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Emotion recognition: Unidimensional ability or a set of modality- and emotion-specific skills?

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ABSTRACT

Research on emotion recognition ability (ERA) can inform the measurement of the emotion perception component in emotional intelligence. However, to date the question of whether ERA is a single unitary ability or whether independent skills are involved in the recognition of different modalities and/or emotions has been neglected. We studied this issue with the help of two ERA tests drawn from two emotion portrayal corpora. In Study 1, we investigated the dimensional structure of ERA in a set of 10 emotions presented in four modalities (audio, video, still picture, audio–video). In Study 2, we investigated a set of 14 emotions in the audio–video modality. Our results suggest that ERA might be conceptualized as a broad ability consisting of related skills involved in the recognition of positive and negative emotions. In addition, correlated residuals between pairs of similar emotions (e.g., irritation and anger) suggest the existence of specific ability facets within the valence-based skill dimensions.

1. Introduction

In the past decade, the conceptualization of emotional intelligence (EI) has been debated between the proponents of two approaches: as a set of self-perceptions and dispositions positively related to social functioning and commonly measured via self-report ("trait EI"; Petrides & Furnham, 2000), or as a cognitive ability encompassing emotional skills and knowledge primarily measured with performance-based tests ("ability EI"; Mayer, Salovey, Caruso, & Sitarenios, 2003).

A construct that has been given a central role in both approaches is the ability to accurately recognize emotions in others from nonverbal expressions (emotion recognition ability [ERA]; e.g., Mayer et al., 2003). In contrast to the relatively recent efforts to measure EI, the measurement of ERA has a long tradition (for an overview of standardized ERA tests, see Bänziger, Grandjean, & Scherer, 2009, pp. 691–692). ERA is commonly measured by asking participants to identify discrete emotions expressed in faces, voices, or postures. Several studies used this paradigm to investigate the links between ERA and EI, with mixed results: on the one hand, Petrides and Furnham (2003) reported higher speed in identifying emotions from faces for individuals high in trait EI, and Austin (2005) found a significant positive relationship between a combined score on several emotion tasks and some trait EI scales. On the other hand, Edgar, McRorie, and Sneddon (2012) found such a relationship only for females, and DeBusk and Austin (2011) reported no empirical link between EI and ERA. Given these inconsistent findings and the psychometric problems of existing performance-based EI tests (e.g., Rossen, Kranzler, & Algina, 2008), some scholars have recently suggested that the development of ability EI measures should draw more closely from ERA testing (Cherniss, 2010).

Although central to test development, the question of the dimensional structure underlying ERA has been neglected by previous research. First, it remains unclear whether emotion recognition in different sensory modalities (e.g., auditory and visual) can be explained by a unitary ability. Some studies suggest that ERA might be modality specific because ERA tests measuring different modalities are correlated only to a low extent (Scherer & Scherer, 2011). However, when Bänziger et al. (2009) presented the same stimuli in different modalities (audio, video, audio–video, still picture), auditory ERA scores on average correlated as highly with the three conditions involving visual information as the visual conditions did with each other.

Second, little is known about the structure of ERA within each modality. Is a person who is good at recognizing one emotion (e.g., happiness) more likely to recognize other emotions? Most previous research has implicitly treated ERA as a single unitary ability by calculating total scores over all emotions (e.g., Bänziger et al., 2009). Nonetheless, some studies suggest that ERA might be emotion-specific by reporting low correlations between the recognition rates of different emotions (Matsumoto et al., 2000).

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In the first study explicitly investigating the structure of emotional sensitivity, Suzuki, Hoshino, and Shigemasu (2010) presented morphed facial expressions to participants and asked them to rate the intensity of six basic emotions for each image. Participants' sensitivity scores for a given emotion were calculated from the respective intensity ratings in all images containing this emotion. Suzuki et al. (2010) found that happiness scores displayed only a low positive correlation with sensitivity to negative emotions and concluded that recognition of positive and negative emotions might require independent skills.

The assumption of emotion-specific ERA might also explain the generally low reliability of ERA tests (Hall, 2001). However, Hall (2001) suggests that low reliability does not necessarily contradict the existence of a common underlying factor: each item in an ERA test might draw on a different facet of a general ability, and thus, all items incrementally contribute a specific part to the measurement of general ERA. Following this (to date empirically untested) approach, items measuring similar emotions, such as anger and irritation, might require more closely related recognition skills than those required for items measuring very different emotions, and thus might represent specific facets of general ERA.

To test this assumption empirically, the present studies include a large set of emotions based on a modal emotion model (Scherer, 1994). In contrast to basic emotion theory (Ekman, 1992), this model characterizes modal emotions by frequently occurring patterns of appraisal without restricting the range of emotions to those with an evolutionary basis and an automatic neuromotor program. Modal emotions can, applying the core affect model of emotion (Russell, 2003), be mapped on a valence-arousal space. To our knowledge, the core affect model itself has not been used in ERA testing.

The question of the dimensional structure of ERA has important methodological implications. If independent skills were involved in the recognition of certain modalities or emotions, the use of total scores in ERA tests would not be appropriate. For example, when studying the link between ERA and psychosocial functioning, emotion- or modality-specific relationships might be overlooked when using the total ERA score. Also, ERA tests using different emotions or modalities might then not be comparable.

Here, we present two studies examining the dimensional structure of ERA. First, we investigated the emotion specificity of ERA within different modalities. In particular, we (a) tested the assumption that recognition performance for all emotions within one modality can be exclusively explained by one ERA factor (strict unidimensional model); (b) tested the assumption of independent abilities underlying recognition performance in positive and negative emotions, as suggested by Suzuki et al. (2010; valence factors model); and (c) revised, following Hall's (2001) approach, the strict unidimensional model by exploring whether recognition scores of similar emotions were more closely related than those of very different emotion pairs and by modeling these relationships (moderate unidimensional model). Second, we examined whether ERA is modality specific. In Study 1, we used a set of 10 emotions presented in four modalities (audio, video, audio–video, still picture). In Study 2, we included 14 emotions drawn from a different emotion portrayal corpus presented in the audio–video modality.

2. Study 1

2.1. Method

2.1.1. Participants

The sample consists of 305 participants (male = 130; age range 18–58, mean age = 29.48, *SD* = 9.56). We recruited 147 participants at the University of Geneva who are French native speakers; the remaining 158 participants were recruited at the University of Magdeburg and are German native speakers.[1] They participated in the study for payment and received feedback on their performance.

2.1.2. Procedure

Participants completed the Multimodal Emotion Recognition Test (MERT; Bänziger et al., 2009) in their native language as part of a battery of questionnaires and tests. The MERT consists of 30 actor portrayals (three portrayals for each of 10 emotions organized in five emotion families: irritation and anger, anxiety and fear, happiness and elated joy, disgust and contempt, sadness and despair) presented in four modalities (still picture, video, audio, audio–video). A standard pseudo-linguistic sentence is used as verbal content. After each of the 120 stimuli, participants were asked to choose which of the 10 emotions had been expressed by the actor. This "forced-choice response format" is commonly used in ERA tests.

2.1.3. Analysis

2.1.3.1. Recognition score calculation. For each participant, a recognition accuracy score for each of the 10 emotions was calculated using the unbiased hit rate (H_u; Wagner, 1993), which accounts for potential biases towards certain response categories. H_u is calculated as the squared frequency of correct responses for a target emotion divided by the product of the number of stimuli representing this emotion and the overall frequency of the emotion category being chosen. Prior to the following analyses, we arcsine transformed the H_u scores, as recommended by Wagner (1993). A more detailed description of H_u is provided in the Supplementary material.

2.1.3.2. Analysis strategy. Using confirmatory factor analysis (CFA; for an overview, see Brown, 2006) on the H_u correlation matrix for each modality and for the emotion scores aggregated over all modalities, we performed the following steps to analyze the question of emotion specificity in ERA:

First, we applied a model with all emotions loading on one factor to test the assumption of (strict) unidimensionality ("strict unidimensional model").

Second, we computed a two-factor model, specifying the positive and negative emotions to load on different factors that were allowed to correlate ("valence factors model").

Third, we modified the strict unidimensional model based on modification indices that reveal the presence of correlated residuals between pairs of variables ("moderate unidimensional model"). These reflect shared variance between variable pairs that is not accounted for by the general factor and can be interpreted in terms of minor factors subsumed by a broader construct (Brown, 2006). In our study, residual correlations can be expected when two emotions share similar cues and, consequently, are often confused. This is especially the case when emotions belong to the same emotion family (e.g., anger and irritation). For such emotion pairs that showed high modification indices, we successively added residual correlations to the model, starting with the pair with the highest expected parameter change (EPC). We did not add residual correlations if the modification indices and EPC were low and did not improve model fit substantially. This exploratory strategy allowed us to identify minor factors without overfitting the model by adding parameters of trivial magnitude.

Finally, to evaluate whether ERA is modality specific or not, we calculated the mean unbiased hit rates over all emotions per

[1] We thank Prof. H.-M. Süß for providing us with the data collected at the University of Magdeburg.

Table 1
Fit statistics for CFA models in Studies 1 and 2.

CFA model	χ^2	*df*	*p*	CFI	RMSEA	SRMR	Correlation between positive and negative factor
Study 1							
Audio							
SUM	68.203	35	.001	.854	.056	.050	–
VFM	61.470	34	.003	.879	.051	.048	.720
MUM	54.383	34	.015	.910	.044	.046	–
Video							
SUM	191.913	35	<.001	.603	.121	.080	–
VFM	103.244	34	<.001	.825	.082	.060	.444
MUM	50.754	31	.014	.950	.046	.041	–
Still picture							
SUM	177.214	35	<.001	.541	.115	.083	–
VFM	106.747	34	<.001	.765	.084	.063	.417
MUM	60.924	31	.001	.903	.056	.048	–
Audio–video							
SUM	210.011	35	<.001	.495	.128	.085	–
VFM	146.520	34	<.001	.675	.104	.077	.363
MUM	64.267	31	.001	.904	.059	.048	–
Modalities combined							
SUM	173.187	35	<.001	.791	.114	.066	–
VFM	143.686	34	<.001	.834	.103	.061	.703
MUM	70.754	31	<.001	.940	.065	.042	–
Study 2							
SUM	283.009	77	<.001	.744	.095	.068	–
MUM	145.386	73	<.001	.910	.058	.050	–
MUM + valence factor	126.555	71	<.001	.931	.052	.045	.774

Note: SUM, strict unidimensional model; VFM, valence factors model; MUM, moderate unidimensional model.

modality and fit a one-factor CFA model to the four modality scores.

We evaluated model fit by inspecting the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Good model fit is indicated by a CFI close to or higher than .95, a RMSEA close to or lower than .06, and an SRMR close to or below .08 (for a discussion, see Vernon & Eysenck, 2007). Analyses were performed with Mplus. To correct for skewed variable distributions, we used the robust maximum likelihood (MLM) estimator.

2.2. Results

2.2.1. Descriptive statistics

H_us, the H_u correlation matrices, and the confusion matrices for each modality are provided in the Supplementary material. H_us for the single modalities ranged from .08 (SD = .15) for sadness in the audio condition to .80 (SD = .26) for anger in the audio condition, with the means over all emotions being .31 (SD = .22) for audio, .45 (SD = .24) for video, .31 (SD = .35) for still picture, and .49 (SD = .24) for audio–video.[2]

2.2.2. Strict unidimensional and valence factors models

Table 1 provides the fit statistics for all CFA models and the correlations between the positive and negative ERA factors for the valence factors models. The strict unidimensional model did not fit the data well in any of the modalities. In all cases, the valence factors model showed better but still insufficient fit. Correlations between the positive and negative ERA factors in the valence factors models were moderate to high.[3]

2.2.3. Moderate unidimensional models

Fit statistics for the moderate unidimensional models are given in Table 1; factor loadings and residual correlations are provided in Table 2.

2.2.3.1. Audio. The modification indices in the strict unidimensional model revealed a residual correlation between irritation and anger. The model, including this residual correlation, fit the data reasonably well according to RMSEA and SRMR, with the CFI being slightly below the recommended .95 threshold.

2.2.3.2. Video. We found residual correlations between the two emotions of four emotion families, namely, joy and happiness, contempt and disgust, fear and anxiety, and despair and sadness. The model, including these correlations, showed good fit.

2.2.3.3. Still picture. Residual correlations were found between the same four emotion pairs as in the video modality. Modeling them resulted in a reasonably well-fitting model according to RMSEA and SRMR, although the CFI was somewhat below .95.

2.2.3.4. Audio–video. We found residual correlations between joy and happiness, irritation and anger, contempt and disgust, and despair and sadness, similar to the other modalities. Allowing the residuals of these emotion pairs to correlate substantially increased model fit.

[2] We did not calculate scale reliabilities, because the concept of internal consistency in terms of similar items reflecting a narrow content domain is not applicable to ERA tests. The variety of ways in which emotions can be expressed (and yet be correctly recognized) can be seen as different aspects of a comparatively broad content domain, so that reliability coefficients can be misleading (for a detailed discussion, see Scherer & Scherer, 2011).

[3] When model fit is insufficient, correlation estimates between the two factors might not be accurate and give only an approximate indication of the correlation magnitude (Brown, 2006).

Table 2
Standardized factor loadings and residual correlations for the moderate unidimensional CFA models in Studies 1 and 2 and correlations between mean unbiased hit rates per modality in Study 1.

Emotion/modality	Study 1					Study 2
	Audio	Video	Still picture	Audio–video	All modalities combined	Audio–video
Anxiety	**.534**	**.329**	.230	**.303**	**.595**	**.593**
Disgust	.152	**.300**	.268	.287	**.416**	**.499**
Happiness	**.477**	**.425**	.275	**.379**	**.538**	–
Anger	**.343**	**.666**	**.748**	**.308**	**.666**	**.431**
Irritation	**.421**	**.558**	.264	**.411**	**.593**	**.655**
Fear	.250	.239	.269	.235	**.318**	**.424**
Sadness	**.368**	.264	.246	.158	**.380**	.280
Elated joy	**.400**	**.305**	**.349**	**.420**	**.515**	**.451**
Contempt	**.463**	**.401**	.295	**.451**	**.544**	–
Despair	.247	.230	**.309**	**.307**	**.404**	**.450**
Pleasure						**.309**
Pride						**.463**
Amusement						**.473**
Surprise						**.318**
Relief						**.508**
Interest						**.491**
Residual correlations						
Joy/happiness	–	.529	.491	.390	.295	–
Irritation/anger	.233	–	–	.405	.278	.416
Sadness/despair	–	.238	.167	.314	.299	.364
Anxiety/fear	–	.247	.170	–	–	–
Disgust/contempt	–	.264	.329	.276	.321	–
Relief/pleasure						.356
Joy/pride						.208
Correlations between mean unbiased hit rates per modality						
Video	.511***					
Still picture	.477***	.546***				
Audio–video	.492***	.557***	.440***			

Note: Factor loadings >.30 are printed in bold.
*** $p < .001$.

2.2.3.5. Modalities combined. Modification indices revealed the same residual correlations as in the audio–video modality. Fit of the resulting model was marginally acceptable, with the CFI and RMSEA being slightly below or above their recommended values, respectively.

2.2.4. Relationships between modalities

The mean scores (across all emotions) of the four modality conditions were moderately correlated (see Table 2). A one-factor CFA showed close fit ($\chi^2 = 3.821$, $df = 2$, $p = .15$, CFI = .995, RMSEA = .055, SRMR = .013).

2.3. Discussion

Regarding the question of emotion specificity, the strict unidimensional model generally failed to adequately reproduce the relationships between the 10 emotions. The valence factors models showed better fit, reflecting the particularly high correlations between joy and happiness recognition as compared to their correlations with the recognition of negative emotions. However, the moderate to high correlations between the two valence factors contradict Suzuki et al.'s (2010) assumption that positive and negative emotion recognition requires largely independent abilities.

In all modalities, a moderate unidimensional model specifying a general ERA factor and between one and four minor factors represented as correlated residuals described the data best. These correlated residuals occurred exclusively between emotions of the same family and can be explained by shared cues leading to high confusion and, consequently, particularly high correlations between them. The magnitude of the residual correlations was low to moderate, supporting their interpretation as minor factors. However, overall, even the moderate unidimensional models did not show close fit to the data, as the CFI generally did not attain the level of .95. We address this issue in more detail in the general discussion.

Regarding the question of modality specificity, our data imply that emotion recognition in the auditory and visual modalities can be explained by a single underlying dimension. Given that even within one modality, different ERA tests are only moderately correlated (Bänziger et al., 2009), the low correlations between modalities found in other studies (Scherer & Scherer, 2011) can be attributed to the different origins of the stimuli in each modality. However, our results could also have occurred because of transfer effects of the same portrayals presented in different conditions. Further research is thus needed to investigate the question of modality specificity in ERA.

A limitation of this study is that only two of the 10 emotions are positive, which does not allow us to test whether the strong association between them can be better modeled as a residual correlation within one general ERA factor or as a separate "positive emotions" factor (these two models are equivalent and thus fit the data equally well). In other words, it remains unclear whether general ERA contains two valence-specific subdimensions in addition to the emotion-family-specific facets. Another limitation is that each emotion was represented by only three portrayals per modality and results might therefore not generalize to other stimulus sets. Further, we did not include the emotional state of surprise, which is neither positive nor negative and might thus play a special role. Hence, in Study 2 we investigated 14 emotions, including six positive emotions and surprise. We also included a higher number of portrayals per emotion. We examined the audio–video modality only, because we consider this modality to have the highest ecological validity.

3. Study 2

3.1. Method

3.1.1. Participants

Two hundred and ninety-five German-speaking participants (male = 82; age 17–74 years, M = 37.1, SD = 13.9) took part in this online study. They were recruited through various websites advertising online studies and received feedback on their performance.

3.1.2. Procedure and stimuli

Participants watched 108 audio–video clips (duration 2–4 s) taken from the Geneva Multimodal Emotion Portrayals (Bänziger, Mortillaro, & Scherer, in press) presented in randomized order. In each clip, one of 10 actors expressed one of 14 emotions: six positive emotions (pride, joy, amusement, pleasure, relief, and interest), seven negative emotions (anger, panic fear, despair, disgust, anxiety, irritation, and sadness), and surprise. In each portrayal, one of two standard pseudo-linguistic sentences was used as verbal content. For each emotion, there were between six and nine portrayals. After each of the 108 portrayals, participants were asked to choose, from the 14 emotion categories, the one that had been expressed by the actor.

3.1.3. Analysis

From the 108 portrayals, we created a new ERA test (Geneva Emotion Recognition Test; see Supplementary material for details) with six portrayals for each of the 14 emotions (except for the despair scale, consisting of only five portrayals), for a total of 83 items. The remaining 25 portrayals were not included in the following analysis. As described in Study 1, we calculated H_us from the six (or five for despair, respectively) items of each emotion subscale. We then fit a strict unidimensional model to the 14 H_us, from which we derived a moderate unidimensional model involving correlated residuals between similar emotion pairs. To test whether ERA can be better conceptualized as two correlated valence-based subdimensions, we modified the moderate unidimensional model by adding a negative emotion factor influencing the seven negative emotions and a positive emotion factor influencing the six positive emotions. Surprise was specified to be correlated with both the negative and the positive factors because surprise can have either a positive or negative valence. The moderate unidimensional model is nested under this two-factor model, allowing for statistical model comparison. Path diagrams of both models are provided in the Supplementary material.

3.2. Results

3.2.1. Descriptive statistics

Descriptive statistics, along with the H_u confusion and correlation matrix, are provided in the Supplementary material. H_us ranged from .30 (SD = .20) for surprise to .74 (SD = .22) for amusement, with a mean of .50 (SD = .22).

3.2.2. CFA results

Table 1 shows fit statistics for all models. The strict unidimensional model did not fit well. We found correlated residuals between anger and irritation, sadness and despair, relief and pleasure, and pride and joy. As in Study 1, the first two emotion pairs belong to the same emotion family. Relief and pleasure are similar in that they are both defined as positive and low arousal emotions, whereas pride and joy are both considered positive and high arousal emotions (Bänziger et al., in press). The moderate unidimensional model that included these relationships fit the data much better, but still performed significantly worse than the nested two-factor model described earlier (χ^2-difference test: $\Delta\chi^2$ = 18.831, Δdf = 2, p < .001). The high correlation between the two valence factors indicated a considerable overlap between positive and negative ERA. Surprise recognition was positively related to both valence factors.

3.3. Discussion

Our results suggest that positive and negative emotion recognition skills can be seen as broad subdimensions of a general ERA that share a relatively large part of the variance (60%). In addition, this study confirmed the finding of Study 1 that minor facets modeling the similarities between certain emotion pairs describe the nature of ERA better than simple one- or two-factor models. However, as in Study 1, our results should be interpreted with caution, given the marginally acceptable fit statistics of the best-fitting model.

Although we found some evidence for valence-specific ERA, our results do not support Suzuki et al.'s (2010) finding of largely independent skills involved in the recognition of positive and negative emotions. One reason might be that Suzuki et al. (2010) used morphed images showing ambiguous mixed emotional expressions, and they calculated ERA from intensity ratings. It is possible that in the presence of cues representing a negative emotion, happiness cues (i.e., smile) are not interpreted as happy anymore but are attributed to a different emotional state. For example, happiness morphed with anger might be interpreted as "arrogance," and consequently, participants might rate the intensity of happiness as low, even if they recognize some degree of smiling. Also, participants might find it contradictory to give high ratings for happiness and a negative emotion in the same image and might thus decide to rate only one of the emotions highly. Happiness sensitivity scores would consequentially be correlated with sensitivity scores for negative emotions only to a low extent. In contrast, our results, obtained with a forced-choice response format (i.e., choosing the emotion category that best reflects the emotion expressed) and portrayals of pure emotions, imply that skills involved in the recognition of positive and negative emotions largely overlap.

4. General discussion

Our data showed that recognition performance *across* sensory modalities can be explained by a single ability dimension. Recognition *within* each modality condition can be tentatively conceptualized as one broad ability consisting of correlated valence-based skills and minor ability facets related to pairs of similar and highly confused emotions. In this respect, our findings support Hall's (2001) view that ERA might be a set of related yet specific skills that incrementally contribute to the measurement of this ability. The four modality conditions investigated in Study 1 can be interpreted as specific facets of a broad general ERA, given the substantial, but not very high, correlations between them.

However, these results should be treated as preliminary, given that some of the fit statistics (particularly the CFI) were lower than generally recommended. One reason for this might be that the emotional expressions in our stimuli are not constrained by posed muscle configurations (Bänziger et al., in press). The resulting "fuzziness" of the actor portrayals, though reflecting their variability in real life, might make it more difficult to obtain extremely well-fitting statistical models. Our fit statistics compare rather favorably, however, to related studies (e.g., Suzuki et al., 2010).

Another reason for the somewhat unsatisfactory fit of our models might be that the structure of ERA is more complex than hypothesized in our models. For example, additionally modeling emotion pairs that do not belong to the same emotion family but nevertheless are often confused in some modalities (e.g., happiness and sadness in the audio modality; see Supplementary material) might increase model fit. On the other hand, we believe that testing more complex statistical models must be based on a theoretical framework explaining the factors and mechanisms underlying the general modality-specific and emotion-specific levels of ERA, which does not yet exist.

Regarding test development in the ERA and EI domains, our results imply that future tests should include a high number of positive and negative emotions and different modalities to cover many facets of the construct and to increase ecological and predictive validity. Most current ways of assessing ERA are far less complex and include few emotions, mostly presented as still pictures. Further, whereas our results generally justify the use of a total ERA score, we recommend considering valence- and emotion-family-specific relationships with variables of interest.

Future research should compare the dimensional ERA models resulting from different operationalizations of ERA in more detail, such as the use of intensity ratings from basic emotions (Suzuki et al., 2010) versus a forced-choice response format with a larger set of modal emotions and the consideration of confusions. In particular, future studies should investigate the predictive validities of the different ERA dimensions found by using different measurement approaches. We believe that our approach has helped inform our general understanding of emotion, supporting the modal emotions perspective. Although basic emotion theory can account for some of the minor factors in our studies (e.g., sadness and despair can be seen as intensity variations of the basic emotion sadness), it cannot readily explain the minor factors found for relief/pleasure and pride/joy because it postulates only one positive emotion, namely, happiness. We also found, consistent with the core affect emotion model, some support for a valence dimension in ERA, although its role does not seem too important in view of the high correlations between positive and negative ERA.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.paid.2012.01.026.

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