Ambivalence, the Person and the Attitude Object:

Individual Differences in Ambivalence

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Abstract

Ambivalence, that is holding positive and negative evaluations about a single topic, has traditionally been studied in relation to specific attitude objects. However, prior findings suggest that some individuals may be more ambivalent than others, regardless of the attitude object. To investigate this possibility, we conducted a registered secondary analysis of two existing datasets. In both datasets, individuals ($ns = 41; 111$) rated multiple stimuli (DS1=29; DS2=61) drawn from widely-used normed sets (IAPS; ANEW). Results indicate that ambivalence varies more strongly with individuals than with stimuli. Individual differences account for 16-28% of variance whereas the differences between stimuli only account for 3-10%. Furthermore, we document substantial individual differences in the relationships between different aspects of ambivalence. These findings show that levels of ambivalence are as much a function of the person as they are of the attitude object.

Life is complicated, and individuals often do not have the luxury of simple, univalent feelings. A beloved friend who consistently keeps us waiting, a delicious but unhealthy snack, or an overly stressful job that pays well are all examples of attitude objects that invoke a mix of positive and negative evaluations. Such experiences of ambivalence are far from uncommon: Mixed feelings make up more than 30% of people's emotional experiences (Trampe, Quoidbach & Taquet, 2015) and play a role in central domains of people's lives, such as intergroup perception (Glick & Fiske, 1996; Katz & Hass, 1988), close relationships (Mikulincer, Shaver, Bar-On, & Ein-Dor, 2010), self-regulation and health decisions (Armitage & Conner, 2000; Berrios, Totterdell & Kellett, 2018; Gillebaart, Schneider & de Ridder, 2015; Povey, Wellens & Conner, 2001) and stances on social issues (Nohlen, van Harreveld, Rotteveel, Lelieveld, & Crone, 2013; Schneider et al., 2015). These experiences of ambivalence have profound psychological consequences, inducing stress (Nordgren, van Harreveld & van der Pligt, 2006) and affecting information gathering and processing (Clark, Wegener & Fabrigar, 2008; Nordgren, van Harreveld & van der Pligt, 2006; Rees, Rothman, Lehavv & Sanchez-Burks, 2013; Van Harreveld, Rutjens, Schneider, Nohlen & Keskinis, 2014). All of this suggests that advancing our understanding of ambivalence is important.

So far, research on ambivalence has taken an object-centered approach, emphasizing that across individuals certain topics induce more ambivalence than others. For example, Glick and Fiske (1996) argue that attitudes towards women are frequently characterized by simultaneous positive and negative evaluations. Katz and Hass (1988) make a similar argument for White American's attitudes towards Black Americans. Perhaps most representative of this approach, however, is the widespread method of manipulating ambivalence by identifying topics that are high in ambivalence and topics that are low in ambivalence, and using these to create

ambivalence (or not) in participants (e.g., de Liver, van der Pligt & Wigboldus, 2007; Nohlen, van Harreveld, Rotteveel, Lelieveld, & Crone, 2013; Schneider et al. 2015). This manipulation is predicated on the principle that some topics reliably induce ambivalence in participants. Indeed, research has shown that there are some topics that consistently make people more ambivalent than others, such as abortion, euthanasia, fast-food (Schneider et al., 2015, Gillebaart et al., 2015; Schneider, Gillebaart, & Mattes, in press; Nohlen et al., 2013; Berger, Hutter & Corneille, 2019)

Conversely, in the current research, we take a *person-centered* approach. We focus on the degree to which ambivalence differs not between attitude objects but between people. Specifically, we examine whether some individuals consistently experience more ambivalence than others. Intuitively, it seems unlikely that a person's level of ambivalence about climate change would tell us something about their feelings towards religious freedom, the paintings of Klee, or chocolate biscuits. However, in light of the correlation of ambivalence ratings with individual difference variables such as self-control (Gillebaart, Schneider & de Ridder, 2015; Schneider, Gillebaart, & Mattes, in press) and Need for Cognition (Thompson & Zanna, 1995), there is reason to assume that person-level factors influence people's experiences of ambivalence toward any given topic.

If there are individual differences in ambivalence, it would substantially affect the field's understanding of the phenomenon's antecedents. Ambivalence has traditionally been conceptualized as a property of attitude strength (Petty & Krosnick, 1995) which varies across topics. Large differences between people would show this to be incomplete. That is, if there are individual differences in people's experiences of ambivalence, our understanding of its causes will expand beyond properties of the attitude object and into the realm of personal factors. Any account of the causes of ambivalence would need to explain why individuals show consistency

across their ratings. Invoking features of the object or situation would be insufficient to explain this intra-individual consistency.

Here, we provide the first direct quantification of individual differences in ambivalence. We conducted a registered secondary analyses of two existing datasets in which respondents rated a large number of stimuli using different ambivalence measures. This crossed design allowed us to identify how much variance can be attributed to individuals and to stimuli, using mixed-effect models (Raudenbusch & Bryk, 2002; Baayen, Davidson & Bates, 2008; Judd, Westfall & Kenny., 2012). Using this approach we are able to separate the contributions of individuals and object to ambivalence, and quantify each in terms of proportion of total variance accounted for.

Previous research on individual differences in ambivalence

Previous work has assessed ambivalence towards the attitude object using two different aspects of ambivalence. *Objective ambivalence* refers to the structural conflict between positive and negative evaluations. It is assessed by taking separate ratings of positivity and negativity towards the attitude object and combining them into a single index tracking both similarity and strength. *Subjective ambivalence* refers to people's experience of ambivalence, and is assessed by asking respondents whether they feel conflicted, mixed or torn on the topic. These measures are intended to give insight to how people experience different attitude objects.

Earlier studies have found that experiences of ambivalence are correlated with individual differences in information processing and decision-making. For example, individuals' ambivalence ratings correlate with Need for Cognition (negatively) and Personal Fear of Invalidity (positively) (Thompson & Zanna, 1995), and trait self-control predicts lower ambivalence ratings of both healthy and unhealthy food (Gillebaart, Schneider and de Ridder,

2015; Schneider, Gillebaart, & Mattes, in press). While these results imply there are individual differences in ambivalence, they do not directly assess how much total variance can be attributed to the individual.

Although the studies reviewed above suggest there are individual differences in ambivalence, they only refer to *related constructs*, rather than ambivalence directly. Perhaps the most direct assessment was provided by Thompson and Zanna (1995) who obtained multiple ratings from each participant and measured the consistency between these scores. In their work, participants rated their objective ambivalence towards a number of topics, and the researchers calculated the Cronbach's alpha of these ratings. They reasoned that a high alpha would indicate that an individual's ratings tend to move together across attitude objects. Across two studies, the authors reported values of .66 and .76, and concluded these indicated individual differences. However, Cronbach's alpha is not intended as a measure of individual differences. Furthermore, the number of stimuli used was low (3 in study 1; 5 in study 2), limiting their ability to accurately assess within-individual variability. Finally, their method quantifies individual differences without accounting for differences between the objects being rated. Their model is partial, in that it neglects an important source of inter-dependency between ratings.

The current research

In the present research, we provide the first direct quantification of individual differences in ambivalence. Our respondents rated a large number of stimuli (DS1=29; DS2=61) on both subjective and objective ambivalence. We use mixed-effect models (Raudenbusch & Bryk, 2002; Baayen, Davidson & Bates, 2008; Judd, et al., 2012) to identify how much variance can be attributed to individuals and to stimuli. A small individual component would indicate ambivalence varies strongly across stimuli, whereas a large value would indicate ambivalence as

relatively consistent within individuals. Importantly, this approach provides results in an interpretable metric (specifically, percentage of variance explained), controls for the effects of stimuli, and smoothly handles missing data.

An additional strength of mixed-effect models is that they can be easily extended to test more complex hypotheses. In addition to our primary research question on individual variability in ambivalence, we also report two extended models testing whether the *relationship* between ambivalence constructs differed between individuals. Although previous researchers have found consistently positive correlations between objective and subjective ambivalence (Newby-Clark, McGregor & Zanna, 2002; Priester & Petty, 2006; Snyder & Tormala, 2017) and between subjective ambivalence and arousal (Van Harreveld, Rutjens, Rottensveel, Nordgren & Van der Pligt, 2009a), the strength of correlation varies substantially between studies. Here we examine whether one contributing factor to this variability is that different people show different levels of association between the constructs.

Method

We apply mixed models to two existing datasets, collected by the second and third authors for different projects (see Schneider, Veenstra, van Harreveld, Schwarz & Koole, 2016). The analysis plan was registered prior to any mixed-effect or similar models being fitted to the data. Thus, we are reporting registered secondary analyses. The time-stamped analysis plan can be viewed online at the Open Science Framework (<https://osf.io/r3kt6/>). The first dataset uses image stimuli from the International Affective Picture System (IAPS; Lang, Bradley, & Cuthbert, 2008), whereas the latter uses words drawn from the Affective Norms English Words (ANEW; Bradley & Lang, 1999). They will be referred to as the IAPS and ANEW data.

All models were fitted using the *lme4* package (Bates, Maechler, Bolker, & Walker, 2015) for R (R Core Team, 2017). Sensitivity analyses were conducted using the *simr* package (Green & McLeod, 2016). Restricted-information maximum likelihood estimation was used for model estimation, except where stated. Confidence intervals for model parameters were estimated using the *lme4* package's bootstrap function to generate 1000 resamples and then taking the 2.5th and 97.5th percentiles.

Participants and stimuli

Our stimuli come from normed stimulus sets (Bradley & Lang, 1999; Lang, Bradley, & Cuthbert, 2008) and were selected to score close to the midpoint of the valence scales used to norm them. Although such midpoint ratings are commonly presented as neutral, they may also reflect ambivalence. On a bipolar scale, a midpoint rating can indicate the absence of strong positivity or negativity but can also mean the exact opposite - namely simultaneous strong positive and negative evaluations (also see Thomsson, Zanna & Griffin, 1995). In a prior analysis of the IAPS data, Schneider et al. (2016) show that these “neutral” stimuli indeed elicit varying levels of ambivalence. The ANEW data were collected as a conceptual replication of the Schneider et al. (2016) study.

In the IAPS data, 41 Dutch student participants rated 29 images (originally 31 were planned, but a technical error in presentation led to data from two images being discarded; see Schneider et al. 2016 for full details). In the ANEW data, 111 Amazon Mechanical Turk Workers rated 61 words. A complete list of stimuli is given in Appendix A.

To ensure the samples were appropriately sized for the current analyses, we ran sensitivity analyses on all our models. For each model, we simulated datasets varying the parameter of interest (keeping all other model parameters the same), and assessed how small an

effect we could reliably detect. Full details are given in the supplementary materials, but in summary the datasets (especially the larger ANEW one) are sufficient to reliably detect effects smaller than the ones we report here.¹

Measures

For the current analyses, the key variables are objective ambivalence, subjective ambivalence, and arousal. These were measured in both datasets. Additional measures not used in the current analysis are described in the supplemental material.

Objective ambivalence. Participants rated positivity (ranging from *not at all positive* [1] to *very positive* [9]) and negativity (ranging from *not at all negative* [1] to *very negative* [9]) for each of the stimuli separately. We subjected these ratings to the following formula to calculate the index for objective ambivalence: $((P+N)/2) - \text{ABS}(P-N)$, where P is positive, and N is negative, and ABS(P-N) is the absolute difference between the two (Kaplan, 1972; Thompson, Zanna, & Griffin, 1995).

Subjective ambivalence. We measured subjective ambivalence by asking participants to rate for each stimulus the degree to which they experienced conflict, (scale anchors IAPS: *not at all* [1] to *very much* [9], scale anchors ANEW: *feel no conflict at all* [1] to *feel maximum conflict* [9]), indecision (scale anchors IAPS: *not at all* [1], to *very much* [9], scale anchors ANEW: *feel no indecision at all* [1] to *feel maximum indecision* [9]), and mixed reactions (scale anchors IAPS: *not at all* to *very much* [9], scale anchors ANEW: *completely one-sided reactions* [1] to *completely mixed reactions* [9]). These were then averaged into a single index (Priester & Petty, 1996).

¹ The one exception was a model which, as will be discussed later, we did not interpret due to convergence issues (specifically, using the IAPs data to estimate individual differences in the relationship between subjective ambivalence and arousal).

Arousal. Participants rated how much each stimulus made them feel (*calm* [1] to *excited* [9]). This provides a single-item self-report measure of arousal (cf. Lang, Bradley, & Cuthbert, 2008).

Comprehension measures (ANEW data only). In addition to ratings outlined above, ANEW respondents indicated if they knew the meaning of each stimulus word, and overall whether they thought their data should be *excluded* (for instance because they were tired or not motivated), with the following answers *definitely use my answers* [1], *probably use my answers* [2], *probably discard my answers*, [3] *definitely discard my answers* [4]. In line with our registered analysis plan, we excluded the 132 ratings where the participant did not know the meaning of the word. No participants indicated we should discard their answers (responses [3] or [4]).

Procedures

The IAPS participants completed their data collection in a laboratory setting. Each stimulus was initially presented for 6 seconds (in line with IAPS recommendations; Lang, Bradley, & Cuthbert, 2008). After each image was presented, participants rated its valence (not used in the current analysis) and their arousal. Each image was then re-presented, and participants rated their objective ambivalence, subjective ambivalence, and image complexity (not used in this analysis). The initial presentation was randomized for each participant, whereas the subsequent presentation was in a standard order.

The ANEW participants were recruited through Amazon's Mechanical Turk platform, and completed the study online using their own computers. The stimuli were presented in a random order for each participant. No time limit was imposed for responses.

Results

Our primary aim was to quantify individual differences in ambivalence ratings. To do this, we fitted a random-intercept model with crossed random effects for individual and stimulus. This model treats the ambivalence rating as a sum of an intercept constant, an individual-specific effect, and a stimulus-specific effect. Individuals and stimuli are treated as sampled from a larger population, and the model attempts to estimate the variance of these populations. Therefore, rather than fitting separate effects for each individual and stimulus, it estimates a total variance for each.

We also examined differences in the relationships between ambivalence constructs. These constructs (objective ambivalence, subjective ambivalence, arousal) are generally positively correlated, but the size of relationship shows substantial variability between samples. One factor contributing to this variability in these relationships may be that different people show different relationships between the constructs. Mixed-effect models can be extended to test this possibility. In these cases the model takes the form of regression equation, with an intercept and slope coefficient. However, the slope can vary across individuals; while a standard regression would return a single slope value, the mixed-model estimates both an average slope and the degree of variability around this value. A large variance estimate indicates different people show very different relationships.

Do individuals differ in their ambivalence?

Our analyses revealed substantial differences between participants in average levels of ambivalence. Across measures and datasets, the differences between individuals accounted for around 16-28% of the variance in ambivalence, whereas stimulus effects only accounted for 3-

10%. This means that the differences between individuals are larger than the differences between stimuli

Separate versions of the model were fitted for objective (Table 1) and subjective (Table 2) ambivalence across the two datasets. Thus, total of four versions were fitted (objective vs. subjective ambivalence; IAPS vs. ANEW data). The key values are the variance scores for individuals and stimuli, which express how much variability there is between individuals and stimuli. In all four cases the value for individuals is larger than the value for stimuli, and the confidence intervals do not overlap. Thus, for both measures and both datasets, the differences between individuals were larger than difference between stimuli.

The differences between individuals were statistically significant. Using a likelihood ratio test, we compared the full model to one without a random effect of individuals (top section of Table 3).² The full model was a significantly better fit for all measures and datasets ($ps < .001$).

However, statistical significance is a low bar to clear; more important is whether the variance between individuals is large enough to be worthy of researchers' attention. To examine the size of the effects, we calculated how much variance can be attributed to baseline differences between people. This quantity is given by the intraclass correlation coefficient (ICC), calculated by dividing the individual variance by the total variance (the sum of the three random effects). We also calculated the same value for the stimulus variance³, and generated 95% confidence intervals via 1000 bootstraps. As can be seen in Figure 1, across dataset and measures, stimulus effects accounted for 3-10% of variance. However, individual differences accounted for 16-28%.

² To allow this test, the models had to be re-fitted using full information maximum likelihood

³ In our registered analysis, we planned to just calculate the ICCs for individual differences. However, in performing the analyses, we realized the corresponding values for stimulus effects were useful as a comparator. Hence, we added these values.

Thus, these measures vary substantially with individuals. Indeed, they vary more strongly with rater than with stimulus; the “who” contributed more than the “what”.

Table 1. *Individual differences in average levels of objective ambivalence. Ambivalence was modeled as a fixed intercept with random effects of individual and stimulus. Separate versions were fitted to the IAPS (photo) and ANEW (word) data.*

	Objective ambivalence			
	IAPS data		ANEW data	
	Fixed effects			
Intercept	2.38	[2.01, 2.80]	1.57	[1.24, 1.88]
	Random effects			
Individual variance	1.11	[0.82, 1.40]	1.38	[1.15, 1.60]
Stimulus variance	0.46	[0.21, 0.66]	0.52	[0.40, 0.65]
Residual	2.49	[2.39, 2.59]	2.36	[2.31, 2.40]
	Model information			
Number of observations	1162		4991	
Number of individuals	41		92	
Deviance	5519.88		23087.76	
AIC	5527.88		23095.76	

Note. Fixed effects are given as unstandardized coefficients; random effects are given as standard deviations; 95% CIs given in square brackets; Deviance = $-2 \times \log(\text{model likelihood})$

Table 2. *Individual differences in average levels of subjective ambivalence. Ambivalence was modeled as a fixed intercept with random effects of individual and stimulus. Separate versions were fitted to the IAPS (photo) and ANEW (word) data.*

	Subjective ambivalence			
	IAPS data		ANEW data	
	Fixed effects			
Intercept	2.96	[2.52, 3.38]	3.22	[2.91, 3.53]
	Random effects			
Individual variance	1.11	[0.82, 1.35]	1.32	[1.12, 1.52]
Stimulus variance	0.64	[0.44, 0.81]	0.62	[0.49, 0.74]
Residual	1.61	[1.55, 1.68]	1.98	[1.95, 2.03]
	Model information			
Number of observations	1162		4997	
Number of individuals	41		93	
Deviance	4572.85		21450.20	
AIC	4580.85		21458.20	

Note. Fixed effects are given as unstandardized coefficients; random effects are given as standard deviations; 95% CIs given in square brackets; Deviance = $-2 \times \log(\text{model likelihood})$

Table 3. *Statistical significance of individual differences. Compares each model to a comparison model without the relevant random effect, using a likelihood ratio test.*

	Model deviances		Test		
	Model	Comparison	Chi-sq	df	p
Primary model: Varying levels of ambivalence					
Objective ambivalence					
IAPS	5519	5649	130.3	1	<.001
ANEW	23086	24275	1188.7	1	<.001
Subjective ambivalence					
IAPS	4572	4896	324.7	1	<.001
ANEW	21448	22830	1381.5	1	<.001
Relationship between objective and subjective ambivalence					
IAPS	4348	4405	57.1	2	<.001
ANEW	19369	20030	661.0	2	<.001
Relationship between subjective ambivalence and arousal					
ANEW	18566	18811	245.2	2	<.001

Note. Models refitted with Full Information Maximum Likelihood in order to allow significance test.

Figure 1. Size of individual differences and stimulus effects. Effects are quantified as intraclass correlation coefficients (ICC), expressing the proportion of variance explained. Lines indicate 95% confidence intervals, calculated via 1000 bootstraps.

Relationship between objective and subjective ambivalence

Our analyses revealed that some people show a stronger relationship between objective and subjective ambivalence than others. Indeed, some people show a regression slope 4-5 times as large as other individuals, indicating a given increase in objective ambivalence would be associated with 4-5 times the increase in subjective ambivalence.

In both datasets, people varied in the relationship between objective and subjective ambivalence. Table 4 shows results from a model which allowed these differences. The fixed effects show the overall regression intercept and slope. Subjective ambivalence generally increases with objective ambivalence (IAPS 0.25; ANEW 0.45), consistent with prior findings of a positive relationship (e.g., Newby-Clark, McGregor & Zanna, 2002; Priester & Petty, 2006; Snyder & Tormala, 2017). However, the non-zero slope variance reflects that people vary in this relationship; the fixed effects just reflect an average individual. In other words, the same increase in objective ambivalence is associated with greater change in subjective ambivalence for some people. As with chronic tendencies, a likelihood ratio test found this variability was statistically significant (middle section of Table 3; $ps < .001$).

Table 4. *Individual differences in the relationship between objective and subjective ambivalence. Subjective ambivalence was regressed on objective ambivalence (represented in the fixed effects). Random effects allow the intercept and slope terms to vary with individual and/or stimuli. Separate versions were fitted to the IAPS (photo) and ANEW (word) data.*

	Subjective ambivalence			
	IAPS		ANEW	
Fixed effects				
Intercept	2.36	[2.01, 2.69]	2.60	[2.34, 2.84]
Objective ambivalence	0.25	[0.19, 0.31]	0.45	[0.38, 0.52]
Random effects				
Individual variance	0.80	[0.57, 1.00]	1.03	[0.87, 1.19]
Slope variance	0.16	[0.11, 0.21]	0.31	[0.26, 0.36]
Corr.	0.40	[-0.05, 0.84]	0.08	[-0.15, 0.31]
Stimulus variance	0.53	[0.36, 0.69]	0.50	[0.39, 0.60]
Residual	1.45	[1.39, 1.51]	1.58	[1.55, 1.62]
Model information				
Number of observations	1162		4987	
Number of individuals	41		92	
Deviance	4354.43		19376.50	
AIC	4368.43		19390.50	

Note. Fixed effects are given as unstandardized coefficients; random effects are given as standard deviations; 95% CIs given in square brackets; Corr = correlation between individual and slope variance; Deviance = $-2 \times \log(\text{model likelihood})$

Are these differences large enough to matter? We compared the model-predicted regression slope for individuals 1 SD above and below average. These are plotted in Figure 2 (setting the intercept at the fixed coefficient). As can be seen, the difference is pronounced, especially for the ANEW data. For the IAPS data, the regression slope 1 SD above average is over 4 times the slope 1 SD below average (0.41 vs 0.09). For the ANEW data, it's more than 5 times the size (0.76 vs 0.14). These differences are substantial – as Figure 2 makes clear, it's the difference between a negligible association and a strong positive relationship.

Figure 2. Individual differences in relationship between subjective and objective ambivalence.

The x-axis gives objective ambivalence values; y-axis gives model-predicted subjective ambivalence values. Solid lines show the regression slope for an average individual (i.e., at the fixed effect). Dashed lines show individuals 1 standard deviation above and below the fixed effect (i.e., those with a strong and weak relationship).

Relations between subjective ambivalence and arousal

Individuals also varied in the association between subjective ambivalence and arousal. Consistent with prior findings (e.g., Van Harreveld et al., 2009a), we found subjective ambivalence positively predicted arousal. However, our analysis shows that this relationship is negligibly small or even mildly negative for some people.

We fitted a model which regressed arousal on subjective ambivalence while allowing for individual differences in the regression slope. The results are given in Table 5. In the ANEW data, the average regression slope was weak but significant (fixed effect = 0.08, 95% CI [0.02, 0.14]). However, as before, the slope variance component showed there was a substantial degree of variability between individuals (0.22). The bottom section of Table 3 shows that these differences were statistically significant ($p < .001$). When we attempted to fit the model to the IAPS data, the bootstrapping procedure failed to converge and returned a confidence interval running to 1.00. These issues can be a sign of over-parameterization (consistent with the smaller sample size of the IAPS data and the supplementary sensitivity analyses) and so, in line with our registered analysis plan, we will not interpret the IAPS results further.

In the ANEW data, the differences are substantial. While some respondents showed a moderate positive relationship between subjective ambivalence, others did not show a positive relationship at all. Figure 3a shows the relationship between subjective ambivalence and arousal at the average (fixed effect) and 1 SD above and below it. At 1 SD above average, people show a notably positive association. However, 1 SD below average, people showed a mild negative relationship.

Table 5. *Individual differences in the relationship between subjective ambivalence and arousal. Arousal was regressed on subjective ambivalence (represented in the fixed effects). Random effects allow the intercept and slope terms to vary with individual and/or stimuli. Separate versions were fitted to the IAPS (photo) and ANEW (word) data.*

	Arousal			
	IAPS		ANEW	
Fixed effects				
Intercept	2.88	[2.41, 3.36]	3.31	[2.93, 3.70]
Subjective ambivalence	0.10	[0.03, 0.16]	0.08	[0.02, 0.14]
Random effects				
Individual variance	0.74	[0.48, 0.99]	1.57	[1.32, 1.82]
Slope variance	0.11	[0.04, 0.18]	0.22	[0.18, 0.26]
Corr.	0.66	[-0.07, 1.00]	-0.51	[-0.68, -0.29]
Stimulus variance	1.05	[0.77, 1.35]	0.96	[0.79, 1.14]
Residual	1.46	[1.40, 1.53]	1.45	[1.42, 1.48]
Model information				
Number of observations	1162		4993	
Number of individuals	41		93	
Deviance	4384.80		18573.08	
AIC	4398.80		18587.08	

Note. Individual | Corr = correlation between individual intercept and slope terms; obs. = observations; Deviance = $-2 \times \log(\text{model likelihood})$

Figure 3. Individual differences in relationship between subjective ambivalence and arousal. (a) Model implied slopes. The x-axis gives subjective ambivalence values, and the y-axis gives model-predicted arousal values. The solid line shows the regression slope for an average individual (i.e., at the fixed effect). Dashed lines show individuals 1 standard deviation above and below the fixed effect (i.e., those with a strong and weak relationship). (b) Histogram of estimated individual slope coefficients.

Finding a negative relationship for some individuals was surprising – a null relationship is plausible, but why would more ambivalence be associated with less arousal? One possibility is that this result is an artifact of our ± 1 SD procedure for visualizing differences. Imagine no individual really shows a negative relationship, but some individuals score much higher than the average. The distribution of individual slopes would be bounded at zero and would show heavy positive skew. In such a case, looking 1 SD below the average would put us outside the range of observed values, and imply some individuals have negative relationships when they do not. To examine this possibility this, we extracted individual slope estimates for each participant, and plotted a histogram (Figure 3b). As can be seen, there is not a pronounced positive skew and a substantial proportion of individuals with a negative slope (albeit a weak one in almost all cases). Thus, it seems that for some, feeling more ambivalence was associated with less arousal.

Discussion

Though much is known about the structure and consequences of mixed thoughts and feelings (for reviews see e.g., van Harreveld, Nohlen & Schneider, 2015; van Harreveld, van der Pligt & de Liver, 2009b; Schneider & Schwarz, 2017) towards specific attitude objects, the question of how these are distributed across individuals has received scant attention. Across two datasets, using different measures and stimuli, we found consistent evidence that individuals differ in their levels of ambivalence across attitude objects. These effects were not just statistically significant but substantial, accounting for 16-28% of variability in scores, and emerged for both photo and word stimuli. The size of this effect is notable; when predicting how ambivalent someone would be towards a new topic, it would be more useful to know about the person than about the topic. We also found individual differences in the relationship between objective and subjective ambivalence and between subjective ambivalence and arousal,

suggesting a novel factor driving study-to-study variation in these correlations (e.g., Newby-Clark, McGregor & Zanna, 2002; Snyder & Tormala, 2017).

One may argue that the individual differences we found primarily indicate differences in acquiescence – that is, a tendency to generally agree with response scales. However, if acquiescence was the dominant factor driving individual variability, the correlation between subjective and objective ambivalence would be the same for each participant. This is not what we found. Instead, we observed substantial individual variance in the regression slope between these constructs. Thus, acquiescence is not a good explanation of the current results.

These findings have an important theoretical implication: Ambivalence is as much about the individual as it is about the attitude object. Traditionally, ambivalence has been seen as a property of attitude strength. That is, the level of ambivalence determines whether an attitude is stable, resistant to persuasion, and consequential for behaviour (reviewed by Connor & Armitage 2008), at least when certainty is high (Clarkson, Tormala & Rucker, 2008; Luttrell, Petty, & Briñol, 2016). This view connects ambivalence with the attitude object. Our data, however, show that ambivalence is not just related to the attitude object, but also the individual. These findings suggest ambivalence may be a distinct phenomenon, with its own unique links to specific person-level features. Learning more about these features will substantially enrich theorizing about the antecedents of ambivalence by moving beyond properties of the attitude object.

These findings also have methodological consequences. Most importantly, it suggests a straightforward and cost-effective method for increasing the power of between-subjects designs. When respondents are randomized into high versus low ambivalence conditions and then rate a single object, these individual effects will become error variance. Meaningful individual

differences become noise, diluting the effect of carefully crafted manipulations. On the other hand, if individual effects could be controlled for (either through a validated self-report scale, collecting additional ambivalence ratings, or using a within-subject design) statistical power will increase substantially.

Finally, our work showcases the breadth of information provided by mixed-effect models. Often, these models are used to remove the effects of stimuli to get cleaner estimates of manipulation effects (for empirical examples, see Judd et al., 2012). However, they can also be used to provide novel insights about different phenomena by quantifying their sources of variance – as we have done here by assessing how much of ambivalence can be attributed to the individual. This variance-components approach has been used in the social perception literature (Kenny, West, Malloy & Albright, 2006; Rauthman & Sherman, 2018) but not widely applied to attitudinal research. A similar approach could be taken with other important phenomena – such as moral conviction (Skitka, Bauman, & Sargis, 2005) or defensive confidence (Albarracín & Mitchell, 2004). In this way, the current analyses can serve as a template for similar investigation of other topics.

In sum, although ambivalence has often been characterized as specific to the attitude object (e.g., de Liver, van der Pligt & Wigboldus, 2007; Nohlen, van Harreveld, Rotteveel, Lelieveld, & Crone, 2014; Schneider et al. 2015) the results reported in this article show that they vary as much with the individual. Some individuals show higher levels across topics, and the relationships between ambivalence constructs vary substantially between individuals. As such, we show that ambivalence is not just a function of the attitude object, but also the person.

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Appendix

IAPS stimuli

Number	Description	Number	Description
1645	Wolf	7034	Hammer
2002	Man	7035	Mug
2214	NeutMan	7041	Baskets
2220	Male face	7045	Zipper
2397	Men	7160	Fabric
2484	Amerindian	7161	Pole
2749	Smoking	7185	Abstract art
2890	Twins	7235	Chair
4302	Erotic female	7242	Building
4550	Erotic male	7476	Ramen
4561	Erotic male	7484	Fish
7000	Rolling pin	7640	Skyscraper
7002	Towel	9070	Boy
7012	Rubberbands	9422	Battleship
7020	Fan		

ANEW stimuli

Description	Description	Description
ad	gallon	pulp
adhere	herd	rattle
apology	hitch	rebuff
barrel	hospital	rigor
belly	hydrant	scissors
bone	icebox	seat
cabinet	impart	sentry
cod	ingest	society
compel	inhabitant	sock
crocodile	ink	squash
daze	intent	steam
descent	intoxicated	storm
desert	knee	stove
dryer	lid	subject
dune	limb	taxi
fervor	liter	tire
flaunt	metal	trick
foot	noisy	van
freezer	pail	vase
frenzy	picket	wolf

SUPPLEMENTAL ONLINE MATERIAL

Additional measures not used in the current analyses:

IAPS data. In addition to the variables outlined above, image valence and complexity were measured. Valence was assessed using a single item (ranging from *pleasant* [1] to *unpleasant* [9]). Complexity was measured with four items which asked participants to rate the degree to which they thought the picture was hard to understand, had multiple meanings, was interpretable in more than one way, and was complicated. These four items were averaged to create an indicator of complexity. Finally, the dataset contains a measure of action/state orientation recorded for unrelated purposes (Kuhl, 1994). None of these variables were used in the current models.

Additional measures in ANEW data. In addition to ratings outlined above, respondents rated the valence of each word using a single item (ranging from *unhappy* [1] to *happy* [9]), and indicated whether participants *liked* the survey. Neither of these variables were used in the current analyses.

Sensitivity analyses:

The purpose of these analyses was to establish the smallest effects which our data were sufficient to detect. To do this, we simulated datasets with known properties and then re-applied our statistical tests to these artificial datasets. Doing this a large number of times allowed us to assess how frequently we would be able to detect a random effect of a given size. By repeating this process with different values for the random effect, we were able to find what size of effect we had adequate power to detect. These procedures were conducted using the *simr* package (Green & McLeod, 2016).

Average levels of ambivalence. For the model which assesses average levels of ambivalence (the chronic tendency model; Tables 1 & 2), we changed the variance of the individual random effect while holding all other parameters constant. We tested ten variances for each version of the model, selecting values which would yield ICCs of .01 to .10 in (.01 increments). We then generated 200 samples for each of these values, and applied our standard techniques – comparing a full model and a comparison model without the individual random effect. The key question is how often the likelihood ratio test is significant.

These simulations yielded two findings: these simple models converge well, and our samples were adequate to reliably detect small effects. The full results are shown in Table S1. The ICC column gives the size of individual random effect. The Conv. column shows how often the models successfully converged. For these simple models there were virtually no convergence issues. The Power column shows how frequently the individual random effect was successfully detected (via a likelihood ratio test). For this purpose, we discarded non-converging cases. Setting the desired power level at .90 (a 90% chance to detect the effect), we can see the IAPs

data reliably detects ICCs of .04 and above. The larger ANEW dataset is even more powerful, reliably detecting ICCs of .02 (objective ambivalence) and .01 (subjective ambivalence).

Table S1. *Simulation-based sensitivity analysis for chronic tendency models.*

ICC	Objective ambivalence				Subjective ambivalence			
	IAPS data		ANEW data		IAPS data		ANEW data	
	Conv.	Power	Conv.	Power	Conv.	Power	Conv.	Power
.01	200	0.22	200	0.90	199	0.24	200	0.91
.02	200	0.57	199	1.00	200	0.67	200	1.00
.03	200	0.79	200	1.00	200	0.86	199	1.00
.04	199	0.92	200	1.00	200	0.94	199	1.00
.05	200	1.00	200	1.00	200	1.00	200	1.00
.06	200	1.00	200	1.00	200	1.00	200	1.00
.07	200	1.00	200	1.00	200	1.00	200	1.00
.08	200	1.00	200	1.00	200	1.00	200	1.00
.09	199	1.00	200	1.00	200	1.00	200	1.00
.10	199	1.00	200	1.00	199	1.00	200	1.00

Note. ICC = Intraclass correlation coefficient for random effect of individual. Conv. = number of simulated datasets for which the models successfully converged. Power = proportion of simulated datasets where the models converged and the random effect of individual was detected via a likelihood ratio test.

Individual slopes models. For the models which assessed the relationship between constructs (the individual slope models; Tables 3 & 4), we were primarily interested in the variance of the slope random effect – i.e. how much individuals differ in their regression slopes. However, simply rescaling this variance without changing the covariance between individual and slope terms would alter the correlation between the two. Hence, we also varied the covariance term to keep the correlation constant. Based on the values in our models, we took 0.01 as a reasonable small effect (as it is a little below the smallest slope variance we observed), and so examined variances from 0.005 to 0.015 (in 0.001 increments).

The results of all simulations are summarized in Table S2, which follows a similar format to Table S1. Looking first at the objective to subjective ambivalence model, it can be seen that both datasets had very few issues with convergence. The smaller IAPs dataset had lower power overall, but was still able to reliably detect effects of size 0.011 and above (translating to a standard deviation of about 0.10, below the observed value of 0.16). The ANEW data had above 90% power for all tested values. Looking next at the subjective ambivalence to arousal model, we can see the IAPS data had major convergence problems. This is consistent with our observations in the main analysis, and supports our decision not to analyze this model on this dataset. The ANEW data, however, had no convergence problems and a high level of power for all tested parameter values.

In conclusion, both datasets are more than adequate for the analyses we describe in the text. The ANEW data is excellently powered for all the models we ran. The IAPS data has good power for detecting chronic tendencies, and acceptable power for detecting individual differences in the slope between potential and subjective ambivalence. However, it is inadequate

for estimating the arousal individual slope model, supporting our decision not to interpret this model.

Table S2. *Simulation-based sensitivity analysis for individual slope models.*

Var.	Objective -> subjective ambivalence				Subjective ambivalence -> Arousal			
	IAPS data		ANEW data		IAPS data		ANEW data	
	Conv.	Power	Conv.	Power	Conv.	Power	Conv.	Power
0.005	187	0.56	200	0.91	153	0.41	200	0.90
0.006	188	0.62	200	0.94	149	0.47	200	0.95
0.007	196	0.67	200	0.99	165	0.51	200	0.98
0.008	195	0.81	200	1.00	151	0.66	200	0.99
0.009	193	0.87	200	1.00	157	0.73	200	1.00
0.010	196	0.87	200	1.00	166	0.78	200	1.00
0.011	197	0.93	200	0.99	169	0.73	200	1.00
0.012	198	0.95	200	1.00	166	0.81	200	1.00
0.013	197	0.96	200	1.00	169	0.89	200	1.00
0.014	197	0.98	200	1.00	164	0.88	200	1.00
0.015	196	0.97	200	1.00	165	0.90	200	1.00

Note. Var = variance of individual slope random effect. Conv. = number of simulated datasets for which the models successfully converged. Power = proportion of simulated datasets where the models converged and the random effect of individual was detected via a likelihood ratio test.

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