Hierarchical Latent-Class Multinomial Processing Tree Model of Affect Misattribution

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Keywords: affect misattribution procedure; latent-class multinomial processing tree model

Introduction

The attribution (and misattribution) of affect is implicated in many important psychological phenomena including subjective well-being (Schwarz & Clore, 1983), depression and mood disorders (Schuckit et al., 2006; Schweizer et al., 2010), and various social judgments (for a review, see Forgas, 1995). Consequently, understanding the psychological mechanisms underlying affect (mis)attribution is of great importance.

The affect misattribution procedure (AMP; Payne, Cheng, Govorun, & Stewart, 2005) is an experimental task that attempts to capture – in a controlled setting – the fundamental aspects of the (mis)attribution of affect. In this task, individuals evaluate the pleasantness of briefly presented Chinese pictographs preceded by briefly presented prime stimuli (Payne et al., 2005). Even though individuals are explicitly instructed to try their absolute best not to let the prime stimuli bias their evaluations, on average pictographs are evaluated more positively when preceded by positive compared to neutral or negative stimuli (Payne et al., 2005; Payne, Govorun, & Arbuckle, 2008).

The AMP has become a popular behavioral task to assess automatic evaluations in many different domains (e.g., tobacco smoking: Payne, McClernon, & Dobbins, 2007; voting behaviors: Payne et al., 2009; implicit prejudice: Gawronski, Peters, Brochu, & Strack, 2008), however, the psychological mechanisms underlying responses in the task remain poorly understood. In addition to the affect misattribution mechanism proposed by the original authors (Payne, Hall, Cameron, & Bishara, 2010), evidence supporting several alternative mechanisms explaining priming effects in the AMP has emerged including a non-affective semantic misattribution process (Blaison, Imhoff, Huhnel, Hess, & Banse, 2012), a pre-potent motor response process (Wentura & Degner, 2010), and process involving both semantic and affective components (Gawronski & Ye, 2013). It is important to note, however, that in each of these cases, the proposed mechanism in question was assumed to apply equally well to each individual in the sample.

In the current project, we took a novel theoretical stance that allows for the (arguably more realistic) possibility that different mechanisms operate in the AMP for different individuals. Hence, it is possible that all of the aforementioned mechanisms operate in the AMP, but that particular processes operate in some individuals but not in others (see Luce, 1995 for similar reasoning). From our perspective, a more theoretically productive – though perhaps more challenging – goal is to identify which process(es) operate(s) in which individuals.

As a first attempt in contributing to this goal, we built upon Payne et al.'s (2010) multinomial processing tree (MPT) model of AMP responses by using a hierarchical latent-class MPT approach (Klauer, 2006) to analyze evaluations in the AMP at the individual-level of analysis. Payne et al.'s MPT model – empirically supported in two studies[1] – separates three component processes whereby affective reactions (A) to the prime are misattributed (M) as affective reactions to the Chinese pictographs (P) (see Figure 1 for full MPT model).

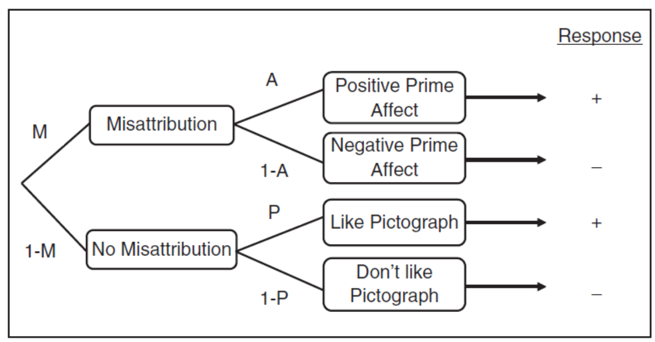

Figure 1: Payne et al.'s (2010) multinomial process tree (MPT) model of the affect misattribution procedure (AMP)

Hence, if a misattribution process takes place, responses should be driven by affective reactions to the prime whereas in the absence of misattribution, responses should be driven by affective reactions to the Chinese pictographs.

The hierarchical latent-class MPT approach (Klauer, 2006) allows for the testing of parameter heterogeneity for the A, M, and P parameters. In the event parameter heterogeneity is found, the approach determines an optimal number of latent classes where persons fall into one of several mutually exclusive classes where parameter homogeneity is assume to hold within each class. The *profile* of parameter estimates within each of these classes

[1]LeBel and Stahl (2013), however, found – in a much larger sample using the same MPT model, task instructions and stimuli as Payne et al. – parameter estimates at the aggregate-level in direct opposition to affect misattribution.

can then be used as a basis for contending that distinct processes are operating in different individuals.

Methods

Design and Materials

143 undergraduate students (104 women) participated for course credit. Participants completed the same AMP task as in Payne et al. (2010) using the exact same instructions, stimuli, and task parameters. The design of the study, also exactly following Payne et al., was a 2 (prime: positive vs. negative) × 2 (pictograph: positive vs. negative) × 2 (pictograph duration: 100 ms vs. 1,000 ms) mixed design, with the duration of the pictograph manipulated between subjects and the other factors manipulated within-subjects.

The task involved 48 trials (plus one practice trial) wherein a positive or negative prime photo appeared on the center of the computer screen for 75 ms, a blank screen for 125 ms, followed by a positive or negative Chinese pictograph presented for either 100 (short duration condition) or 1000 ms (long duration condition). A black-and-white pattern mask was subsequently presented and remained on screen until participants indicated a pleasant or unpleasant response.

Analyses

For ease of exposition, we report results from the short duration condition only. We used a hierarchical latent-class MPT model approach to analyze participants' responses in the AMP. Under this approach, the analysis allowed for and tested parameter heterogeneity and also modeled correlations among parameters, avoiding potential artifacts of aggregation. Model analyses were based on the model depicted in Fig.1. It was extended to allow for separate A parameters for positive (Ap) and negative (An) primes, as well as separate P parameters for positive (Pp) and negative (Pn) targets. An analysis of the aggregated data yielded the following parameter estimates: M = .82, Ap = .65, An = .41, Pp = .99, Pn = .37. Critically, the analysis yielded clear evidence for heterogeneity in these parameters across participants, S1(df=7) = 301, $p<.001$ (i.e., the observed variability was not accounted for by the model). This indicates that individuals differed with regard to the underlying processes assessed with these parameters. We therefore used a hierarchical latent-class modeling approach to further investigate this variability across individuals. To do so, it was necessary to fix the parameters Pp and Pn (reflecting the evaluation of the Chinese pictographs) to the values obtained in the aggregated analysis. The latent-class analysis proceeded by fitting models with an increasing number of latent classes until the observed variability was adequately accounted for (i.e., until the S1 statistic, measuring the discrepancy between observed and predicted variability, was no longer statistically significant).

Results and Discussion

Parameter heterogeneity was adequately accounted for by a model with four latent classes, S1(df=1)=2.72, $p>.05$, by allowing for different sets of parameter estimates for each class. Parameter estimates for these four classes, as well as the proportion of the data they represent, are given in Table 1. There was substantial variability across latent classes for all three parameters (smallest $\Delta\chi^2(df=3) = 39$, $p<.001$).

Table 1: Parameter estimates within each latent class

Class	M	Ap	An
1 [37%]	.99 [.89,>1]	.70 [.66,.74]	.58 [.53 .63]
2 [24%]	.98 [.90,>1]	.88 [.84,.92]	.25 [.19,.31]
3 [27%]	.41 [.29,.53]	.41 [.25,.57]	.13 [<0,.34]
4 [12%]	.89 [.73,>1]	.27 [.16,.38]	.46 [.37,.55]

As can be seen in Table 1, different parameter estimate profiles emerged in the different classes. Individuals in classes 1 and 2 had relatively high levels of misattribution, but differed in the magnitude of the priming effect (i.e, the difference between estimates of Ap and An, with class 2 showing a stronger priming effect). Individuals in class 3, however, had relatively low levels of misattribution with a relatively weak priming effect whereas individuals in class 4 showed relatively high levels of misattribution with a reverse priming effect. These different profiles of parameter estimates in the distinct classes suggest that different psychological processes are operating during the AMP for different individuals, consistent with recent electrophysiological (ERP) evidence suggestive of distinct attentional processes across individuals (Hashimoto et al., 2012). Our results show that an affect misattribution process – as proposed by Payne et al. (2010) – appears to apply for only about 61% of individuals (Classes 1 and 2). For the remaining individuals, alternative processes are likely operating (e.g., a non-compliant process might be operating for Class 4 individuals given the reverse priming effect). These results have important psychometric implications for using the AMP to assess attitudes and also for understanding replication difficulties in studies using the AMP.

Acknowledgments

Study supported by a SSHRC fellowship to the first author.

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