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Redundancy analysis of autonomic and self-reported, responses to induced emotions☆

Bruce H. Friedman[a,*], Chad L. Stephens[b], Julian F. Thayer[c]

[a] Department of Psychology (0436), Virginia Polytechnic Institute and State University, Blacksburg, VA 24061-0436, United States
[b] Virginia Polytechnic Institute and State University, and NASA Langley Research Center, United States
[c] Department of Psychology, The Ohio State University, United States

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ABSTRACT

The issue of concordance among the elements of emotional states has been prominent in the literature since Lang (1968) explored the topic in relation to therapy for anxiety. Since that time, a consensus has emerged that concordance among these components is relatively low. To address this issue, *redundancy analysis*, a technique for examining directional relationships between two sets of multivariate data, was applied to data from a previously published study (Stephens, Christie, & Friedman, 2010). Subjects in this study listened to emotion-inducing music and viewed affective films while a montage of autonomic variables, as well as self-reported affective responses, were recorded. Results indicated that approximately 27–28% of the variance in self-reported affect could be explained by autonomic variables, and vice-versa. When all of the constraints of this emotion research paradigm are considered, these levels of explained variance indicate substantial coherence between feelings and physiology during the emotion inductions. These results are considered vis-à-vis the low levels of coherence that have often been reported in the literature.

1. Redundancy analysis of autonomic and self-reported responses to induced emotions

Much of the current discussion of emotional concordance can be traced to anxiety research that emerged in the late 1960s, and has wielded an enduring influence on the study of emotion. In this research, concordance (or *synchrony*) among the various features of anxiety was considered in the context of its clinical and conceptual implications, which were viewed as interdependent. Various theoretical models and abundant empirical work ensued in this era, which have been particularly influential in guiding subsequent research on anxiety therapy.

Moreover, this line of work extends beyond the realm of anxiety into emotion theory in general. Mapping the relationship among the components of emotion, which are frequently characterized in terms of their physiological, behavioral, and experiential response patterns, has been a fundamental issue in psychology since seminal writings on emotion by William James (1884, 1890; see Friedman, 2010, for a review). Biopsychological research has generally been guided by this view of emotion as patterns of distinct response types, the interrelationships of which have been variously represented (Carlson, 2013).

Methodology bears heavily on the interpretation of data and its extrapolation to theory; the case of emotional concordance is no exception to this precept. Decisions on variable selection and analysis method can have a profound impact on inferences drawn from data, and the comparability of results across studies (Campbell & Fiske, 1959; Cone, 1998; Nesselroade & Jones, 1991). Studies employing univariate analyses are especially susceptible to such effects. In contrast, multivariate designs have distinct advantages in unpacking relationships between physiological variables and psychological constructs (Thayer & Friedman, 2000).

In reference to the topic at hand, we and others have applied these principles to emotion research utilizing multivariate *pattern classification analysis* of autonomic nervous system (ANS) and self-report variables (Christie & Friedman, 2004; Kreibig, Wilhelm, Roth, & Gross, 2007; Nyklicek, Thayer, & Van Doornen, 1997; Rainville, Bechara, Naqvi, & Damasio, 2006; Stephens et al., 2010). In this paper, *redundancy analysis*, another multivariate technique is applied to previously published data (Stephens et al., 2010) with the aim of addressing the issue of concordance among physiological and experiential aspects of emotion. Redundancy analysis is specifically used here to examine bi-directional relationships among autonomic and self-reported responses to laboratory induced emotional states.

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* Corresponding author. Tel.: +1 540 231 9611; fax: +1 540 231 3652.
E-mail address: bhfriedm@vt.edu (B.H. Friedman).

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Toward this end, we begin with a historical review of the anxiety-concordance literature, using the influential work of Peter Lang and associates as a focal point. This body of work sets the context which is then related to emotion theory, particularly in reference to discrete emotion models based on evolutionary concepts. Next, we outline how multivariate analyses in general, and redundancy analysis in particular, are beneficial in assessing the interrelationships among various components of emotion. Finally, redundancy analysis of physiological and self-reported responses to affective stimuli is utilized to demonstrate how these areas collectively speak to the issue of emotional concordance.

2. Concordance among components of emotion: fear and avoidance

Clinical research in the 1960s on the development of cognitive-behavioral therapy was pivotal in launching the study of emotional concordance. A highly influential and oft-cited paper in this literature was an exposition on the role of the components of fear in systematic desensitization treatment of anxiety disorders (Lang, 1968). Three fundamental categories of fear responses were identified: verbal-cognitive, overt-motor, and somatic. Use of this schema was directed at objective fear assessment in anxiety therapy research, independent of theoretical orientation. These three fear response systems were observed to vary in terms of their synchrony and to dissociate under some conditions. Empirical examples were offered in which bivariate correlations among indices of these components were rather low. The implication for treatment was that therapy directed at one aspect of anxiety may not effect change in other aspects, and so clinical research should aim to identify techniques specific to each system that will be most effective at achieving the desired therapeutic change.

It was subsequently argued that the de-coupling of fear and avoidance behavior has specific implications for therapy (Rachman & Hodgson, 1974). "Concordance" was inferred in the presence of high correlations among cognitive, behavioral, and somatic aspects of fear; "discordance" was defined by inverse or independent relations among these components ("synchrony" and "desynchrony" more specifically referred to *changes* in these components that vary together, independently, or inversely). Three types of phobia treatments were used as examples of distinct temporal covariance patterns between fear feelings and avoidance. In desensitization, fear reduction was thought to precede the decline of avoidance; the opposite pattern was observed in flooding. Fear and avoidance were said to decrease synchronously in participant modeling. Ultimately, all three therapies led to similar reductions in fear and avoidance, but did so by different synchrony-desynchrony pathways. These examples demonstrated the fluid relationship between fear and avoidance, which can situationally uncouple. However, the authors remarked in closing that "...most often, fear and avoidance are in fact closely linked" (p. 318).

Inspired by influential cognitive models of the 1970s, Lang (1979) expanded his concept of the structure of fear and emotion in proposing *bio-informational theory*. This conception of emotion, with specific reference to imagery, integrates psychophysiology with information processing theories that were prominent in this era of cognitive psychology. Such models represented information as networks of constructs that are logically related by *propositions* (Anderson & Bower, 1973; Kieras, 1978; Kintsch, 1974; Paivio, 1971; Plyshyn, 1973). Bio-informational theory depicts emotional images as propositional networks that include both stimulus and response information. The nodes of these networks are not necessarily activated uniformly; therein lies the potential for varying degrees of concordance among the observed responses to emotional stimuli, which in this case, are images. It is worth noting that these models were advanced prior to the widespread use and publication of brain imaging studies and concomitant emergence of the cognitive neuroscience paradigm; as such, little or no attempt was made to match the models with workings of the brain.

Bio-informational theory holds that the propositional structure of an emotional image includes efferent output matched to that image. This output includes motor actions and their supporting autonomic changes. Also included are subjective feelings and perceptual qualities of the stimulus context. This model is also derived from the aforementioned research on behavior therapy, and so was specifically related to anxiety hierarchies used in systematic desensitization. Such hierarchies may employ scripts in which the client is instructed to imagine participating in anxiety-provoking scenes. So, for example, in the case of snake phobia, the script may describe a chance encounter with a long snake that evokes heart palpitations plus feelings of fear and the need to flee. If one can vividly imagine being in this scene, the various components of the propositional network for that image will be collectively activated, leading to high concordance. Reports of substantial positive correlations between heart rate increases and both self-reported fear and image vividness support this view of high concordance between emotional experience and physiology under such conditions (Grossberg & Wilson, 1968; Lang, Melamed, & Hart, 1970; Marks & Huson, 1973; Van Egeren, Feather, & Hein, 1971).

Lang (1979) further argued, with supportive data, that image scripts containing response propositions (e.g., run away, heart pounding) increase concordance between physiological changes and other fear indices. Priming the response propositions acts to "...increase the magnitude of those responses which are *part of an affective reaction to which the subject is already predisposed*" (p. 506; italics added). This comment appears to refer to phobic individuals who are predisposed to respond to specific stimuli with feelings of fear, sympathetic nervous system activation, and behavioral avoidance. However, such phobias are more likely to be of stimuli that have evolutionary significance (e.g., threatening animals; Ohman, 1986). As such, these tendencies and their associated propositional networks are part of the human evolutionary heritage, and are present in varying degrees across individuals. Of course, these networks can be modified by individual experience; successful therapy for phobias attests to this. Indeed, Lang proposed that chances for successful therapy for phobias are enhanced by the ability to vividly imagine the phobic stimulus and activate the full propositional network, particularly the visceral and motor response propositions. In other words, initial concordance among fear components predicts successful outcome in anxiety therapy.

Lang and his colleagues shifted gears in the 1980s in a number of ways that advanced theoretical development (Lang, 1995; Lang & Bradley, 2010). Focus moved away from behavior therapy for anxiety disorders in particular toward a broader purview of emotion theory. Concurrent with this change was the usurpation of mental imagery as the primary emotion-elicitor by affective pictures, typically in conjunction with startle probe methodology. These standardized pictures (the *International Affective Picture System*), grounded in a two-factor valence-activation model of emotion, remain widely in use in contemporary emotion research (Center for the Psychophysiological Study of Emotion & Attention, 1994). Another development was the de-emphasis of cognitive models based on information-processing views in favor of a neuroscientific perspective based on animal models and brain imaging data.

Of relevance to concordance is the view that emotions are primarily driven by two motivational tendencies that map onto distinct neural systems: appetitive and aversive. These systems have been shaped by evolutionary forces that link them with survival of the individual; furthermore the species' emotions are viewed as "action tendencies" driven by these motives. Consistent with bio-informational theory's tripartite construction, human emotions were seen as expressed in language (self-report), physiological changes, and behavior. Also in harmony with previous views, Lang asserted that "...correlations among and within [these] systems are often quite modest..." (Lang, 1979, p. 373). However, this statement is inconsistent with above-cited studies in which concordance between emotional experience and physiological changes was rather high, under conditions of high image vividness, and with Rachman & Hodgson's (1974) contention that fear and avoidance are in general closely linked, in spite of a variety of situations in which they may uncouple. Both Lang & Rachman's positions are best captured by Lang's concept of fear as a non-unitary complex of loosely coupled verbal, physiological, and behavioral systems (Lang, 1978; Rachman, 1978).

Reflecting on this work, it would seem that the question is not appropriately framed, "Are the various features of emotions, as assessed clinically and in research, concordant with each other?" Nor should it be, "To what degree are the components of emotion concordant with each other?" A wide range of concordances have been reported, and these vary with a variety of factors. Hence, the most apt phrasing of the question should be, "What are the contextual factors and individual differences that mediate concordance among cognitive, behavioral, and physiological measures of emotion, and in what manner do these factors operate?" For example, conditions of high demand to approach a feared object (or not to avoid, as is the case in flooding), measures of avoidance show lower correlations with physiological and self-report measures than conditions of low demand (Miller & Bernstein, 1972; Zingbarg, 1998). One might expect that conditions designed to elicit basic emotions, from an evolutionary perspective, would evoke well integrated response patterns. In the next section, we outline why this prediction makes sense from a discrete emotions perspective, which is built upon evolutionary foundations.

3. Concordance and emotion theory: an evolutionary perspective

It is here this line of research intersects with discrete emotions theory and its evolutionary foundations. This view holds that a small set of basic emotions evolved for adaptive value in specific contexts (e.g., Ekman, 1992, 1994; Frijda, 1994; Izard, 1977; Levenson, 1994a; Plutchik, 1980, 2000). Moreover, this perspective is consistent with the James' (1884, 1890) functionalist model of emotion, which echoed Darwin (1872) in positing a finite set of discrete, universal "standard" or "coarse" emotions that are distinct in bodily expression. In this model, emotions organize behavioral, facial expressive, and ANS response patterns to be effectively matched to environmental demands. The ANS sustains a restricted number of basic emotion-behavior pairings, which underpins its evolutionary affective value, and forms the basis for the existence of basic emotions (Levenson, 1988, 1994b).[1]

Autonomic specificity is an essential tenet of this perspective. It follows that relatively distinct ANS patterns would be called upon in support of behaviors matched to specific situations that evoke these basic emotions. Research on laboratory-induced emotions has frequently supported the existence of discrete ANS patterns associated with basic emotions (see Ekman, 1994; Friedman, 2010; Kreibig, 2010; Levenson, 2003, for reviews), although dissenting views exist on this point (e.g., Barrett, 2006; Cacioppo, Berntson, Larsen, Poehlmann, & Ito, 2000). Moreover, ANS specificity for basic emotions instantiates the general psychophysiological principle of *stimulus-response specificity*, which holds that certain stimulus contexts are associated with specific patterns of physiological responding (Lacey, 1959, 1967). This principle is based on similar evolutionary logic in assuming that adaptive response patterns appear in common form within species and the boundaries of individual variation.

Concordance among behavioral, cognitive, and physiological is implicit in the existence of ANS-specific emotional states, in that these elements are harmonized in accord with their adaptive value. Hence, relatively high concordance among these elements would be expected in contexts in which relatively pure, basic emotions are evoked. Film and music excerpts were selected for their ability to elicit such states in Stephens et al. (2010), in which support was found for ANS specificity of discrete emotions. A similar logic was invoked in the widely influential study by Ekman, Levenson, and Friesen (1983), in which prototypical facial expressions of basic emotions were evoked, resulting in concomitant emotion-specific ANS patterns. It is for this reason that we chose to use data from Stephens et al. (2010) to examine emotional concordance. Moreover, self-reported affective responses from Stephens et al. (2010) further confirmed that the stimuli successfully elicited their target discrete emotions.

A few caveats should be expressed. The type of emotional state sought in Stephens et al. (2010) (i.e., pure, high intensity) is fairly rare in everyday life. Rather, daily life is typified by lower intensity, mixed affective states (Norris, Gollan, Berntson, & Cacioppo, 2010). Indeed, recent evidence indicates that pure and mixed emotions differ both in intensity and physiological patterning (Kreibig, Samson, & Gross, 2013). Moreover, the various components of emotion can and do uncouple to adapt to commonly encountered situations. For example, the desire to physically flee is usually suppressed when one faces everyday anxieties, as it is similarly suppressed in various forms of behavior therapy for anxiety. Civilization is not marked by the kinds of challenges faced by human evolutionary ancestors, and so high concordance may be the exception rather than the rule. Hence, Lang's (1968) description of fear as being an amalgam of loosely coupled components is apt—it implies flexibility in response coordination that can adapt situationally. In some ways, this is not unlike the arrangement within the ANS, whereby its components can be viewed as a network of flexibly linked bio-oscillators that facilitate adaptation to changing environments (Friedman, 2007; Thayer & Friedman, 2004). Finally of note is the careful approach by Stephens et al. to adhere to the strict methodological desiderata prescribed by Cacioppo, Klein, Berntson, and Hatfield (1993) in conducting the original study of emotion-specific ANS activity.

In sum, the conditions of daily life compel an accommodating relationship among the behavioral, cognitive, and physiological components of emotion. However, in homogeneous states of basic emotion, a greater degree of concordance among these elements might be expected. That higher concordance may be expected under this specific circumstance is consistent with the broader view that the relation between physiological data and theoretical constructs has a limited range of validity because it holds only under certain situations (Cacioppo & Tassinary, 1990). Additionally, the vast majority of studies of concordance, particularly those from the behavior therapy literature have addressed this issue with univariate analyses, in particular with bivariate correlations. The weaknesses of this approach are substantial, as is described below.

4. Emotional concordance: a multivariate approach

The appropriateness of multivariate designs for psychophysiological research in general, and for ANS studies of emotion in particular, has been often articulated (e.g., Cacioppo et al., 1993; Stephens et al., 2010; Thayer & Friedman, 2000). These arguments

[1] The existence of discrete basic emotions has been the topic of an intense debate in the literature (e.g., Barrett, 2006; cf. Izard, 2007), but an extensive consideration of this issue the boundaries of this paper.

extend logically to concordance, which examines the relationship among broad domains of emotional responding. The use of analytic methods that are sensitive to multiple response systems is requisite to explore such issues (Fridlund & Izard, 1983). Accordingly, we have previously employed various multivariate techniques such as pattern classification analysis and P-technique factor analysis to investigate the relationship among autonomic and experiential components of emotion (Christie & Friedman, 2004; Friedman & Santucci, 2004; Nyklicek et al., 1997; Stephens et al., 2010).

The primary advantage of such techniques is that they are capable of simultaneous consideration of the multiple response variables that constitute emotional states (Fridlund & Izard, 1983). This approach optimizes broad sampling of the manifold autonomic and experiential variables that comprise emotions. As such, multivariate analyses more fully capture the variables dimension, which together with persons and occasions, make up the three fundamental factors of data (Cattell, 1988). In contrast, most concordance studies have used single indicators of the components of emotion, and so have significantly undersampled the variables dimension.

Redundancy analysis is a multivariate technique that offers similar benefits for examination of emotional concordance. Redundancy analysis yields directional indices of shared variance between two data sets by allowing one set of variables to be viewed as predictive of the other (van den Wollenberg, 1977). The assignment of predictor and criterion are then reversed, with explained variance now going from the second set to the first. As such, unlike standard canonical correlations, redundancy indices are inherently asymmetric (Lambert, Wildt, & Durand, 1988). Redundancy analysis is valuable in contexts in which one variable set can be seen as predictive of the amount of variance in the other, as opposed to mutual dependence.

Lambert et al. (1988) provide a well written overview of the relative advantages and disadvantages of redundancy analysis relative to other related multivariate interset association techniques such as canonical correlations and multivariate multiple regression. Whereas all of these techniques allow for the assessment of associations among sets of variables, redundancy analysis offers some specific advantages for the examination of concordance between self-report and physiological indices of emotion.

First, as noted above, it is important to analyze the variables as sets, that is, in a multivariate context. Second, also as noted above, redundancy analysis is asymmetric and thus allows for the examination of directionality in the sense that one set of variables can be viewed as "predictors" of the other set of variables. And third, redundancy analysis allows one to examine the underlying structure of the variables in the "predictor" set much like factor analysis allows for the examination of latent structure in a set of variables. All of these features are absent in the usual univariate analysis of concordance that has characterized the field to this point.

Redundancy analysis allows for assessment of mutual dependence shared by two variable sets, successively extracting a maximum proportion of the unexplained variance of the criterion variables with each predictor variate, and forming mutually uncorrelated linear combinations of criterion variables that correspond to the predictor variates. However, the applicability of this technique is a function of research aims. The limitations of redundancy analysis for certain aims have been previously identified in the literature (Lambert et al., 1988). Specification of the fine-grained relationship of criterion and predictor variables is not possible with redundancy analysis. In contrast, multivariate multiple regression or canonical correlation analysis permit assessment of mutual dependence shared by the two variable sets, estimation of biorthogonal criterion and predictor variates, and measurement of explained criterion-set variance and estimation of predictor variates that are influenced by intercorrelations of the criterion variables. The interested reader is referred to Lambert et al. (1988) for two illustrative examples that demonstrate the contrasts among multivariate multiple regression, canonical correlation analysis, and redundancy analysis. Nevertheless, when applied appropriately, with careful consideration for these limitations, redundancy analysis can be useful in revealing multivariate relationships among subjective and objective variables sets.

A full mathematical description of redundancy analysis is beyond the scope of the present paper. However a few points will be made here. For a more thorough explication the reader is referred to Lambert et al. (1988) and Varmuza, Filzmoser, Liebmann, and Dehmer (2012). First, like principle components analysis, the "predictor" variables are successively derived as uncorrelated linear combinations of the predictor variables (eigenvectors) with the added distinction that they maximize the explained variance in the "criterion" set. However, unlike canonical correlations, redundancy predictor variates do not seek to successively extract the maximum proportion of variance in the criterion set via uncorrelated linear variates of the criterion set. Thus the predictor and criterion variates derived, while being mutually uncorrelated, are not biorthogonal except in special cases. Second, because of the asymmetrical nature of redundancy analysis, the variance explained in the "criterion" set by the "predictor" set is not the same as the variance explained by the "criterion" set in the "predictor" set when the analyses are repeated with the reverse designations of "predictor" and "criterion". Thus, examination in both directions may be informative with respect to the underlying associations and the related theoretical implications of the interset associations. These unique aspects of redundancy analysis, relative to other related multivariate techniques for the examination of interset associations, may make redundancy analysis particularly appropriate for the examination of emotion concordance as we detail below.

We have previously used redundancy analysis to examine the methodological issue of facial muscle activity contamination of anterior EEG site recordings (Friedman & Thayer, 1991). This technique was selected for its ability to simultaneously examine the relationship of activity at multiple facial electromyographic and EEG sites. By analogy, redundancy analysis offers similar benefits in assessing the relationship among autonomic and experiential variables in basic emotions. That is, by taking into account the correlation *among* these variable sets, the associations *between* the variable sets can be better explained. Bivariate correlations between single indicators of these sets have assumed a symmetrical relationship between the two. There are numerous reasons why this may not be the case. First, various forms of behavior therapy assume a directional relationship between components of emotion. For example, systematic desensitization presupposes that physiological inducement of relaxation will reduce the cognitive and behavioral aspects of fear. In contrast, more cognitively oriented techniques assume the opposite relationship. More broadly, directional arguments have been made for cognitive (Lazarus, 1984) and somatic (Zajonc, 1984) primacy in affective states. This debate goes back to James (1884), and has been the impetus behind much research on emotion. For the purposes of this paper, in addition to providing an inroad into the concordance issue, redundancy analysis also offers some insight into the causal relationship between physiological and cognitive (i.e., "feelings) aspects of emotion.

5. The present study

The primary aim of the present study was to use the multivariate technique redundancy analysis to examine the issue of emotional concordance. Previous univariate studies have typically found correlations in the 0.30 range. For example, Lang (1979) reports that the correlation in men between their imagery scores and their heart rate responses was near zero (−0.08 to −0.22) but with response-proposition training the correlation increased to 0.43 thus suggesting increased concordance (p. 506). In the present study, previously published data were utilized to examine multivariate concordance (Stephens et al., 2010). In this study, a montage of ANS measures and self-reported affective responses were acquired from subjects who viewed affective film clips and listened to music excerpts selected for their emotional qualities. We hypothesized that the emotional concordance assessed via redundancy analysis would exceed the 0.30 range of the typical univariate studies.

5.1. Method

The methods of the present study fully described in Stephens et al. (2010) are summarized here to provide an essential understanding of the experimental procedures. The reader is referred to the published report for technical details, particularly regarding affect induction stimuli, physiological recording equipment, and data acquisition/signal processing.

5.1.1. Subjects

Fifty undergraduates at Virginia Tech (27 women and 22 men, $M = 19.3$, $SD = 1.3$ years, range = 18–26 years) were recruited for participation. One subject was excluded from the analysis due to technical difficulties and loss of physiological and self-report data. Subjects were screened using the Beck Depression Inventory-II (BDI-II; Beck, Steer, & Brown, 1996) and the Toronto Alexithymia Scale (TAS-20; Bagby, Taylor, & Parker, 1994; Bagby, Parker, & Taylor, 1994), to exclude subjects who scored in range of at least mildly depressive symptomatology and identification of alexithymia, respectively, based on established norms. Subjects were likewise excluded if they indicated a history of cardiovascular or neurological disease, were currently on medication for hypertension, depression, or anxiety, or were smokers. Subjects were instructed to abstain from caffeine and/or alcohol for at least 12 h prior to the study. This study received approval from the Institutional Review Board at Virginia Tech.

5.1.2. Apparatus

5.1.2.1. Music clips. Music clips that were piloted during the selection phase were used to elicit the discrete emotions: amusement, anger, contentment, fear, sadness, surprise, and a relatively neutral state. The selection criteria for the musical pieces were (a) maximal response on the discrete emotion item from self-report, (b) a small standard deviation in self-reported affect, and (c) high factor loadings on the two factors labeled valence and activation. Two musical pieces for each emotion were employed during the experimental phase of the study; six of these pieces were the same as those used in Nyklicek et al. (1997). The average duration of the clips, which varied in length and were presented via headphones, was 113 s.

5.1.2.2. Film clips. Standardized film clips were presented to elicit the discrete emotions amusement, anger, contentment, fear, sadness, surprise and a relatively neutral state (Fredrickson & Levenson, 1998; Gross & Levenson, 1995; Rottenberg, Ray, & Gross, 2007). The clips varied in length, with an average duration of 145 s, and were presented on a desktop computer monitor. A washout audio/video piece consisting of 65 s of repeating colored vertical "screen test" bars was presented before each music and film clip, using the neutral noncommercial clip standardized by Gross and Levenson (1995).

5.1.3. Self-report questionnaire

A 23-item affect self-report scale was completed electronically immediately following each emotion elicitation (ASR; modified from Christie & Friedman, 2004, and Nyklicek et al., 1997). The ASR contained items (i.e., emotion labels) in accord with both discrete and dimensional models of affect. The predictions of this paper are based on discrete emotions theory, so analyses were limited to five items consistent with that theory (content, amused, fearful, angry, sad) plus the neutral item. Moreover, the emotional stimuli were selected to correspond with these emotions. Each emotion item was rated on a seven-point Likert scale in regard to how much of each emotion was felt during each music and film clip.

5.1.4. Physiological recording equipment

Physiological signals were acquired using pre-gelled electrodes (Surtrace; ConMed Co., Utica, NY). Electrocardiogram (ECG) was recorded using a BIOPAC amplifier (ECG100C; BIOPAC Systems Inc, Goleta, CA) with thoracic electrodes placed in a Lead II configuration. Impedance cardiogram (ICG) was recorded using the Minnesota Impedance Cardiograph (Instrumentation for Medicine, Minneapolis, MN) with a four spot electrode array as per Sherwood et al. (1990). Skin conductance (SC) was recorded using an isolated SC coupler (V71-23; Coulbourn Instruments, Allentown, PA) with electrodes placed on the thenar and hypothenar eminences of the left palm (Dawson, Schell, & Filion, 2007). Respiration was recorded from thoracic and abdominal sites using two aneroid chest bellows connected to resistive bridge strain gage couplers (V94-19 and V71-23; Coulbourn Instruments, Allentown, PA). An IBS SD-700A automated BP monitor (Industrial & Biomedical Sensors Corp., Waltham, MA) was used to measure systolic (SBP) and diastolic blood pressures (DBP).

5.1.5. Quantification of physiological data

The following subset of the ANS variables reported in Stephens et al. (2010) were used for the redundancy analysis in the present paper: Cardiac inter-beat-interval (IBI in ms); respiratory sinus arrhythmia (RSA in ms); cardiac pre-ejection period (PEP in ms); respiration rate (RR in breaths per minute); mean arterial pressure (MAP in mmHg); and SC level (SCL in μS). These ANS variables were included in the redundancy analysis together with the affective discrete self-report items: Amused, Angry, Content, Fearful, Sad, and Surprised. The redundancy analysis which included 13 dimensional self-report items (Activation, Agitation, Bad, Calm, Excitement, Good, Indifferent, Negative, Passive, Pleasant, Positive, Relaxed, and Unpleasant) were matched with 13 ANS variables: left ventricular ejection time (LVET in ms), stroke volume (SV in % Δ), cardiac output (CO in % Δ), total peripheral resistance (TPR in % Δ), inspiration time (TI in ms), expiration time (TE in ms), SBP, DBP, IBI, RSA, PEP, RR, and MAP. The selected sets of ANS variables broadly sample ANS function across organ systems.

ECG, ICG, and RR were processed using the Vrije Universiteit-Ambulatory Monitoring System software suite (VU-AMS, Vrije Universiteit, Department of Psychophysiology, Amsterdam, The Netherlands) and RSA was processed using HRV Analysis Software v1.1 (The Biomedical Signal Analysis Group, Department of Applied Physics, University of Kuopio, Finland). SCL data were analyzed using the BIOPAC AcqKnowledge software (BIOPAC Systems Inc, Goleta, CA). ICG data were analyzed using the AMSIMP program, a component of the VU-AMS software package. RR was computed using the AMSRES program, a component of the VU-AMS software package.

IBI was defined as the mean R-wave to R-wave interval. The AMSRES program used the R-wave to R-wave intervals time series of the ECG to extract two IBIs per breath: the shortest IBI and the longest IBI. These IBIs were used to calculate RSA according to the peak-trough method (Grossman, van Beek, & Wientjes, 1990). PEP was defined as the time between ECG Q-wave onset and B-point in the ICG. MAP was defined as DBP + 1/3 (SBP–DBP) (Stern, Ray, & Quigley, 2000). Change scores were used, in accord with Stephens et al., and were calculated by subtracting the mean scores from the

Table 1
Redundancy correlation coefficient (R_c) among the primary pairs of redundancy variates and dimensional self-report variables for each of the six combined, music, and film emotion inductions.

	Induced emotion					
	Amused	Angry	Content	Fearful	Sad	Surprised
Primary Variate Pair						
Combined	0.862	0.869	0.826	0.807	0.923	0.862
Music	0.896	0.861	0.846	0.853	0.804	0.804
Film	0.844	0.821	0.815	0.843	0.891	0.854

Table 2
Redundancy correlation coefficient (R_c) among the primary pairs of redundancy variates and discrete self-report variables for each of the six combined, music, and film emotion inductions.

	Induced emotion					
	Amused	Angry	Content	Fearful	Sad	Surprised
Primary Variate Pair						
Combined	0.521	0.569	0.549	0.528	0.696	0.645
Music	0.575	0.576	0.594	0.630	0.580	0.590
Film	0.650	0.585	0.602	0.603	0.690	0.651

last 60 s of the preceding washout period from the mean scores of the last 60 s of the music/film stimulus for each autonomic variable (emotion induction minus baseline).

5.1.6. Procedure

All experimental sessions were conducted in a sound attenuated room with subjects seated in a comfortable chair and the experimenter in a separate room observing via a two-way mirror. Stimuli were presented in one of two sequences with music pieces and film clips alternating in a partially counterbalanced fashion. Consistent with Christie and Friedman (2004), negatively valenced film clips alternated with positively or neutrally valenced film clips. The two sequences of presentation were the reverse of each other. Each emotion was evenly distributed throughout the entire experiment and the same emotion induction was not experienced two times in a row.

Subjects were instructed to pay close attention to how they felt as they watched the film clips and listened to the music pieces, and were told that following each clip they would be asked to describe how they felt. After a ten-minute laboratory adaptation period, a one-minute baseline recording, during which subjects were presented with the one-minute and five second washout clip, confirmed proper equipment functioning and subjects completed a baseline ASR followed by the first clip. After each music/film stimulus, subjects completed the ASR scale to assess affective response during the presentation. Upon completion of the scale, subjects were presented with the same one-minute and five second washout clip, during which they were instructed to sit quietly and clear their mind of all thoughts, feelings, and memories. The next stimulus presentation then commenced. This procedure was repeated for the remaining stimuli conditions in a manner closely approximating that of both Nyklicek et al. (1997) and Christie and Friedman (2004).

5.1.7. Statistical analyses

All statistical analyses were conducted using IBM® SPSS® Statistics Premium GradPack 21 for Mac. The SPSS menu driven graphical user interface does not permit redundancy analysis (achieved via the canonical correlation analysis macro). Hence, all redundancy analyses were conducted using the built-in "Canonical correlation.sps" macro through the SPSS syntax window. The cancorr macro was a standard component of the specified version of SPSS and was located in a computer subdirectory where SPSS was installed.

5.2. Results

Redundancy analyses inputting physiological variables (either 13 or 6 variables to correspond with the second set) in the first set and either dimensional (13 variables) or discrete (6 variables) self-reported variables in the second set resulted in redundancy correlation coefficients (R_c). See Table 1 for the R_c calculated for the primary pairs of redundancy variates (physiology and dimensional self-report variables) resulting from each of the six combined music and film, music, or film emotion inductions. R_c values computed for the primary pairs of linear combinations (physiology and discrete self-report variables) created for each of the six combined music and film, music, or film emotion inductions can be found in Table 2. Immediately apparent is that the size of the R_c's for the physiological responses and the dimensional emotion scale items is greater than those for the physiological responses and discrete emotion scale items.

Keeping in mind that the focus of the current study is redundancy analysis, the correlations (i.e., the R_c's) for the primary redundancy variates are of most interest (denoted in Tables 1 and 2). The strongest values are used to derive the redundancy index and indicate, based on magnitude of the relationships, that a redundancy analysis is appropriate (Hair, Black, Babin, Anderson, & Tatham, 2010). The Stewart-Love redundancy index (R_d) was developed to represent the amount of overlapping or "redundant" variance in one set of variables that can be explained by the variables in the other set (Stewart & Love, 1968). Much like the value of R^2 equals the correlation coefficient used in multiple regression, this index serves as a measure of explained variance. Specifically, redundancy analysis creates linear composites (i.e., variates) that are orthogonal and derived so that the fit between the variate and set of variables is maximized. The first variate represents the maximum variance explained for that set of variables; the next variate is orthogonal to the first one, and the maximum amount of variance in these variables is explained by the second variate.

The redundancy indices (R_d) computed from the physiological and dimensional emotion scale indicate how well the independent redundancy variates predict the values of the original dependent variables. Although the variance explained for the individual variables ranges from zero to at most 11.7%, the pooled redundancy coefficients indicate that the variate can account for no less than 21.6% and upwards of 32.1% of the variance in the dimensional S-R variables when considered together (see Table 3). The R_d indicating how well the independent dimensional emotion scale redundancy variates predict the values of the physiological variables range from zero up to 12.1%. The pooled redundancy indices account for at least 22.4% and at most 32.2% of the variance for the six emotion inductions across combined, music, and film (see Table 4). These results indicate substantial predictive capability in both directions.

Analysis of the smaller dataset of physiological and discrete emotion scale reveals R_d indicating the ability of the independent

Table 3
The pooled redundancy coefficient (R_d) assesses the effectiveness of all the physiological redundancy variates in the solution in capturing the variance of the dimensional self-report variables during combined, music, and film induced emotions.

	Induced emotion					
	Amused	Angry	Content	Fearful	Sad	Surprised
Pooled R_d dimensional variables						
Combined	0.308	0.274	0.250	0.287	0.293	0.285
Music	0.216	0.295	0.261	0.310	0.246	0.321
Film	0.321	0.317	0.261	0.281	0.272	0.261

Table 4
The pooled redundancy coefficient (R_d) assesses the effectiveness of all the dimensional self-report redundancy variates in the solution in capturing the variance of the physiological variables during combined, music, and film induced emotions.

	Induced emotion					
	Amused	Angry	Content	Fearful	Sad	Surprised
Pooled R_d physiological variables						
Combined	0.263	0.310	0.301	0.252	0.292	0.228
Music	0.259	0.274	0.300	0.235	0.242	0.232
Film	0.263	0.322	0.294	0.290	0.252	0.224

Table 5
The pooled redundancy coefficient (R_d) assesses the effectiveness of all the physiological redundancy variates in the solution in capturing the variance of the discrete self-report variables during combined, music, and film induced emotions.

	Induced emotion					
	Amused	Angry	Content	Fearful	Sad	Surprised
Pooled R_d dimensional variables						
Combined	0.089	0.123	0.125	0.130	0.164	0.196
Music	0.092	0.138	0.134	0.151	0.071	0.146
Film	0.088	0.163	0.130	0.150	0.178	0.131

canonical variate to predict the values of the variables in Set 2. The variance explained for the individual variables ranges from zero to at most 8.9% across the six emotion inductions during combined, music, and film. The pooled redundancy coefficients indicate that the redundancy variate can account for up to 19.6% of the variance in the discrete variables when considered all together (see Table 5).The R_d indicates how well the independent discrete emotion scale variate predicts the values of the physiological variables. Again the variance explained for the individual variables is minimal across the six emotion inductions, ranging from zero to 8.1%. The pooled redundancy coefficients account for over 8% of the variance but peak at 18% (see Table 6). Overall, the predictive capability of the linear composites is considerable, especially considering the selection of the variables was not systematically optimized in any way and was completely theory driven.

5.3. Discussion

The pooled redundancy coefficients indicate variance explained in self-reported affective states by physiological variables acquired during those states, and vice-versa are in the 7–19% range when using the discrete S-R items and matched ANS variables, and considering all six emotion states and forms of induction (Tables 5 and 6). The same redundancy coefficient values calculated for the dimensional S-R items and matched ANS variable sets are in the 22–32% range (Tables 3 and 4). Considerably more variance is explained when using the latter analyses, and so the focus here will be on them. Inspection of Tables 3 and 4 indicates: (1) if one looks at the average redundancy calculated across the six inductions, the amount of variance explained in S-R by the ANS variables and vice versa is very similar (∼27% vs. ∼28%, respectively),

Table 6
The pooled redundancy coefficient (R_d) assesses the effectiveness of all the discrete self-report redundancy variates in the solution in capturing the variance of the physiological variables during combined, music, and film induced emotions.

	Induced emotion					
	Amused	Angry	Content	Fearful	Sad	Surprised
Pooled R_d physiological variables						
Combined	0.112	0.101	0.105	0.141	0.153	0.175
Music	0.087	0.123	0.134	0.133	0.095	0.180
Film	0.131	0.164	0.118	0.150	0.167	0.150

and (2) there is little difference in variance explained across the two forms of induction (i.e., film vs. music: average redundancies range from ∼26% variance in ANS explained by S-R in the music induction, to 28.5% variance in S-R explained by ANS in the film induction). As such, the average redundancy index taken over the six induced emotions, with film and music combined, is ∼27–28%, and is a representative figure of the coherence between experiential and physiological variables in this study.

The magnitude of these values at first blush may seem somewhat modest, but in fact, they suggest that the canonical correlations (r equivalent) between these variable sets are in the .52–.53 range. These are well above the correlations that have typically been reported in the literature between self-report and physiological variables with univariate analyses. Hence, by taking into account the correlation *among* the various sets of variables, the associations *between* the sets of variables can be better accounted for.

A few initial comments are in order. First, it is interesting to note that coherence levels as revealed by redundancy indices did not differ in any systematic or substantive way between film and music inductions. Hence, it appears that comparable levels of emotional coherence were attained in the two induction methods. Next, although an aim of using redundancy analysis is to detect asymmetrical relationships between variable sets, in the present case, S-R and ANS variables appeared to explain very similar amounts of variance in each other. To some extent, this finding is consistent with James' (1884) theory that physiology has a causal relationship in emotional feelings, but is also in accord with contemporary biopsychosocial models of emotion that posit a bi-directional relationship between physiology and feelings (Pinel, 2010) These results can be viewed in a different light when their boundaries are taken into account. It is traditional to consider the limitations of a study at the conclusion of the discussion, but it may be more appropriate in this case to consider these limits in forethought in order to place the findings in their proper interpretive context. Therefore, we catalog these constraints below, not necessarily in order of importance.

First, the variables employed in this study were aimed at broadly sampling affective and autonomic space, but of course, they do not fully capture either. Although the autonomic montage used in this study was fairly comprehensive, it was certainly not exhaustive—nor is such a sampling of the ANS domain possible with existing technology. The multivariate utilization of multiple ANS measures is certainly a vast improvement over prior practices of using single variables such as heart rate to globally represent autonomic "arousal", but it still falls short of a fully inclusive representation of ANS function. Similarly, self-report descriptors do not necessarily capture the entirety of emotional feelings, nor do they always fit the language subjects themselves would use to describe their feelings (Scherer, 2005). Most likely this consideration has much to do with why the dimensional S-R variables and its associated ANS set accounted for considerably more variance in each other than the corresponding discrete S-R sets —there was more extensive sampling of variables in the former. Nonetheless, considerable measurement error of the constructs of emotional feelings and ANS responses must be acknowledged in this study (and, for that matter, virtually all laboratory emotion research).

A related issue is that the ANS variables reflect multiple simultaneous psychophysiological demands, not just the processing of the affective stimuli in the study (Berntson, Cacioppo, & Grossman, 2007; Cacioppo & Tassinary, 1990). These demands include ongoing physiological regulation unrelated to the experimental context, and information processing functions that are relatively independent of emotional qualities. In other words, psychophysiological responses are multiply determined, and various unassessed mechanisms provide continuous input into ANS responses in psychophysiological studies (Porges, 2007). This consideration would seem to particularly apply to emotion induction paradigms, which by nature invoke more subjectivity than more limited and reflexive paradigms such as the measurement of the startle response via eye blink strength.

Lab-based inductions of discrete emotions via standardized stimuli certainly have benefits in terms of experimental control and simplification of quantitative analysis of affective states. However, as effective as these inductions may be, they will always have an artificial quality about them when compared to emotions experienced in the field (Wilhelm & Grossman, 2010). Emotions induced via stimuli such as film are likely less potent than the "real life" situations in which those emotions are experienced. Many evolutionary theories view emotions as action tendencies; in the lab, subjects are aware at some level that no action will be taken in response to the stimuli. So, although genuine feelings (and their accompanying ANS responses) are undoubtedly evoked in lab inductions, these feelings remain vicarious, and so the strength of the action tendency is diminished. Consequently, it is possible if not probable that coherence would be higher in basic emotion studies conducted in naturalistic settings.

Differences in time course both between S-R and ANS responses, and among the ANS measures, are also another likely source of error in coherence estimates. These issues have generally been noted in emotion involving S-R and ANS indices (Mauss, Levenson, Wilhelm, McCarter, & Gross, 2005). Like many studies of this kind, subjects retrospectively reported their emotions immediately after the induction, while ANS responses were acquired during the induction itself. Ideally, coherence would be examined "in the moment" —i.e., simultaneous acquisition of experiential and physiological variables. Moreover, these data would then be examined with temporally-sensitive analytic techniques. The present study was not designed with the intent to examine coherence (although it does allow for this), and so these conditions cannot be met with this data set.

Finally, this study was conducted with a nomothetic design, which entails prediction of variance across individuals who may differ in their reactions to stimuli, self-report response tendencies, and characteristic physiological responses (Nesselroade & Ford, 1987). Although pattern classification analysis revealed enough inter-subject consistency in these responses to reliably distinguish among the induced emotions (Stephens et al., 2010), coherence is still likely to be higher in idiographic designs in which variance is explained within, not across, individuals. In other words, idiosyncratic responses (i.e., "individual response stereotypy") is likely to have diluted the redundancy indices and inferred coherence among the measures in the study (Engel, 1960; Lacey, 1959).

In sum, considering the margins of this study and others in the same paradigm, variance explained in S-R variables in by ANS indices and vice-versa the 27–28% range, corresponding to correlations above .50, indicate considerable coherence exists between feelings and physiological responses in core basic emotions. This high coherence is consistent with evolutionary emotion theory, in that functional emotions should be composed of coordinated elements. Additionally, these results complement pattern classification studies cited above that revealed discrete emotional states distinguishable by their ANS response patterns. Hence, the present analyses not only suggest high coherence in conditions of relatively "pure" emotions, but also supply evidence in support of discrete emotions theory.

As also mentioned above, these data do not suggest that high coherence typifies the everyday state of affairs in emotional life. On the contrary, this is not likely to be so, because people most rarely encounter the kinds of situations in which these basic emotions evolved. Indeed, it is often necessary to regulate emotions such that these primitive response patterns are not fully enacted. Nonetheless, the core of these propositions, as Lang depicted them, remains, ready to be activated by real or virtual stimulation.

The notion of emotional coherence is also broadly compatible with core psychophysiological framework of stimulus-response specificity. If distinct response patterns exist for basic emotions that have some degree of commonality across individuals, and these patterns evolved for adaptive value, then it is most plausible that the components of these patterns cohere with each other. It is only in this manner that these emotion-specific patterns would be functional in their originating contexts. The fact that these contexts are very infrequent in contemporary life suggests that in the "real-world", coherence may be much lower than in the lab. In fact, the task of emotion regulation often entails a suppression of coherence in the service of socially adaptive functioning. For example, it is usually maladaptive to respond with behavioral aggression and sympathetic activation to anger provocation, although nature has wired humans and other mammals to do so.

A number of future lines of research are suggested by this study. First, multivariate techniques are strongly suggested in the study of coherence, in that previous univariate studies may have grossly underestimated the degree of coherence among the components of emotion. Redundancy analysis is one such technique that might be used. Next, idiographic designs bear consideration, because higher coherence is likely to be revealed within individuals than between individuals. Third, more temporally sensitive designs and analytic techniques may further increase coherence estimates. Finally, to the degree to which sampling includes episodes of relatively pure basic emotions, field studies might also detect enhanced coherence, because of the real possibility of action in such situations.

6. Summary and conclusion

The present results demonstrate the advantages of multivariate techniques for capturing the gestalt of diverse types of responses in emotion. These benefits were apparent in pattern classification analysis studies of ANS specificity for emotion (Christie & Friedman, 2004; Kreibig et al., 2007; Nyklicek et al., 1997; Rainville et al., 2006; Stephens et al., 2010), and appears to extend to the use of redundancy analysis in application to the issue of emotional coherence. Indeed, the present results complement these pattern classification studies in that they are consistent with a functional view of emotion that emphasizes coordinated activity across multiple response systems (Ekman, 1992; Frijda, 1994; Levenson, 1994a; Plutchik, 2000). In this paradigm which was directed at eliciting basic emotions, the inductions were not only distinguishable from each other based on their ANS response patterns, but a substantial level of coherence emerged between those responses and self-reported experience, when all the constraints of those findings are considered.

The present results are also informative when considering the body of literature that depicted synchrony and desynchrony in the components of clinical anxiety. The general consensus of those studies was that correlations among feelings, physiology, and behavior are often rather low. The univariate nature of the vast majority of those studies may partly explain that conclusion. Another point from that body of work, which is not disputed here, is that coherence varies as a function of context. Thus, the depiction of "loosely coupled" components remains apt; in situations invoking basic, core emotions, those couplings may be tightened considerably.

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