condition 2 did not outperform M_{Base}, the other $M_{\text{ECG+EEG}}$ models (i.e., 10 out of 12 $M_{\text{ECG+EEG}}$ models) produced better results than M_{Base} (though we could not confirm statistical significance for a part of models due to the limited amount of samples). Similarly, M_{EEG} models outperformed M_{Base} in 10 out of 12 cases. The M_{ECG} models that resulted in better model fitting than M_{Base} also output better prediction accuracy. In summary, similarly to the model fit results, the prediction accuracy evaluation results also suggest that physiological responses to a movie measured by ECG and EEG have predictive utility for marital satisfaction that is independent of questionnaire measurements of psychological characteristics.

B. RQ2: IS GENDER DIFFERENCE A FACTOR IN THE PREDICTIVE UTILITY OF BRAIN AND CARDIAC RESPONSES TO MOVIES?

We compared M_{EEG} and M_{ECG} models of the same movie and gender. Table 7 shows the results. For males, M_{ECG} is better than its corresponding M_{EEG} for all three metrics in two out of three movies (TTR and TGT). On the other hand, for females, M_{EEG} is superior to M_{ECG} for all three metrics in two out of three movies (TGT and JSW). In addition, in TTR,

TABLE 5. Model comparison results for RQ1.

		M_{Base}	$M_{\text{ECG+EEG}}$			M_{EEG}			M_{ECG}		
			TTR	TGT	JSW	TTR	TGT	JSW	TTR	TGT	JSW
Male	AIC ↓	120.9	**96.1**	**112.2**	**114.6**	**109.6**	**111.9**	**113.8**	**102.9**	**104.3**	120.9
	BIC ↓	140.2	**116.4**	**131.5**	**132.0**	**126.0**	**129.2**	**133.1**	**124.2**	**126.6**	140.2
	Adj. R^2 ↑	0.484	**0.693**	**0.585**	**0.537**	**0.574**	**0.561**	**0.551**	**0.642**	**0.632**	0.484
	$RL(M_{\text{X}}, M_{\text{Base}})$		.000	.013	.043	.003	.011	.029	.000	.000	1.00
	$PO(M_{\text{X}}, M_{\text{Base}})$		.000	.013	.016	.000	.003	.029	.000	.001	1.00
	RL(best_mov, worst_mov)		*RL*(TTR, JSW)=.000			*RL*(TTR, JSW)=.122			*RL*(TTR, JSW)=.000		
	PO(best_mov, worst_mov)		*PO*(TTR, JSW)=.000			*PO*(TTR, JSW)=.029			*PO*(TTR, JSW)=.000		
Female	AIC ↓	129.2	**106.6**	**98.0**	**125.4**	**112.4**	**102.2**	**124.7**	**119.6**	129.2	129.2
	BIC ↓	140.8	**127.8**	**119.3**	**137.0**	**131.7**	**123.4**	**138.3**	**131.2**	140.8	140.8
	Adj. R^2 ↑	0.352	**0.616**	**0.676**	**0.399**	**0.563**	**0.648**	**0.416**	**0.464**	0.352	0.352
	$RL(M_{\text{X}}, M_{\text{Base}})$		.000	.000	.148	.000	.000	.106	.008	1.00	1.00
	$PO(M_{\text{X}}, M_{\text{Base}})$		.001	.000	.148	.011	.000	.278	.008	1.00	1.00
	RL(best_mov, worst_mov)		*RL*(TGT, JSW)=.000			*RL*(TGT, JSW)=.000			*RL*(TTR, JSW)=.008		
	PO(best_mov, worst_mov)		*PO*(TGT, JSW)=.000			*PO*(TGT, JSW)=.000			*PO*(TTR, JSW)=.008		

M_{X} is either $M_{\text{ECG+EEG}}$, M_{EEG}, or M_{ECG}. The results better than M_{Base} are shown in bold fonts. The results in grey cells are equal or inferior to M_{Base}.

AIC and $Adj.R^2$ of M_{EEG} are better than those of M_{ECG} and the difference in BIC between the two models is marginal ($PO(M_{\text{ECG}}, M_{\text{EEG}}) = .779$). This suggests it is also likely in TTR that M_{EEG} is closer to the true model than M_{ECG}.

These results indicate that there is gender difference in predictive utility of brain and cardiac responses to movies. That is, for male marital satisfaction, cardiac responses tend to have greater predictive utility compared to brain responses, whereas, for female marital satisfaction, brain responses have greater predictive utility. While we cannot argue the above gender difference are confirmed by the results since we examined only three movies, this gender difference is in line with the claim by Pennebaker and Roberts [27], [28] about gender difference in how physiological responses are associated with emotions. We will discuss this in section V.

C. RQ3: DO COUPLES' SIMILARITIES IN PHYSIOLOGICAL RESPONSES TO THE SAME MOVIE HAVE PREDICTIVE UTILITY?

Finally, we compared the models that used couples' similarities in physiological responses and those that did not (i.e., +sim and -sim models, respectively). Table 8 shows the results. As shown in the table, incorporating the similarities of physiological responses did not necessarily produce better results. This is true for both brain and cardiac responses. Specifically, there are only three out of six conditions where $M_{\text{EEG+sim}}$ resulted in better fitting than $M_{\text{EEG-sim}}$. In the other conditions, the similarities of brain responses did not contribute to the prediction, which is not in line with what Li et al. [37] and Parkinson et al. [29] reported, i.e., similarities of brain responses between two persons while watching videos are predictors of their relationship. In the next section, we will discuss differences between their study and ours associated with this discrepancy.

V. DISCUSSION

A. PRACTICAL IMPLICATIONS

To begin with the practical impact, we confirmed that physiological responses to movies provide predictive information on marital satisfaction, and that the predictive utility is independent of questionnaire measurements of their psychological characteristics. Matchmaking services could benefit from this finding. Currently, most rely on the questionnaire measurements to predict psychological compatibility of user pairs, based on which they select and recommend potential partners to users. According to our results, using physiological responses to movies in addition to the questionnaire measurements would significantly improve the accuracy of this prediction, making it more likely for their users to find a good partner that could lead to a happy married life.

One thing that should be noted is that the participants of the present study were married couples, while users of actual matchmaking services are unmarried or even unacquainted with each other. Therefore, one might doubt if users' physiological responses to movies measured before they get married would predict marital satisfaction after they get married.

However, we posit that the physiological responses measured before marriage would be significant predictors of marital satisfaction after marriage. We posit so because the individuals' physiological responses to audiovisual stimuli reflect their psychological characteristics according to the literature [17], [18], [19], [20], [21], [22], [23] as discussed in section I. Although physiological responses and psychological characteristics are different in nature, i.e., the former is highly context-dependent whereas the latter is context-independent, they are tightly connected. Emotions and stress induced by the stimuli are moderated by one's psychological characteristics. Therefore, physiological responses caused by emotions and stress reflect psychological characteristics.

TABLE 6. Prediction accuracy evaluation results.

CV1

		M_{Base}	$M_{\text{ECG+EEG}}$			M_{EEG}			M_{ECG}		
			TTR	TGT	JSW	TTR	TGT	JSW	TTR	TGT	JSW
Male	MAE ↓	2.25	**1.64**	**2.24**	**2.09**	**2.06**	**2.08**	**2.17**	**2.11**	**1.83**	2.25
	RMSE ↓	2.73	**2.19**	**2.69**	**2.64**	**2.71**	**2.46**	2.74	**2.71**	**2.28**	2.73
	MAPE ↓	11.04	**7.98**	**10.99**	**10.18**	**10.11**	**10.04**	**10.54**	**10.60**	**8.91**	11.04
	Spearman ↑	.522	**.707**	**.587**	**.615**	**.562**	**.647**	**.556**	**.620**	**.640**	.522
	Sig_base*		***	-	-	-	-	-	-	*	-
Female	MAE ↓	1.85	**1.67**	**1.70**	**1.84**	**1.63**	**1.38**	**1.68**	**1.66**	1.85	1.85
	RMSE ↓	2.35	**2.14**	**2.19**	2.39	**2.08**	**1.74**	**2.25**	**2.06**	2.35	2.35
	MAPE ↓	8.98	**8.15**	**8.24**	**8.93**	**7.98**	**6.71**	**8.14**	**8.23**	8.98	8.98
	Spearman ↑	.610	**.679**	**.668**	.591	**.688**	**.801**	.596	**.648**	.610	.610
	Sig_base*		-	-	-	-	**	*	*	-	-

CV2

		M_{Base}	$M_{\text{ECG+EEG}}$			M_{EEG}			M_{ECG}		
			TTR	TGT	JSW	TTR	TGT	JSW	TTR	TGT	JSW
Male	MAE ↓	2.30	**1.78**	2.33	**2.10**	**2.14**	**2.12**	**2.07**	**2.26**	**1.74**	2.30
	RMSE ↓	2.80	**2.29**	2.86	**2.64**	**2.78**	**2.56**	**2.56**	**2.80**	**2.16**	2.80
	MAPE ↓	11.26	**8.63**	11.47	**10.21**	**10.63**	**10.19**	**10.04**	**11.20**	**8.39**	11.26
	Spearman ↑	.482	**.714**	**.483**	**.570**	**.548**	**.570**	**.598**	**.536**	**.667**	.482
	Sig_base*		***	-	-	-	-	-	-	**	-
Female	MAE ↓	1.84	**1.56**	**1.48**	**1.81**	**1.54**	**1.35**	**1.70**	**1.68**	1.84	1.84
	RMSE ↓	2.30	**2.04**	**1.87**	**2.27**	**2.02**	**1.68**	**2.20**	**2.08**	2.30	2.30
	MAPE ↓	8.97	**7.70**	**7.19**	**8.81**	**7.60**	**6.53**	**8.22**	**8.31**	8.97	8.97
	Spearman ↑	.597	**.720**	**.755**	**.606**	**.720**	**.804**	**.597**	**.649**	.597	.597
	Sig_base*		*	**	-	**	***	-	-	-	-

Bold fonts denote the result is better than M_{Base}.

Sig_base shows statistical significance of the difference in MAE from M_{Base}. *: $p < .10$, **: $p < .05$, ***: $p < .01$

TABLE 7. Model comparison results for RQ2.

		TTR		TGT		JSW	
		M_{EEG}	M_{ECG}	M_{EEG}	M_{ECG}	M_{EEG}	M_{ECG}
Male	AIC ↓	109.6	**102.9**	111.9	**104.3**	**113.8**	120.9
	BIC ↓	126.0	**124.2**	129.2	**126.6**	**133.1**	140.2
	Adj. R^2 ↑	0.574	**0.642**	0.561	**0.632**	**0.551**	0.484
	RL(better, worse)	*RL*(M_{ECG},M_{EEG}) =.035		*RL*(M_{ECG},M_{EEG}) =.022		*RL*(M_{EEG},M_{ECG})=.029	
	PO(better, worse)	*PO*(M_{ECG},M_{EEG}) =.407		*PO*(M_{ECG},M_{EEG})=.273		*RL*(M_{EEG},M_{ECG})=.029	
Female	AIC ↓	**112.4**	119.6	**102.2**	129.2	**124.7**	129.2
	BIC ↓	131.7	**131.2**	**123.4**	140.8	**138.3**	140.8
	Adj. R^2 ↑	**0.563**	0.464	**0.648**	0.352	**0.416**	0.352
	RL(better, worse)	*RL*(M_{EEG},M_{ECG})=.027		*RL*(M_{EEG},M_{ECG})=.000		*RL*(M_{EEG},M_{ECG})=.105	
	PO(better, worse)	*PO*(M_{ECG},M_{EEG})=.779		*RL*(M_{EEG},M_{ECG})=.000		*RL*(M_{EEG},M_{ECG})=.287	

Bold fonts denote the better of M_{EEG} and M_{ECG}. The results in grey cells are equal or inferior to M_{Base}

Generally, psychological characteristics such as personalities and values are stable especially in adults and would remain almost the same before and after marriage at least in a short period of time (a few years or so) [80]. As evidenced by the existing literature [7], [8], [9], [10], [11], [12], [13], [14], [15], these psychological characteristics are significant predictors of marital satisfaction, thus so are the physiological responses that reflect the psychological characteristics. Hence, we consider that the physiological responses measured before marriage would be significant predictors of marital satisfaction as long as the couples' psychological characteristics remain the same.

From a practical perspective, another point to be noted is that our findings were derived from EEG measurements.

TABLE 8. Model comparison results for RQ3.

		M_{EEG}						M_{ECG}				
		TTR		TGT		JSW		TTR		TGT		JSW
		-sim	+sim	-sim	+sim	-sim	+sim	-sim	+sim	-sim	+sim	
Male	AIC ↓	116.9	**109.5**	**111.9**	113.8	116.9	**113.8**	119.3	**102.9**	104.3	104.3	
	BIC ↓	134.3	**125.0**	**129.2**	135.1	134.3	**133.1**	140.6	**124.2**	125.6	125.6	
	Adj. R^2 ↑	0.515	**0.574**	**0.561**	0.557	0.516	**0.551**	0.506	**0.642**	0.632	0.632	*1
	RL(+sim, -sim)	.025		N/A		.212		.000		1.00		
	PO(+sim, -sim)	.010		N/A		.549		.000		1.00		
Female	AIC ↓	116.1	**112.4**	**102.2**	109.3	**124.7**	129.2	124.0	**119.6**			
	BIC ↓	133.5	**131.7**	**123.4**	128.6	**138.3**	138.9	135.6	**131.2**			
	Adj. R^2 ↑	0.523	**0.563**	**0.648**	0.589	**0.416**	0.341	0.415	**0.464**	*1		*1
	RL(+sim, -sim)	.157		N/A		N/A		.111				
	PO(+sim, -sim)	.407		N/A		N/A		.111				

The better of +sim and –sim is shown in bold fonts. *1: The ECG measurements do not have significant predictive power.

Other than using EEG, it would also be possible to use fMRI to predict marital satisfaction based on the study of Li et al. [37]. They confirmed the brain responses to video clips measured by fMRI are significantly associated with marital satisfaction. Compared to fMRI, we consider EEG-based prediction is more advantageous for matchmaking services. One is cost. An EEG device costs much less to purchase and maintain. In addition, knowledge and skill required for staff to obtain EEG measurements are not so extensive contrast to fMRI, i.e., cost to train and employ staff is less with EEG. The other is flexibility in terms of time and place by which EEG measurements can be obtained. Given the recent trend of companies commercializing wearable devices with EEG (e.g., [24], [25]), we envision a future where EEG can be easily measured whenever and wherever people want. In contrast, a portable, lightweight fMRI device has yet to be developed and skilled staff needs to operate the fMRI machine, both limit the accessibility of fMRI measurements.

Apart from obtaining affordable and accessible insights about brain function, a tight temporal resolution can make EEG the method of choice. EEG provides an excellent temporal resolution, being able to capture electric brain activity in millisecond granularity (2 ms in our study), whereas the fMRI measures in the order of tens to hundreds of milliseconds at most (e.g., 2 s in [37]). Using EEG signal processing techniques, quantitative features on amplitudes, spectrum of frequencies, and fluency can be obtained [81]. Thus, while fMRI with high spatial resolution cannot provide respectable temporal sampling, and the EEG offering high temporal resolution albeit with inadequate localization of signal sources, it comes with little surprise that the integration of these two in a hybrid concurrent acquisition is now highly sought to overcome the inherent limitations of each and increase the diversity of analyses that can be carried out (see [81]). While this integration is still to arrive, we view our EEG-based investigation to provide a different angle of analyses on, as well as prediction of, marital satisfaction, thereby adding to the fMRI-based predictions such as that of [37].

B. THEORETICAL IMPLICATIONS

From a theoretical standpoint, we acquired two notable results. One is about the similarities of brain responses to stimuli for which the following two questions have been left uninvestigated. The first is (A) whether the stimuli affect the utility of brain response similarities in predicting human relationship. Li et al. [37] and Parkinson et al. [29] presented multiple video clips to their participants, i.e., six clips of social interaction between marriage partners in [37] and 14 clips raging from debate between journalists to a comedy skit in [29]. However, in [29] and [37], the brain responses to all the clips were examined as a whole, i.e., the brain response similarities were not examined for each individual clip. The second is (B) whether the brain response similarities have predictive utility that is independent of individual brain responses, as well as independent of the similarities of psychological characteristics measured by questionnaires. Neither of them was controlled in [29] and [37]. We addressed these two questions and found that whether or not the brain response similarities have such independent predictive utility depends on which movies are watched. We discuss the possible reasons for this in the following.

Our regression analyses showed that the similarities of psychological characteristics determined by questionnaires had in themselves predictive utility for marital satisfaction. Given this and that (i) individual brain responses reflect psychological characteristics [18], [19], [20], [21], [22], [23] and (ii) the individual brain responses had predictive utility independent of the questionnaire measurements, we posit that brain response similarities should also have independent predictive utility. However, we could not confirm this for some movies.

We consider one of the reasons would be because brain response similarities to these movies did not adequately reflect the similarity of psychological characteristics. For instance, the similarity of Stimulation (*ST*; one of the SBV value dimensions) in the regression analyses was identified as a predictor of marital satisfaction in all the male models (the less husband's *ST* score - wife's *ST* score is, the higher the husband's satisfaction is; denoted as SBV_ST_diff in Table 10∼13 in Appendix B). While an *ST* score measured by the SBV questionnaire is supposed to represent how an individual values daily life that is stimulating, we consider the score would not represent the entire aspect of stimulation due to the limitations of the SBV questionnaire measurement. If the individual brain responses of husband and wife reflect this stimulation value to a greater extent than their individual *ST* scores, then similarities in their brain responses would have predictive utility that is independent of the similarities in their *ST* scores. According to our results, this would have been the case for TTR and JSW, but not for TGT (see male's M_{EEG} results in Table 8). The results indicate that brain responses to TGT would not have adequately reflected an individual's stimulation value (reflected this value to a lesser extent than the brain responses to TTR and JSW). That is, the extent to which brain responses reflect psychological characteristics would depend on the movies, which we consider is one of the possible reasons why the similarities in brain responses to some movies did not have independent predictive utility.

Another possible reason is the EEG's limited spatial resolution.We speculate that it would also be plausible that there were actually brain responses to TGT that reflected the value of stimulation more than the questionnaire measurements, but the EEG failed to detect them. This can be examined in the future by comparing or synergizing the EEG and fMRI.

The other notable result is how gender difference affects the predictive utility of brain and cardiac responses. That is, cardiac responses have more predictive utility than brain responses for male marital satisfaction, whereas brain responses are more predictive of female marital satisfaction. We consider this result supports the claim made by Pennebaker and Roberts [27], [28] who argued for the differences in how emotions arise in relation to gender. Thus far, many studies have reported that males have greater interoceptive capabilities (e.g., [82], [83], and [84]). Based on these studies, Pennebaker and Roberts who hypothesized that interoception affects the process in which emotions arise, argued that males having greater interoception compared to females usually pay more attention to their internal bodily state and rely more on interoception as a source of information for their emotional experiences. On the other hand, females, who have lesser interoception compared to males but are able to experience more emotions [85], [86], rely less on interoception and more on exteroception, i.e., they pay more attention to external situational cues, such as others' facial expressions and tone of voice [87] as source of information for their emotional experience.

Based on Pennebaker and Roberts [27], [28], we interpret our results as follows. We consider that (1) an individual's own emotional experiences in movies and (2) how a partner's emotional experiences is similar to (1) would be predictors of marital satisfaction because (1) would reflect their individual psychological characteristics and (2) would reflect the psychological compatibility with their partner. For male marital satisfaction, given that males rely more on interoception for their emotional experiences, the cardiac responses would reflect (1) and thus would also enable determining (2). For females, since it is exteroception that affects their emotional experiences to a greater degree, we speculate their being keen to external cues would reflect (1) more than cardiac responses do and thus enable determining (2).

VI. LIMITATION AND FUTURE DIRECTION

The generalizability of our finding is the limitations of the present study. One is generalizability about stimuli (i.e., movies). As discussed in section IV-A1, movies to be presented to users significantly affect prediction accuracy. However, due to the limited number of movies, we could not formulate generalizable conditions as to which movies are not useful and which should be used. In addition, given that the best accuracy was obtained from different movies across gender, the conditions should be formulated for males and females separately. Future study is warranted to account for such conditions.

The other is generalizability in terms of culture. We conducted the present study on Japanese subjects. However, existing studies reported that there are significant difference between Asians and Westerners in their interoception [88], [89] (e.g., Asians are less sensitive to cardiac activity compared to American Caucasians [88]). Since the interoception affects how emotions arise as discussed in the previous section, the extent to which the physiological responses reflect emotions might also differ across cultures. This might affect the validity of our findings in other cultures.

VII. CONCLUSION

We confirmed that brain and cardiac responses to movies have predictive utility for marital satisfaction that is independent of questionnaire measurements of psychological characteristics, which most of today's matchmaking services rely on to identify potential couples. Given that our results were derived from low-cost EEG measurements, we consider our study will provide matchmaking services with a promising way of identifying pairs of users who will be more likely to lead a happy married life compared to the methods used by services today.

APPENDIX A
PREPROCESSING OF THE EEG SIGNALS

In this section, we describe how we preprocessed the EEG signals. The preprocessing consisted of the following steps.

A. APPLY BANDPASS FILTER

We applied a FIR bandpass filter of 1 −40 Hz (5,000th) to the EEG signals measured at position (a) and (e) and the electrooculography (EOG) signals measured at (c) and (d). For the positions of the electrodes, refer to Fig. 1.

B. REMOVE NOISE COMPONENTS FROM THE EEG SIGNALS

We conducted independent component analysis (ICA) on four-dimensional time-series data that consists of EEG and EOG signals (signals measured at (a), (c), (d), and (e)) and extracted EEG signal components that are independent of the noise components caused by eye movements and blinking. We manually checked the outputs of ICA to determine which components corresponded to the EEG signal components.

However, in contrast to our setting, ICA is typically used in a setting with a large number of EEG channels (e.g., 32 or more) because a small number of channels provides limited spatial information and poses a challenge in effectively separating the noise from the neural signals. Although (e)

TABLE 9. Notations of the independent variables.

Name	Meaning
BF and SBV	
M/F	Independent variables for BF and SBV scores of M (husband) or F (wife)
BF_X	A score of a BF dimension X; X is either O (Openness), C (Conscientiousness), E (Extraversion), A (Agreeableness), or N (Neuroticism).
SBV_X	A score of a SBV dimension X; X is either ST (Stimulation), SD (Self-direction), UN (Universalism), BE (Benevolence), CO (Conformity), TR (Tradition), SC (Security), PO (Power), AC (Achievement), or HE (Hedonism)
Sim	Independent variables for a couple's similarity of BF or SBV
BF/SBV_diff_X	A difference between spouses in scores of BF/SBV dimension X (calculated by husband-wife).
BF/SBV_Cossim	A cosine similarity of couple's BF/SBV scores
BF/SBV_Eucdist	A Euclid distance between couple's BF/SBV scores
BF/SBV_Shape	A Pearson correlation coefficient between a couple's BF/SBV scores
BF/SBV_Mean	An absolute difference between husband and wife's mean BF/SBV scores across all the dimensions
BF/SBV_Var	An absolute difference between husband and wife's variances of BF/SBV scores
BF/SBV_ICC	Intraclass correlation coefficients (ICC) of husband's and wife's BF/SBV scores
Brain response	
M/F	Independent variables for an individual's EEG features (M: husband, F: wife)
Fz/Oz_X_Y	Statistics of power values within an individual frequency band or a composite score calculated from EEG signals measured at Fz or Oz. X denotes either an individual frequency band (α, β, γ, δ, θ) or a composite score (S1, S2). Y denotes statistics, i.e., mean, max. min, or standard deviation (sd).
Sim	Independent variables for a couple's similarity of EEG measurements
PLV_Fz/Oz_X	A PLV value of an individual frequency band at Fz/Oz. X denotes either an individual frequency band (α, β, γ, δ, θ) or whole frequency band (all)
Cardiac response	
M/F	Independent variables for an individual's ECG features (M: husband, F: wife)
HR_X	Statistics of heart rate (HR). X denotes statistics, i.e., mean, max, or min.
SDNN	Standard deviation of all NN intervals
RMSDD	The root mean square of successive differences between NN intervals
LF	A power value of the low frequency band (0.04-0.15 Hz)
HF	A power value of the high frequency band (0.15-0.4 Hz)
LF/HF	A ratio of LF-to-HF power
Sim	Independent variables for a couple's similarity of ECG measurements
CCC	A cross-correlation coefficient of couple's NN intervals
POMS	
M/F	Independent variables for POMS scores of M (husband) or F (wife)
POMS_X	A score of a POMS dimension X; X is either AH (Anger-hostility), CB (Confusion-bewilderment), DD (Depression-dejection), FI (Fatigue-inertia), TA (Tension-anxiety), VA (Vigor-activity), or F (Friendliness)
Sim	
POMS_diff_X	A difference between spouses in scores of POMS dimension X (calculated by husband-wife).
POMS_Cossim	A cosine similarity of couple's POMS scores
POMS_Eucdist	A Euclid distance between couple's POMS scores
POMS_Shape	A Pearson correlation coefficient between a couple's POMS scores
POMS_Mean	An absolute difference between husband and wife's mean POMS scores across all the dimensions
POMS_Var	An absolute difference between husband and wife's variances of POMS scores
POMS_ICC	An intraclass correlation coefficient (ICC) of husband's and wife's POMS scores

TABLE 10. M_{Base}.

			M_{Base}					
			1		2		3	
Male	Age		**Wife_age**	**-.317*** **	**Wife_age**	**-.300*** **	**Wife_Age**	**-.323*** **
	BF and SBV	M	BF_O	.195	**BF_O**	**.214***	**BF_O**	**.233***
			SBV_CO	**.233** **	**SBV_CO**	**.224***	**SBV_CO**	**.292** **
		F	**BF_A**	**-.229** **	**BF_A**	**-.252** **	**BF_A**	**-.236***
			SBV_TR	**.271** **	**SBV_TR**	**.265** **	**SBV_TR**	**.267** **
							SBV_UN	.017
		Sim	BF_Cossim	-.171	BF_shape	-.153	BF_ICC	-.142
			SBV_diff_ST	**-.215***	**SBV_diff_ST**	**-.211***	**SV_ICC**	**.218***
							SBV_diff_ST	-.154
	Model fitting metrics	AIC	120.8		121.4		120.9	
		BIC	136.3		136.9		140.2	
		Adj. R^2	0.468		0.462		0.484	
Female	Age							
	BF and SBV	M	**BF_O**	**.322***	**BF_O**	**.367*** **	**BF_O**	**.381** **
		F	SBV_BE	.168	SBV_BE	.110	**SBV_BE**	**.240***
			SBV_UN	.185	SBV_TR	.095	SBV_UN	.144
					SBV_UN	.170		
		Sim	BF_Cossim	-.098	BF_shape	-.173	**SV_ICC**	**.287** **
			BF_diff_O	.101			BF_diff_O	.099
	Model fitting metrics	AIC	134.8		133.6		129.2	
		BIC	146.4		145.2		140.8	
		Adj. R^2	0.277		0.294		0.352	

TABLE 11. $M_{\text{ECG+EEG}}$.

			$M_{\text{ECG+EEG}}$					
			TTR		TGT		JSW	
Male	Age				**Wife_age**	**-.314*** **	**Wife_age**	**-.220***
	BF and SBV	M	**BF_O**	**.270*** **	**BF_O**	**.264** **	**BF_O**	**.236** **
			SBV_CO	.117	**SBV_CO**	**.256** **		
		F	**BF_A**	**-.272*** **	**BF_A**	**-.232** **	**BF_A**	**-.234** **
			SBV_UN	.133	**SBV_TR**	**.289*** **	**SBV_TR**	**.259** **
					SBV_UN	.065		
		Sim	**BF_ICC**	**-.300*** **	SBV_diff_ST	-.121	**SBV_diff_ST**	**-.300*** **
			SBV_diff_ST	**-.231*** **				
	Brain response	M					Fz_S2_sd	.168
		F	Fz_S1_max	-.114	**Oz_S1_sd**	**.236** **	**Oz_S1_mean**	**.302*** **
		Sim	**PLV_Fz_All**	**.400*** **			**PLV_Fz_θ**	**.212** **
	Cardiac response	M	**HR_max**	**.288*** **				
		F			**HR_min**	**-.307*** **		
		Sim	**CCC**	**.311*** **				
	Model fitting metrics	AIC	96.1		112.2		114.6	
		BIC	116.4		131.5		132.0	
		Adj. R^2	0.693		0.585		0.537	
Female	Age							
	BF and SBV	M	**BF_O**	**.388*** **	**BF_O**	**.392*** **	**BF_O**	**.455*** **
		F	**SBV_BE**	**.198***	SBV_UN	.118	SBV_BE	.191
			SBV_UN	.063			SBV_UN	.071
		Sim	**SBV_ICC**	**.236** **	**SBV_ICC**	**.210** **	**SBV_ICC**	**.269** **
					SBV_diff_UN	-.160		
	Brain response	M	**Oz_S2_max**	**.220** **				
			Oz_S1_mean	-.152				
		F			**Fz_δ_min**	**.417*** **		
			Fz_S1_max	**-.272*** **	**Fz_S2_mean**	**-.316*** **	**Fz_S1_min**	**.241** **
					Oz_S2_min	**-.231** **		
		Sim	**PLV_Fz_β**	**-.162***	PLV_Fz_All	.091		
			PLV_Fz_δ	.111	PLV_Oz_All	.116		
	Cardiac response	M	**HR_min**	**-.240** **	**HR_min**	**-.295*** **		
		F						
		Sim						
	Model fitting metrics	AIC	106.6		98.0		125.4	
		BIC	127.8		119.3		137.0	
		Adj. R^2	0.616		0.676		0.399	

TABLE 12. M_{EEG}.

			M_{EEG}											
			TTR				TGT				JSW			
			+sim		-sim		+sim		-sim		+sim		-sim	
Male	Age				Wife_age	-.277 **	Wife_Age	-.276**	Wife_Age	-.299***	Wife_Age	-.252**	Wife_Age	-.253 **
	BF and SBV	M	BF_O	.278**	BF_O	.231**	BF_O	.194*	BF_O	.228**	BF_O	.245**	BF_O	.226 **
			SBV_CO	.227**	SBV_CO	.229**	SBV_CO	.204*	SBV_CO	.254**	SBV_CO	.159		
		F	BF_A	-.362***	BF_A	-.362***	BF_A	-.231**	BF_A	-.234**	BF_A	-.227**	BF_A	-.153
					SBV_TR	.214*	SBV_TR	.235**	SBV_TR	.277***	SBV_TR	.271**	SBV_TR	.217 *
							SBV_UN	.083					SBV_UN	.176
		Sim	BF_ICC	-.276**	BF_ICC	-.148	BF_ICC	-.108	SBV_diff_ST	-.180	SBV_diff_ST	-.261**	SBV_diff_ST	-.299
			SBV_diff_ST	-.230**	SBV_diff_ST	-.187*	SBV_diff_ST	-.183						
	Brain response	M									Fz_S2_sd	.129	Fz_S2_sd	.188
		F	Fz_S1_max	-.236**	Fz_S1_max	-.250**	Fz_S2_sd	.306***	Fz_S2_sd	.306***	Oz_S1_mean	.261**	Oz_S1_mean	.353 ***
							Oz_S1_sd	.252**	Oz_S1_sd	.263**				
		Sim	PLV_Fz_δ	.384***							PLV_Fz_θ	.204**		
	Model fitting metrics	AIC	109.5		116.9		113.8		111.9		113.8		116.9	
		BIC	125.0		134.3		135.1		129.2		133.1		134.3	
		Adj. R^2	0.574		0.515		0.557		0.561		0.551		0.516	
Female	Age													
	BF and SBV	M	BF_O	.422***	BF_O	.441 ***	BF_O	.394***	BF_O	.342***	BF_O	.433***	BF_O	.416***
		F	SBV_BE	.215*	SBV_BE	.217 *	SBV_UN	.083	SBV_HE	.224*	SBV_BE	.113	SBV_BE	.200
			SBV_UN	.053	SBV_UN	.106			SBV_TR	.113	SBV_UN	.122	SBV_UN	.082
									SBV_UN	.171				
		Sim	SBV_ICC	.185*	SBV_ICC	.225 **	SBV_ICC	.229**	SBV_ICC	.223**			SBV_ICC	.292**
							SBV_diff_UN	-.203						
	Brain response	M	Oz_S1_mean	-.166	Oz_S1_mean	-.118			Fz_δ_mean	-.266***				
			Oz_S2_max	.241**	Oz_S2_max	.260 **								
					Oz_δ_max	-.068								
		F	Fz_S1_max	-.244**	Fz_S1_max	-.262 **	Fz_S2_mean	-.305***	Fz_S2_mean	-.479***	Fz_S1_min	.277**	Fz_S1_min	.179
							Fz_δ_min	.332 ***	Fz_δ_min	.349***			Oz_δ_min	.181
							Oz_S2_min	-.193*	Oz_S2_min	-.231**				
									Fz_S2_sd	-.019				
		Sim	PLV_Fz_β	-.182*			PLV_Fz_all	.089						
			PLV_Fz_δ	.122			PLV_Oz_all	.151						
	Model fitting metrics	AIC	112.4		116.1		109.3		102.2		119.6		124.0	
		BIC	131.7		133.5		128.6		123.4		131.2		135.6	
		Adj. R^2	0.563		0.523		0.589		0.648		0.464		0.415	

TABLE 13. M_{ECG}.

			M_{ECG}											
			TTR				TGT				JSW			
			+sim		-sim		+sim		-sim		+sim		-sim	
Male	Age		Wife_age	-.261***	Wife_age	-.276 **	Wife_age	-.318***	Wife_age	-.318***	Wife_age	-.323***	Wife_age	-.323***
	BF and SBV	M	BF_O	.330***	BF_O	.256 **	BF_O	.230**	BF_O	.230**	BF_O	.233*	BF_O	.233*
			SBV_CO	.224**	SBV_CO	.171	SBV_CO	.330***	SBV_CO	.330***	SBV_CO	.292**	SBV_CO	.292**
		F	BF_A	-.224**	BF_A	-.253 **	BF_A	-.216**	BF_A	-.216**	BF_A	-.236*	BF_A	-.236*
					SBV_TR	.186	SBV_TR	.266***	SBV_TR	.266***	SBV_TR	.267**	SBV_TR	.267**
			SBV_UN	.077	SBV_UN	.055	SBV_UN	.096	SBV_UN	.096	SBV_UN	.017	SBV_UN	.017
		Sim	BF_ICC	-.204**	BF_ICC	-.168	BF_ICC	-.109	BF_ICC	-.109	BF_ICC	-.142	BF_ICC	-.142
			SBV_ICC	.240**	SBV_diff_ST	-.214 *	SBV_diff_ST	-.278***	SBV_diff_ST	-.278***	SBV_ICC	.218*	SBV_ICC	.218*
			SBV_diff_ST	-.143							SBV_diff_ST	-.154	SBV_diff_ST	-.154
	Cardiac response	M					HR_min	.339***	HR_min	.339***				
		F	HR_max	-.259***	HR_max	-.195 *	HR_min	-.276***	HR_min	-.276***				
					HR_min	-.206 *								
		Sim	CCC	.377***										
	Model fitting metrics	AIC	102.9		119.3		104.3		104.3		120.9		120.9	
		BIC	124.2		140.6		125.6		125.6		140.2		140.2	
		Adj. R^2	0.642		0.506		0.632		0.632		0.484		0.484	
Female	Age													
	BF and SBV	M	BF_O	.478***	BF_O	.404 ***	BF_O	.381**	BF_O	.381**	BF_O	.381**	BF_O	.381**
		F	SBV_BE	.274**	SBV_BE	.224 *	SBV_BE	.240*	SBV_BE	.240*	SBV_BE	.240*	SBV_BE	.240*
			SBV_UN	.135	SBV_UN	.148	SBV_UN	.144	SBV_UN	.144	SBV_UN	.144	SBV_UN	.144
		Sim	SBV_ICC	.346***	SBV_ICC	.346 ***	SBV_ICC	.287**	SBV_ICC	.287**	SBV_ICC	.287**	SBV_ICC	.287**
							BF_diff_O	.099	BF_diff_O	.099	BF_diff_O	.099	BF_diff_O	.099
	Cardiac response	M			HR_min	-.261 **								
		F												
		Sim	CCC	.331***										
	Model fitting metrics	AIC	119.6		124.0		129.2		129.2		129.2		129.2	
		BIC	131.2		135.6		140.8		140.8		140.8		140.8	
		Adj. R^2	0.464		0.415		0.352		0.352		0.352		0.352	

(Oz) and (b) (EOG) in our setting were positioned far apart and thus would provide spatially different information from each other, we posited that the noise would remain to some extent even after ICA. In addition, noise caused by other factors (e.g., body movement, muscle potential) could not be removed by ICA.

Therefore, we annotated the signals that would contain the remaining noise so that we could exclude features extracted from these signals after the feature extraction. Specifically, we divided EEG signals into 10 s segments and checked whether each segment contained any signals that were $>80\,\mu$V or $<-80\,\mu$V. If so, we annotated the segment as "contaminated segment." We did not exclude these segments in this step because Fourier transform and bandpass filters in the feature extraction could not be applied if there are missing data in time-series.

C. EXTRACT FEATURES

We extracted both individuals' features and couples' similarity features from the EEG data obtained in the second step by the procedures described in section III-B1.

D. EXCLUDE FEATURES EXTRACTED FROM CONTAMINATED SIGNALS

Finally, we excluded features extracted from the contaminated segments. This was done for both individuals' features and couples' similarity features.

APPENDIX B
SELECTED VARIABLES OF THE REGRESSION MODELS AND THEIR PARTIAL COEFFICIENTS

Table 10∼13 show the selected variables of the regression models and their partial coefficients. In the tables, statistical significance is denoted as follows: ***: $p < .01$, **: $p < .05$, and *: $p < .10$. For the notations in these tables, refer to Table 9. Note that we z-standardized all the variables (both the dependent and independent variables) before conducting the regression. Therefore, the results show standardized partial coefficients. Also note that the results show only the independent variables that were used in the linear regression. That is, those that were not selected by LASSO are not shown in the results.

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YUICHI ISHIKAWA received the B.E. and M.E. degrees in information and communication engineering from The University of Tokyo, Japan, in 2000 and 2002, respectively. He is currently pursuing the Ph.D. degree in information science with Kyushu University, Fukuoka, Japan. When the present study was conducted, he was a Senior Research Scientist with KDDI Research Inc., Japan, where he led a research team in the area of computational psychology. His research interests include personality recognition from daily behavior and personalization in various services based on personality.

NAO KOBAYASHI received the Ph.D. degree in global information and telecommunication studies from Waseda University, Japan. He is currently the Senior Manager with the Healthcare Medical Group, KDDI Research Inc., Japan. His research interests include human behavior analysis based on smartphone sensor data, behavior modeling, and neuroscience.

ROBERTO LEGASPI received the Ph.D. degree in engineering from Osaka University, Japan. For more than two decades, his research has focused on human behavior computing for human-centric AI interactions. Broadly, to enable an AI to unobtrusively detect and understand human behavioral cues in order to adapt its responses to human needs. His current research interests include computing for human sense of agency, persuasive behavior, and counterfactual causal inference for human-AI interactions.

KAE NAKAJIMA received the Ph.D. degree in engineering from the Toyohashi University of Technology. She is currently a Research Engineer with the Brain Function Analysis and Imaging Laboratory, Center for Information and Neural Networks, National Institute of Information and Communications Technology, Kobe, Japan.

YASUSHI NARUSE received the Ph.D. degree in complexity science and engineering from The University of Tokyo. He is currently the Director of the Brain Function Analysis and Imaging Laboratory, Center for Information and Neural Networks, National Institute of Information and Communications Technology, Kobe, Japan. His research interests include signal processing and modeling of neural activities, and brain imaging.