The associations between discrete emotions and political learning: A cross-disciplinary meta-analysis and systematic review

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Abstract

In the last 25 years, the number of studies examining the role of emotions in individual learning about politics increased in political psychology; a field characterized by its interdisciplinary research from political science, communication science, and psychology. This cross-disciplinary meta-analysis and systematic review aimed to systematically synthesize research regarding associations between discrete emotions and various aspects of learning about political matters, such as political attention, information seeking, discussions, knowledge and knowledge gain. The final dataset included 66 publications with 486 effect sizes, involving more than 100,000 participants. Most of the effect sizes were based on negative-activating emotions (64%; mainly anxiety, 31%, and anger, 19%) and positive-activating emotions (32%; mainly enthusiasm, 15%). Based on meta-analytic multilevel random-effects models, we found small positive associations for activating emotions, of both, negative (in particular, anger) and positive valence (e.g., enthusiasm, but limited to cross-sectional designs), but no relations for deactivating emotions. Overall significant correlations ranged from .05 to .13. Therefore, the more intense or frequent the emotions experienced, the more participants engaged in learning about politics. The findings provide the first numeric synthesis of this research field, revealing directions for future research and implications for political educators. Additionally, we provide recommendations for reporting in future studies, in order to foster research synthesis on cross-disciplinary topics.

Keywords: emotions, political learning, political knowledge, meta-analysis, systematic review, cross-disciplinary

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Emotions undoubtedly play a role in political activism, political campaigns and political learning (find ref). It has been speculated that emotions may even trump rationality in politics, with Weston (2007) remarking that ‘In politics, when emotion and reason collide, emotion invariably wins’. This role of emotions in politics was long neglected in research, but interest in this field has rapidly increased since the 1980s (Brader & Marcus, 2013). This increase in research attention may be due to the emotionally laden political events of recent years, with studies examining emotions regarding the Brexit referendum (REF, REF), the Trump election campaigns (REF; REF) and (find another example).

Particularly, there is a great number of studies addressing questions on whether and how emotions are related to different aspects of political learning, e.g., political attention, information seeking or political knowledge. Building on different theoretical perspectives on emotions and mainly focusing on a few negative discrete emotions (Brader & Marcus, 2013; Crigler & Just, 2012), these studies emophasize that when looking at political learning, the role of emotions should not be overlooked. However, there are a wide variety of approaches, study designs and even results. For example, while studies quite consistently show positive relations between anxiety and an increase of political knowledge (e.g., Marcus & MacKuen, 1993; Valentino et al., 2008), results are less clear when it comes to attention to politics (e.g., Huddy et al., 2007; Just et al., 2007 versus Marcus et al., 2000) and information seeking (e.g., Park, 2015; Redlawsk et al., 2007; Valentino et al., 2008).

The wide variety of studies have rarely been considered in a common theoretical framework on learning, and to the best of our knowledge, no systematic review or meta-analysis on politics and emotions has been conducted. Learning about politics takes place in various settings and frequently in informal contexts. It requires learners’ attention to political matters, and further involvement, e.g., via discussions or seeking for more information, in order to result in gaining political knowledge. A prominent theory on the role of emotions in learning is the control-value theory of achievement emotions (Pekrun, 2006). The control-value theory details what factors may contribute to the experience of emotions during learning, and how they affect learning processes and outcomes. It is broadly supported by research from other domains (e.g., foreign language learning: Shao et al., 2020) and has recently also been investigated in informal learning contexts (Beymer et al., 2022). Although it has rarely been applied to the political context (as an exception, see Graf et al., 2022), it can serve as a theoretical framework for this meta-analysis due to its focus on learning and its incorporation of a broad range of discrete emotions. As outlined in more detail below, the theory suggests that while some emotions foster learning due to increased attention and motivation, others can be detrimental for the learning process.

With this study, we aim to review which emotions are analyzed in the context of political learning and to synthesize evidence on whether and how discrete emotions are related to political learning. Specifically, we encompass a broad perspective on learning, including processes like attention to politics, discussions, information seeking, and outcomes like knowledge, and knowledge gain. Previous research has argued that emotions are central to politics (e.g., 'politics is inherently social and emotional' [Crigler and Just, 2012, p. 211]; 'key feature of politics' [Lynggaard, 2019, p. 1201]) and that political learning is crucial in the making of informed political decisions and political participation (Schlozman et al., 2018),. As such, a detailed overview on the functioning of emotions in this context is of great relevance for political communication, political educators and in general, the functioning of democracy. For example, emotional political information can help to decrease preexisting knowledge-gaps on political matters (Bas & Grabe, 2015). Additionally, by synthesizing existing studies into a thorough overview of the cross-disciplinary research, this meta-analysis reveals blind spots to be addressed in future research and builds a basis for further theory development in the field.

Emotions

Researchers have established various theories in order to define emotions and conceptualize their functioning. Emotions are frequently considered to be multi-component constructs with affective, cognitive, motivational, expressive-behavioral, and physiological components (e.g., Crigler & Just, 2012; Lange & Zickfeld, 2021; Pekrun, 2006). In contrast to general moods or feelings, emotions are typically characterized by an object focus (Crigler & Just, 2012; Pekrun, 2006, 2023), thus related to an event, a situation, action or physiological object (Pekrun et al. 2023). Emotions in politics are thus triggered or focused on political aspects, such as political leaders or current events (Capelos & Chrona, 2018). Political emotions, for example, might be experienced while watching a heated debate between candidates before the election day, reading a newspaper article about a recent corruption scandal, or when running into a protest of climate activists on the street.

Generally, theories applied on emotions experienced in the context of politics differ in whether they see emotions on a single valence dimension (e.g., positive versus negative emotions) or as discrete emotions (e.g., anger and anxiety; Brader and Marcus, 2013). Which perspective fits best to explain emotional processes is often dependent on the specific research question at hand. Nevertheless, recent theoretical developments tried to combine both (i.e., a dimensional and discrete perspective on emotions; Dreisbach, 2022; Lange & Zickfeld, 2021). While different (i.e., discrete) emotions can be distinguished in terms of semantic concepts of prototypical patterns of emotional experience (Russell & Barrett, 1999), some emotions are more similar to one another (e.g., distress and frustration) and therefore also more similar in their functioning. Two important dimensions used to distinguish the affective basis of emotions are valence and arousal, thereby placing emotions on a two-dimensional space between unpleasant and pleasant experience and with low to high arousal (Russell, 1980). To illustrate, enthusiasm is typically experienced positively (i.e., pleasant) and is activating (i.e., high arousal), anxiety as negative (i.e., unpleasant) and is activating (i.e., high arousal), and boredom as unpleasant and deactivating (i.e., low arousal).

The intertwined nature of emotion and cognition (Dreisbach, 2022), suggests that emotions play a crucial role when learning. Emotions are an integral component of the learning process, as they can attract our attention towards the object to be learned (e.g., emotions like surprise; Muis et al., 2018). However, emotions can also act as a barrier for this attention (e.g., if experiencing boredom; Pekrun et al., 2010). One theory specifically developed to explain the role of emotions for learning is control-value theory (Pekrun, 2006; Pekrun et al., 2023), that primarily focuses on achievement emotions in academic setting and aims to explain their antecedents and effects on learning. Similar to the before-mentioned two-dimensional taxonomy of the circumplex-model (Russell, 1980; Russell & Barrett, 1999), control-value theory suggests that in order to explain learning, differentiating emotions along the dimensions of activation (activating versus deactivating) and valence (positive and negative) can provide fruitful insights (Pekrun, 2006). Specifically, it proposes that positive-activating emotions are positively related, and negative-deactivating emotions negatively related to learning, with observations about positive-deactivating and negative-activating emotions being more complex (Pekrun, 2006).

Learning about Politics

Political learning and its aimed outcome, political knowledge, are important prerequisites for many aspects of the political life. Knowledge about current political events, policy positions of candidates, or electoral processes are a substantial resource for political participation, specifically for voting (Schlozman et al., 2018). It not impacts whether one participates or not, but also “the quality of political decision making, and thus the quality of citizenship” (Delli Carpini, 2009, p. 41). While an essential foundation of political knowledge is acquired during early family socialization and civic education in schools (Schlozman et al., 2018), political learning can be viewed as a life-long process, especially given the vast amount of political information and rapid change of current political facts (Lupia, 2016). It takes place in various contexts in daily life, with media and peers being a main source for new political information.

Looking at political learning as a process therefore requires incorporating various aspects of learning. Most current studies directly referring to political learning use measures on recall of political information (e.g., Park, 2015; Valentino et al., 2008), knowledge about policy positions (Marcus & MacKuen, 1993), or knowledge about political regulations (Nadeau et al., 1995), and therefore focus only on outcomes of the learning process. Learning about politics, however, is a complex process, which requires exposure to political content but also a motivation to select and retain political information (Niemi & Junn, 1998). Important aspects of the learning process consequently also include motivation, learning strategies, cognitive resources, and self-regulation (Pekrun, 2006). In the context of daily informal learning, political behaviour like attention to politics, information seeking, and political discussions are important aspects of the political learning process.

Emotions Experienced in the Context of Politics and Learning

Studies on the role of emotions in learning about politics have primarily focused on enthusiasm, anxiety, and anger (Brader & Marcus, 2013). These three emotions are at the heart of the affective intelligence theory, which is widely used in studies on emotions in politics and seeks to explain how emotions influence political information processing, judgement, and behavior (Marcus, 2000; Redlawsk & Mattes, 2022). It distinguishes between two fundamental emotional systems: disposition and surveillance. The surveillance system, which is activated by threat and causes anxiety, is assumed to facilitate learning by interrupting reliance on political habits (e.g., partisan heuristics during political decisions; Marcus, 2000; 2013). Though this theory makes assumptions about how anxiety, anger, and enthusiasm relate to political learning, it appears to be less useful for explaining relationships between emotions and learning across a broader range of discrete emotions.

Political learning is often investigated in the context of (mock) election campaigns or focused on specific policy issues. In line with before mentioned attention as a function of emotions, both anxiety and enthusiasm have been shown to positively relate to interest in political campaigns and attention to political news (Marcus et al., 2000). However, other studies could not replicate this relationship (Huddy et al., 2007), whilst others still found a negative relationship between anxiety and political attention (Otto et al., 2020). Anger has often been shown to relate negatively to information seeking (e.g., Redlawsk et al., 2007; Valentino et al., 2008), with enthusiasm and anxiety positively affecting information seeking (Redlawsk et al., 2007). Similarly, studies have shown positive relations of anxiety with the discussions of politics with friends, family, co-workers and neighbours (Huddy et al., 2007). The most consistent findings have been regarding emotions and political knowledge gains about politics, with mainly positive relations reported between anxiety and an increase of political knowledge (Marcus & MacKuen, 1993; Marcus et al., 2000; Nadeau et al., 1995; Park, 2015; Valentino et al., 2008).

Given the at times contradicting results and increasing number of studies looking at the role of emotions in political learning, it seems to be high time to thoroughly summarize the existing literature and investigate whether there is systematic variance in reported effect sizes. Prior reviews on the topic focused more generally on the antecedents and various functions of emotions in politics (e.g., also for political behavior like participation or decision taking; Brader & Marcus, 2013; Groenendyk, 2011, Redlawsk & Mattes, 2022) or emotions in political communication in general (Crigler & Just, 2012). While the latter is the only review reporting a systematic literature search on emotions and politics, until now and to the best of our knowledge, no systematic quantitative synthesis of the effect sizes found in empirical studies on emotions and political learning has been published. While we know that emotions are experienced frequently in the context of politics (Crigler & Just, 2012), and they can foster or even prevent us from learning related processes, there is no existing extensive overview on political emotions and their association with political learning.

The Present Research: Aims of the Meta-Analysis and Systematic Review

With this study, we attempt to fulfill various objectives. First, we aim to gather a sufficient overview on which emotions are included in existing studies on political learning and to what extent they are analyzed. Second, we synthesize these studies using multilevel random-effects models in order to find out if, and indeed which, emotions are related to political learning. For this purpose, we apply a novel theoretical framework by analysing results through the lens of the control-value theory of achievement emotions (Pekrun, 2006). More specifically, when categorizing emotions in (1) positive-activating, (2) positive-deactivating, (3) negative-activating, and (4) negative-deactivating emotions, we expect that positive-activating emotions (e.g., enthusiasm) are related to increased political learning and learning outcomes, while negative-deactivating emotions (e.g., boredom) are related to less political learning and learning outcomes. For positive-deactivating (e.g., relaxation) and negative-activating emotions (e.g., anxiety, anger), consequences for learning are not that clear, as it often depends on the specific emotion or learning aspect considered (Pekrun et al., 2011; for the political context, see Huddy et al., 2007 who show different associations between anxiety and anger with, for example, news consumption).

Based on control-value theory, we hypothesise the following:

Hypothesis 1 Positive-activating emotions (e.g., enthusiasm) are positively associated with learning.

Hypothesis 2 Negative-deactivating emotions (e.g., boredom) are negatively associated with learning.

Further, we tested, in exploratory analysis, how negative-activating emotions (e.g., anger and anxiety), as well as discrete emotions, are related to learning.

Open Practices

The current study was preregistered via Prospero in October 2020. Data, accompanying analysis scripts, and supporting information are available via OSF [link to be added]. Data were processed and analysed in R (R Core Team, 2022), utilizing the following packages: tidyverse (Wickham et al., 2019) for data wrangling; esc (Lüdecke, 2019) and metafor (Viechtbauer, 2010) for effect size calculation; metafor (Viechtbauer, 2010), dmetar (Harrer et al., 2019), and metaforest (van Lissa, 2020a) for the analysis; and metaviz (Kossmeier et al., 2020), meta (Balduzzi et al., 2019), and robvis (McGuinness, 2019) for visualization.

Methods

Inclusion and Exclusion Criteria

The aim of this meta-analysis was to identify studies assessing the associations between emotions experienced in the context of politics and political learning. Therefore, the main inclusion criteria was that studies conducted an empirical analysis and reported at least one quantitative outcome on the relation between a discrete emotion and political learning. We included both experimental and observation studies, but separated them in the quantitative analysis. Only studies including emotions focusing specifically on politics (e.g., a political candidate, policy issue, or political process) were considered as relevant. Emotions were either analyzed as discrete emotions (e.g., enjoyment, anger, anxiety) or as a common emotion measure which could be categorized to be either positive-activating, positive-deactivating, negative-activating or negative-deactivating. Emotions could be measured via self-report scales or, in the case of experimental studies, induced by an experimental manipulation. Concerning the outcomes, we focused on the learning process in daily politics and its most important concepts in the literature. Specifically, we included studies on political information seeking, political discussions, political knowledge, and a knowledge gain.

Studies which could not be obtained in full text, or were duplicates based on the same data and measures, or which did not report a relation between emotions and learning were excluded. For studies with the same data source and measures, the one with the more recent publication date was included. Additionally, for quantitative synthesis, studies which did not supply adequate measures, or which did not measure emotion and learning at the same time point were excluded. A detailed description of the concepts, inclusion, and exclusion criteria is available in the supplemental file A.

Information sources

The aim of the search strategy was to conduct a thorough search that allowed for the detection of published and unpublished work related to the topic. The systematic literature search was based on several databases (i.e., PsycINFO, IBSS, ERIC, ProQuest Dissertation and Thesis, ProQuest Education and Politics Collection), with a search string including a large number of discrete emotions, combined with phrases used for the defined learning concepts and the word ‘politics’ (see supplemental file A). Additionally, we consulted conference proceedings of the main conferences across disciplines (i.e., annual meetings of the International Society of Political Psychology (ISPP), American Political Science Association (APSA), International Communication Association (ICA) and European Association for Research on Learning and Instruction (EARLI)) and used pertinent articles and authors for citation search and author consultation. Finally, an additional search focused on core journals of the disciplines related to the topic (Political Psychology, Journal of Social and Political Psychology, Cognition and Emotion, Political Communication, and Journal of Affective Science). The full search strategy can be found in the supplemental file A.

Deviation from study protocol

It should be noted that during the search process, the search string and strategy detailed in the first preregistration was revised (i.e., search within titles *and* abstract), in order to gain more accurate search results. Additionally, due to resource restrictions, only a subsample of search results was double screened. Finally, some variables were added in the coding (e.g., percentage of male and female participants, discipline).

Study Selection

Search results (k = 336) were screened with regards to the inclusion and exclusion criteria by the first author, and two subsamples were double coded after training by the second author. If the decision could not be based on title and abstract, the full text was consulted. A first unsupervised double-coded sample (k = 35) revealed an intercoder agreement of 77 % (κ_w = .74), which increased to 85 % (κ_w = .63) in a second round (k = 20). Unclear cases were resolved by joint discussion and arriving at consensus.

Data Collection

The studies included were coded on three levels: (1) publication level, (2) study level and (3) effect size level. We coded the type, aim of the publication, and main theoretical approach on publication level. On study level (relevant if one publication reports several studies), data source (if not using primary data), study design, sampling and sample characteristics (e.g., number of participants, country, age and percentage of male and female participants) were coded. Additionally, we assessed characteristics of study quality, for example, whether response rate and missing data handling were reported. Finally, regarding effect size, details about the emotion and learning measurements (type of measurement, items used, reliability, mean and standard deviation if applicable) and their association were coded.

If no standardized bivariate relation was reported, the public data (if available) were used, and authors consulted to add effect sizes. Ten percent of the studies (*N* = 8) were double coded by the first and third author. The agreement rate for most of the variables was satisfying (Krippendorf's α > .70 for 71 % of the variables, *M* = .73, *SD* = .45). Disagreement was discussed to clarify underlying reasons for the remaining variables and if necessary, coding revised. The full codebook with a detailed description of each variable can be found in the supplemental file (section B), and the corresponding agreement rates for double coding are displayed in Table C1 in the supplemental file (section C).

Methods for Assessing Risk of Bias

For quality assessment, study design, sampling strategy, reported response rates, missing values, and reliability measures were assessed. For experimental studies, allocation of participants was additionally included in the quality assessment. Based on common thresholds used in the literature (e.g., Graham, 2008; Reed et al., 2008), we categorized studies into low risk of bias, unclear (if information was missing), and high risk (see section D of the supplemental file for details of categorization).

Summary Measures

In order to calculate effect sizes, all statistics were converted to correlation coefficients. We standardized effect sizes into correlation coefficients and converted them to Fisher's z-scale. The R script used for effect size calculation is available in the supplemental material.

Methods for Synthesis

Effect sizes were synthesized separately for cross-sectional and experimental designs for each emotion(group)-learning relation. We separated our analysis by research designs as underlying research questions usually differ fundamentally (effect versus relationship; Borenstein & Hedges, 2019). Furthermore, we conducted separate analyses focusing on the discrete enthusiasm, anger, and anxiety, as they are studied more frequently in the context of politics (Brader & Marcus, 2013) and a sufficient number of effect sizes were available to be synthesized. We used multilevel random-effects models, which allowed us to account for dependency in the data (i.e., if more than one effect size stemmed from the same authors/dataset). Specifically, we added random effects for effect size-ID and data-ID, the latter corresponds to the study level (with the exception of two study-pairs, where the same data but different measures were used and therefore assigned the same data-ID). Additionally, we used the Knapp-Hartung adjustment to account for non-normal distribution of coefficients (Assink & Wibbelink, 2016). In line with suggestions by Assink and Wibbelink (2016), we performed tests for heterogeneity for within-study variance and between-study variance separately, using log-likelihood-ratio tests in which we compare models where the variance on a respective level is fixed to zero with the model where it is freely estimated. A significant amount of heterogeneity implies a moderator analysis is needed in order to identify possibly explanations for the observed variance.

As no a priori hypotheses concerning moderators were formulated in our preregistration, we took an exploratory, data-driven approach to identify possible moderators. With a high number of coded variables (i.e., possible moderators) accompanied by only a small number of studies and effect sizes included in the models, traditional moderator analysis can be problematic due to multicollinearity and overfitting, as well as increased risk of type 1 errors due to multiple testing (Parr et al., 2022; van Lissa, 2020b). To overcome this problem, we used a machine-learning based exploratory approach to identify relevant moderators, which is specifically suitable for small-scale meta-analyses and can account for dependency in the data (van Lissa, 2020b). Specifically, we applied a random forests algorithm separately for each emotion group. We included the variables' sample size, publication status, discipline, target population, country, sampling, type of emotion measure, state vs. trait emotion measure, type of discrete emotion, learning category, a dummy for whether the learning measure focuses attitude-(in)congruent information, and type of learning measure in the model. We did not include sample characteristics due to high number of missing values (mean age: 51.9%, and percentage of female participants: 32.3% missing values).

In a first step, these variables were evaluated regarding their recursive importance values to predict the effect sizes in the studies. In order to avoid overfitting, we only included variables with a positive variable importance in more than half of the bootstrapped samples. In a second step, models were tuned using cross-validation and evaluated regarding their predictive explained variance (R^2 from out-of-bag estimation, and R^2 from cross-validation). Both represent an estimation of how much variance will be explained by the model in a new (i.e., unused) data set, the former one based on data that was not used during bootstrapping while applying the random forest algorithm, and the latter based on the data not used in cross-validation (Parr et al., 2022; van Lissa, 2020b). The final model also estimated variable importance metrics, which can be interpreted analogous to standardized regression coefficients (van Lissa, 2020b) and analysed for significant moderation in multilevel random-effects models.

Publication Bias and Selective Reporting

In order to assess the possibility of publication bias, we (1) tested whether publication status moderates the effect size in the multilevel random-effects model, (2) visually inspected funnel plots and (3) used an adaption of Egger's regression test suitable for meta-analyses with dependencies in effect sizes (Rodgers & Pustejovsky, 2021). For the funnel plots, we calculated the mean values in order to show only one effect size per study. For Egger's regression test, we excluded studies from unpublished sources (dissertations, theses, and conference papers). We used the inverse sample size as a moderator in the multilevel random-effects model, which is a more suitable measure of precision if using correlations as a common effects measure (Viechtbauer, 2020). Due to the low number of studies available for models on negative-deactivating emotions, the publication bias analyses were not applied to this emotion group.

Results

Study Selection

From the systematic literature search, 336 publications were screened for inclusion and exclusion criteria, of which 80 were coded and 66 included in the final dataset. Thus, the meta-analysis included 78 studies and 486 effect sizes (for details, see Figure 1, PRISMA flow chart).

Study Characteristics

The systematic search with various sources utilized revealed mainly journal articles (68%), almost all from peer reviewed journals. Additionally, we managed to find and access eight conference papers and six unpublished dissertations or theses. Four studies came from book chapters and three monographs on the topic were included. Publications were predominantly produced within the last 20 years (see Figure 2 and, based on the first authors' affiliations, within departments of political science (55%) and communication science (35%). Additionally, a majority of the studies was conducted in the US (71%) and mainly focused on adults (53%) or university and college students (32%). Table F1 in the supplemental file (Section E) provides a summary of the aims and measures of included studies.

The studies included in the meta-analysis are characterized by a considerable heterogeneity in methodological approaches and reporting standards. The majority of the studies utilized experimental designs (54%), followed by cross-sectional studies (27%), and longitudinal (17%) studies, which included specific designs like dynamic process tracing environments (e.g., Ditonto et al., 2017). Regarding reporting standards, from 486 coded effect sizes, 170 were only available in an unstandardized format. For 13 studies (10 publications), we could use published data to calculate bivariate standardized statistics, and additionally received bivariate standardized statistics for 12 studies (10 publications) from contacted authors.

We identified 19 discrete emotions which were measured or induced in the studies (see Figure 3). However, the vast majority of the effect sizes focused on anxiety (32%), anger (19%), and enthusiasm (15%). Emotions were mainly analyzed in the context of election, with a focus either on the campaign (33%) or on candidates (16%). Specific policy issues, for example immigration, health issues, or terrorism, were addressed by 30% of the effect sizes. A small number of emotions were assessed with a focus on a political event (5%) or the general political situation (4%). In terms of learning processes, 40% of the effect sizes investigated the relations between emotions and information seeking, 24% focused on attention to politics, 15% on discussions, and eleven percent each on knowledge and knowledge gain[1]. Studies utilized various methods to assess learning, ranging from self-report questions (63%), behavioral measures (17%; especially with information seeking), to knowledge tests (20%) either based on general political knowledge or specific information provided during the studies.

Results of Individual Studies

Results of individual studies are summarized in Table F1.

Synthesis of Results

For synthesizing effect sizes, we first conducted multilevel random-effects models for group of emotions (positive-activating, negative-activating), and for the discrete emotions

[1] In the preregistration and initial codebook, we differentiated between knowledge gain and information acquisition. However, as both address and increase in knowledge and we had difficulties to clearly differentiate between them, we collapsed both to one group

enthusiasm, anger, and anxiety. Both analyses were conducted for studies with cross-sectional and experimental designs separately.

Associations between Emotions and Learning from Cross-Sectional Studies

Positive-activating emotions.

Details about the estimated models are displayed in Table 1. In line with hypothesis 1, the model based on positive-activating emotions (e.g., enthusiasm, hope, curiosity) revealed an overall positive association between emotions and learning (r = .13, 95% *CI* [.06, .19]). Enthusiasm showed a small positive association with learning in cross-sectional designs (r = .10, 95% *CI* [.01, .19]; see Figure G1 in section G of the supplemental file).

Negative-deactivation emotions.

Our second hypothesis, which assumed negative associations between negative-deactivating emotions and learning, was not supported (r = .03, 95% *CI* [-.16, .22]), but results should be interpreted with caution as the model is based on only three effect sizes.

Negative-activating emotions.

The overall correlation between negative-activating emotions and learning was small and positive (r = .05, 95% *CI* [.01, .09]). However, as shown in figure G2, there was a great variation of effect sizes. The model on anxiety did not reveal a significant overall association between anxiety and learning (r = .03, 95% *CI* [-.02, .07]). In contrast, anger revealed a small positive overall correlation with learning (r = .06, 95% *CI* [.01, .12]).

Associations between Emotions and Learning from Experimental Studies

Positive-activating emotions.

Our model, including effect sizes from positive-activating emotions and experimental design, did not reveal a significant overall correlation (r = .06, 95% *CI* [-.12, .23]. The same finding holds for the model on enthusiasm (r = .00, 95% *CI* [-.06, .07]). For this model, only five publications including ten effect sizes about enthusiasm were included (see Figure G3).

Negative-deactivating emotions.

Again, we could use only few effect sizes to test hypothesis 2 on negative-deactivating emotions, which was not supported (r = .00, 95% *CI* [-.22, .23]).

Negative-activating emotions.

Similar to the model on cross-sectional designs, we found a small, positive overall correlation between negative-activating emotions and learning in experimental designs (r = .06, 95% *CI* [.01, .11]). Regarding discrete emotions, no significant association could be found for anxiety (r = .06, 95% *CI* [-.04, .15]), but a small positive effect for anger (r = .11, 95% *CI* [.03, .19]).

Moderator Analysis

Heterogeneity tests revealed significant variance within and between studies for the models on positive-activating and negative-activating emotions (see Table 1: significant variance components are displayed in bolt; detailed model results can be found in the supplemental file [Table H1 and H2]). We therefore proceeded to moderation analysis with these models.

However, the results of the exploratory approach based on random forests to identify possible moderators was not suggestive for meaningful and significant moderators. Specifically, for the model on positive-activating emotions in cross-sectional designs, none of the included variables passed the preselection threshold of 50% for recursive variable importance as none of the included variables indicated positive variable importance values in more than half of the bootstrapped samples. Second, while one to four variables were preselected for the remaining models, the estimations indicated a negative predictive explained variance for two models (positive-activating emotions in experimental designs: R^2 = -.41, R^2 = .89; negative-activating emotions in cross-sectional designs: R^2 = -.78, R^2 = .52). This indicates overfitting (van Lissa, 2020b) and that the effect size is a better predictor than the model-implied predictions (Curry et al., 2018), hence no important moderators could be identified.

Finally, the model on negative-activating emotions in experimental designs revealed positive estimates for predictive explained variance (R^2 = .09, R^2 = .28). However, the importance metrics of the selected moderators (discipline, type of emotion and learning measure, discrete emotion) in the tuned models were smaller than 0.003. This measure can be interpreted similarly to standardized β, it therefore seems to approach a null effect. Whether it is still a significant predictor can only be tested using traditional moderator analysis. We thus used traditional moderator analysis to test whether sampling and type of emotion measure moderate the effect size in models on negative-activating emotions using experimental designs. The models did not reveal significant moderation ($F(10, 93) = 1.18$, $p = .31$; see Table I1 in section I in the supplemental file).

Assessment of Internal Validity of Individual Studies

A visual summary of the quality assessment of included studies is displayed in figure D1 (see section D in the supplemental file). While almost half of the studies (41%) used random sampling (or comparable techniques, e.g., online sampling service aiming a representative sample), a similar amount is based on convenience sampling (44%). Studies using experimental designs mainly relied on random allocation to experimental and control groups. Regarding response rate, missing values and measurement error, the risk of bias remains broadly unclear (62-92%) due to poor reporting standards.

Publication and Reporting Bias

We used publication status as a moderator in order to test whether reported effect sizes were dependent on the status of the manuscript. The test was not supported for any of the models (see Table 2). Results of the adapted Egger's regression test are shown in Table 3. The inverse of the sample size was included as a moderator in the multilevel models as a measure of precision. We found significant, negative effects in the model of negative-activating emotions of cross-sectional designs, indicating funnel-plot asymmetry (see Figure J1 in section J of the supplemental file). Thus, studies with lower precision (i.e., smaller sample size) had larger effect sizes. For experimental designs, the same occurred in models of positive-activating emotions and anxiety (see Figure J2)

Discussion

We present the first cross-disciplinary meta-analysis and systematic review specifically focusing on the role of emotions in political learning. Prior general reviews on emotions in politics (Brader & Marcus, 2013; Crigler & Just, 2012; Groenendyk, 2011) published around ten years ago already noted an increase in interest in the topic. This trend that appears to have continued since then, particularly in the age of emotionally laden political events such as Brexit and the Trump election. Thus, it has been high time to systematically search and analyze which emotions are currently investigated, and how they relate to political learning.

Positive Associations between Emotions and Learning

The aim of this study was to analyze how emotions investigated in the literature are associated with learning in the context of politics. Our hypotheses based on control-value theory (Pekrun, 2006) were partially supported, and we found very interesting results regarding negative-activating emotions in our exploratory analysis. The first hypothesis, that positive-activating emotions were positively related to learning, was partly supported by cross-sectionally designed studies. Only few experimental studies focusing on positive emotions were available (k = 6; N = 16), with correlations mainly representing null-effects. The great attention to negative emotions (e.g., anger or anxiety) compared to positive emotions has also been noticed in prior reviews (Crigler & Just, 2012). Given the predominance of deficit-view studies in psychology research, where the focus has mainly been on the negative and symptomatic (Fredrickson, 2004), it is not surprising that very few studies centering positive emotions have been conducted. A positive psychology research approach placing the focus on positive emotions in political learning (Seligman & Csikszentmihalyi, 2014) may be a fruitful avenue for future research.

For negative-activating emotions we did not have predefined hypotheses, as relations often vary depending on the emotion and facet of learning (Pekrun et al., 2011). Interestingly, negative-deactivating emotions were positively related to learning in both, experimental and cross-sectional, study designs. In contrast to studies of political psychology which usually highlight the benefits of anxiety rather than anger for political learning (for example, see affective intelligence theory, Marcus et al., 2000), we found positive, though small, associations between anger and learning. Though in the academic context anger is often found to increase task-irrelevant thinking, it can also increase motivation if success is expected (Pekrun & Stephens, 2012). The positive association is consistent with the classification of anger as an approach emotion and its mobilizing effect for political participation (Redlawsk & Mattes, 2022; Elliot et al., 2013). Anger, thus, motivates for political action and can increase learning. Anger-related learning, on the other hand, may be focused on information and arguments to defend one's own political attitudes (Redlawsk & Mattes, 2022).

The hypothesis on negative-deactivating emotions was not supported, but models were based on very few effect sizes and studies. This reveals one of the blind spots of the current research, since there is only a limited number of studies with focus on deactivating emotions. Though, for example, boredom is a recurring theme in qualitative studies on civic education and civic engagement among youth (e.g., Kahne & Middaugh, 2008; Zukin et al., 2006), we could not find any study including boredom when looking at political learning. Given the negative association between boredom, hopelessness, or confusion experienced during discussions of political and social issues in class with student's engagement, motivation, and knowledge (Graf et al., 2022), investigating and further tackling these deactivating emotions specifically related to political objects seems of great relevance in order to foster informed and active citizenship.

Blind spots in the literary landscape on emotions and political learning

Our systematic literature search revealed a number of blind spots in the landscape of existing evidence. First, the majority of the study is based on the US (70%), only 12% of the studies are including non-western countries. Predominance of western, education, industrialized, rich, and democratic samples in psychological research has often been criticized (i.e., WEIRD-samples Henrich et al., 2010), which seems to apply to the current meta-analysis, too. As political context might be of great relevance to citizen's experienced emotions and their learning motivation, diversifying targeted samples is a major task for future research.

Most studies identified were based on adults. Studies on adolescents and school students, who are in a critical period of their political socialization (Sears & Brown, 2013), are few and far between. The limited number of studies focusing on political emotions among youth has already been noticed by Barrett and Pachi (2019). This limits the generalizability of the current findings, as emotions in the context of politics might play a specific role for adolescents during the impressionable years of political learning. Moreover, a great amount of political learning takes place in formal settings of civic education at school (Schlozman et al., 2018), a context where the role of emotions with a few exceptions (e.g., Bayram Özdemir et al., 2016; Graf et al., 2022) has been overlooked entirely. We therefore implore researchers who conduct studies on civic education to include emotions as an important aspect of the learning process.

Implications for Theory, Practice, and Future Studies

Overall, results are partly in line with the control-value theory (Pekrun, 2006), and at first sight contradict assumptions of the affective intelligence theory (Marcus et al., 2000), one of the main theories applied for emotions in politics. Of all 66 studies included in this systematic review, 42 refer to the theory of affective intelligence in their literature review. While one of the core assumptions of the theory is that anxiety in contrast to anger is the main driver of political learning by interrupting habits and heightened alertness to new information (Marcus et al., 2000) we did not find overall associations for anxiety, but slight positive associations for anger. One explanation might be that we were interested in bivariate relations in the current study, therefore not controlling for shared variance and mutual effects of anger and anxiety. Additionally, for experimental designs Egger's regression test has shown that models on anxiety are affected by publication asymmetry. Surprisingly, it seems that in this meta-analysis, specifically small (imprecise) studies with positive relations between anxiety and learning are missing. We can only speculate about the reason for this pattern. It could be due to excluding studies that did not report standardized effect sizes. If correcting for missing studies in the estimated overall effect size, it seems that anxiety could reveal similar associations as anger. Linking back to the theory, this would mean that all types of activating emotions seem to relate to learning. The high number of experimental designed studies conducted even imply causal paths from negative-activating emotions to learning processes.

According to Lupia (2016), civic educators (e.g., teachers, journalists, or campaign leaders) need to attract voters' attention in order to facilitate political learning, which can be achieved through addressing voters' fears and aspirations. This already addresses the motivational role of emotions for learning, which is supported with our results on negative-activating emotions, specifically, anger, and associations of positive-activating emotions with learning. For example, Otto et al. (2020) found in their experience sampling studies that anger correlated positively with attention towards political news, while contentment even had negative lagged effects on attention. Therefore, civic educators may specifically address citizens' activating emotions in order to capture their attention and stimulate further engagement with new information. Still, researchers and civic educators need to be cautious of possible unintended side-effects of emotion-induced learning, as for example anger has been shown to negatively relates to institutional trust (e.g., Erhardt et al., 2021) and positively with populist attitudes (e.g., Rico et al., 2017).

Though we could not identify moderators to the overall effects in this meta-analysis, we found considerable variation between these effect sizes. We encourage future studies to look further into possible moderators and identify under which circumstances, and for which populations these effects occur. For example, in the study of Bas and Grabe (2015) the inclusion of emotions in political texts showed promising results to decrease knowledge gaps between higher and lower educated groups. Though politically sophisticated individuals are more likely to experience emotions in politics (Miller, 2011), it might be that less sophisticated individuals learn more once the emotions are experienced and their attention focuses on politics.

Finally, a great challenge for the cross-disciplinary synthesis was diverging reporting standards. Many effect sizes were excluded as only unstandardized betas from multivariate regression were reported. We recommend future studies to include descriptive and bivariate measures in their manuscripts, no matter whether published or unpublished. These measures are essential for research synthesis and allow a less biased assessment of an overall effect size. Additionally, basic sample characteristics and quality measures such as missing data handling and reliability of included measures were missing in a considerable amount of the studies included. This limited our possibilities for moderator analysis and the assessment of the risk of bias of the current meta-analysis. In line with the APA journal reporting standards for quantitative studies (American Psychological Association, 2019), we recommend future studies to:

- Report basic demographic characteristics of the sample(s), at least including age and gender.
- Report the sampling method, response rate, number of missing values, and if applicable, any exclusions and discuss how this might affect results of the study.
- Describe in detail the measures used, ideally with at least one sample item to illustrate the measurement. We additionally recommend providing the full study material, for example via an online appendix.
- Assess and report reliability measures of included variables of interest.
- Provide descriptive characteristics of variables of interest, including mean and standard deviation and bivariate correlations between these variables.

Conclusion

The results of this cross-disciplinary meta-analysis and systematic review emphasize the important role of emotions for political learning. The findings imply that political educators and communicators should not keep emotions unaddressed when targeting political learning. In particular, positive-activating emotions like enthusiasm and negative-activating emotions like anger can help to raise attention and keep citizens informed about current political matters. The role of emotion in political learning should therefore not be underestimated.

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Table 1

ML-Random-Effects Model Results

Model	*k*	*N*	*r*	CI	*t (df)*	*p*	% Variance (I^2) Level1	Level 2	Level 3
Cross-sectional Designs									
Pos.-Act. Emotions	12	42	.128	[.061, .194]	3.846 (41)	.000	5.768	**38.251**	**55.981**
Enthusiasm	6	19	.101	[.008, .191]	2.288 (18)	.034	4.918	**60.576**	34.506
Neg.-Act. Emotions	22	83	.049	[.009, .089]	2.407 (82)	.018	7.279	**32.795**	**59.926**
Anxiety	19	45	.027	[-.019, .072]	1.188 (44)	.241	7.692	**27.607**	**64.702**
Anger	12	32	.061	[.006, .116]	2.257 (31)	.031	8.370	**49.334**	42.296
Neg.-Deact. Emotions	2	3	.032	[-.160, .222]	0.721 (2)	.546	28.143	0.000	71.857
Experimental Designs									
Pos.-Act. Emotions	6	16	.057	[-.120, .231]	0.685 (15)	.504	5.810	**10.982**	**83.207**
Enthusiasm	5	10	.002	[-.064, .068]	0.054 (9)	.958	60.333	39.667	0.000
Neg.-Act. Emotions	19	104	.061	[.013, .108]	2.537 (103)	.013	11.900	**52.135**	**35.965**
Anxiety	16	45	.055	[-.036, .146]	1.219 (44)	.230	7.017	0.787	**92.196**
Anger	13	25	.109	[.029, .188]	2.797 (24)	.010	20.060	0.000	**79.940**
Neg.-Deact. Emotions	3	10	.004	[-.223, .231]	0.043 (9)	.967	14.896	0.000	**85.104**

Note. *k* = Number of studies with unique datasets, *N* = Number of effect sizes; Variance on level 1 refers to the sampling variance, level 2 to the variance within studies using the same data, and level 3 to the variance between studies. Significant variability in the variance between effect sizes and studies is displayed in bolt.

Table 2

Moderator Analysis of Publication Status

Model	Predictor	*k*	*N*	estimate	se	*t* (df)	*p*	CI
				Cross-Sectional Designs				
Pos.-Act. Emotions	Intercept	12	42	0.134	0.071	1.882 (40)	.067	[-0.01, 0.277]
	Status			-0.005	0.082	-0.064 (40)	.950	[-0.171, 0.161]
Enthusiasm	Intercept	6	19	0.115	0.141	0.82 (17)	.423	[-0.182, 0.413]
	Status			-0.015	0.150	-0.102 (17)	.920	[-0.331, 0.301]
Neg.-Act. Emotions	Intercept	22	83	0.072	0.040	1.782 (81)	.079	[-0.008, 0.152]
	Status			-0.031	0.047	-0.658 (81)	.513	[-0.124, 0.062]
Anxiety	Intercept	19	45	0.012	0.052	0.237 (43)	.814	[-0.092, 0.117]
	Status			0.018	0.058	0.309 (43)	.759	[-0.099, 0.134]
Anger	Intercept	12	32	0.090	0.110	0.819 (30)	.419	[-0.135, 0.315]
	Status			-0.031	0.114	-0.273 (30)	.787	[-0.264, 0.202]
				Experimental Designs				
Pos.-Act. Emotions	Intercept	6	16	-0.125	0.205	-0.61 (14)	.552	[-0.566, 0.315]
	Status			0.218	0.225	0.972 (14)	.348	[-0.264, 0.7]
Enthusiasm	Intercept	5	10	-0.130	0.109	-1.189 (8)	.269	[-0.381, 0.122]
	Status			0.141	0.113	1.251 (8)	.246	[-0.119, 0.402]
Neg.-Act. Emotions	Intercept	19	104	-0.024	0.089	-0.273 (102)	.785	[-0.2, 0.152]
	Status			0.092	0.092	0.996 (102)	.321	[-0.091, 0.275]
Anxiety	Intercept	16	45	-0.005	0.137	-0.034 (43)	0.973	[-0.28, 0.271]
	Status			0.067	0.145	0.462 (43)	0.646	[-0.226, 0.36]
Anger	Intercept	13	25	-0.079	0.153	-0.516 (23)	0.611	[-0.395, 0.237]
	Status			0.201	0.158	1.271 (23)	0.216	[-0.126, 0.527]

Note. *k* = Number of studies with unique datasets, *N* = Number of effect sizes; Status indicated the publication status, with 1 = published and 0 = unpublished.

Table 3

Results of Egger's Regression Test

Model	Predictor	*k*	*N*	estimate	se	*t* (df)	*p*	CI
				Cross-Sectional Designs				
Pos.-Act.	Intercept	9	36	0.067	0.076	0.886 (34)	.382	[-0.087, 0.222]
Emotions	Inverse of N			32.458	31.403	1.034 (34)	.309	[-31.361, 96.277]
Enthusiasm	Intercept	5	18	0.130	0.099	1.32 (16)	.205	[-0.079, 0.339]
	Inverse of N			-14.209	40.905	-0.347 (16)	.733	[-100.923, 72.505]
Neg.-Act.	Intercept	16	69	0.082	0.030	2.709 (67)	.009	[0.022, 0.143]
Emotions	Inverse of N			-26.206	12.438	-2.107 (67)	.039	[-51.032, -1.38]
Anxiety	Intercept	15	38	0.073	0.034	2.147 (36)	.039	[0.004, 0.142]
	Inverse of N			-27.111	13.826	-1.961 (36)	.058	[-55.152, 0.93]
Anger	Intercept	11	31	0.105	0.041	2.553 (29)	.016	[0.021, 0.19]
	Inverse of N			-25.044	16.229	-1.543 (29)	.134	[-58.236, 8.148]
				Experimental Designs				
Pos.-Act.	Intercept	5	13	0.371	0.114	3.269 (11)	.007	[0.121, 0.621]
Emotions	Inverse of N			-64.448	23.702	-2.719 (11)	.020	[-116.615, -12.28]
Enthusiasm	Intercept	4	9	0.111	0.091	1.216 (7)	.264	[-0.105, 0.326]
	Inverse of N			-20.476	17.836	-1.148 (7)	.289	[-62.652, 21.7]
Neg.-Act.	Intercept	17	80	0.106	0.034	3.14 (78)	.002	[0.039, 0.174]
Emotions	Inverse of N			-6.549	5.013	-1.306 (78)	.195	[-16.529, 3.432]
Anxiety	Intercept	14	38	0.184	0.061	3.015 (36)	.005	[0.06, 0.307]
	Inverse of N			-22.444	8.406	-2.67 (36)	.011	[-39.492, -5.396]
Anger	Intercept	12	24	0.087	0.069	1.265 (22)	.219	[-0.056, 0.23]
	Inverse of N			5.673	8.510	0.667 (22)	.512	[-11.976, 23.323]

Note. k = Number of studies with unique datasets, *N* = Number of effect sizes;

Figure 1

PRISMA flow chart about the number of studies resulting from the literature search

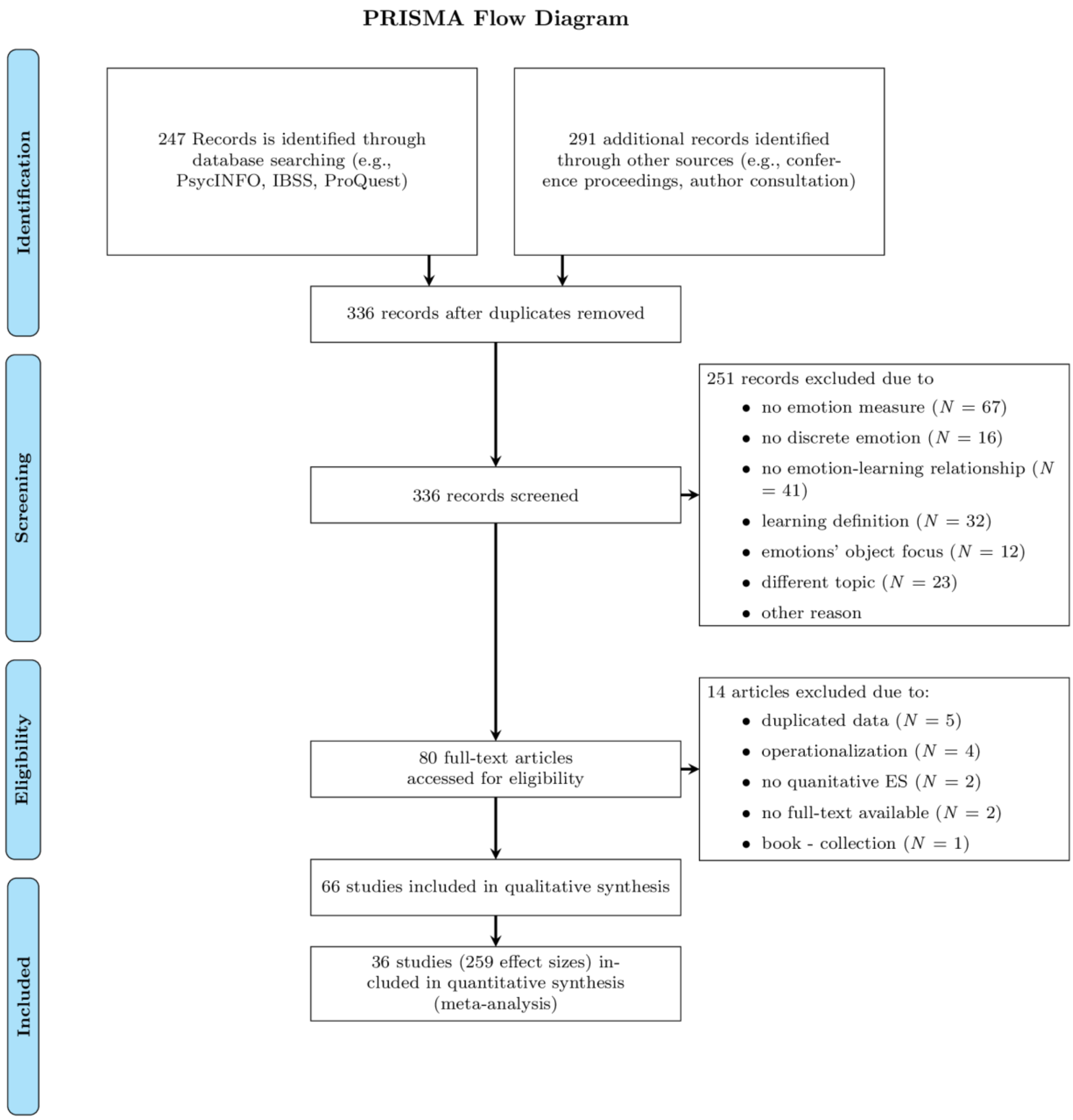


Figure 2

Number of Publications per Year and Discipline

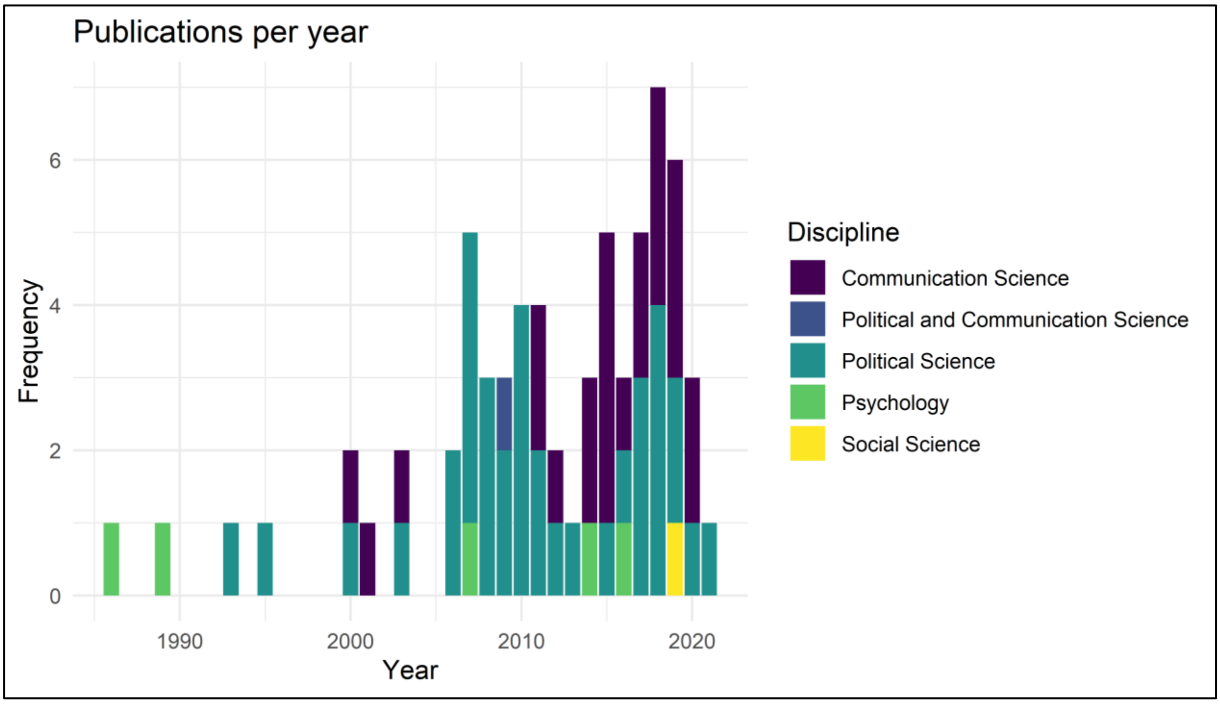
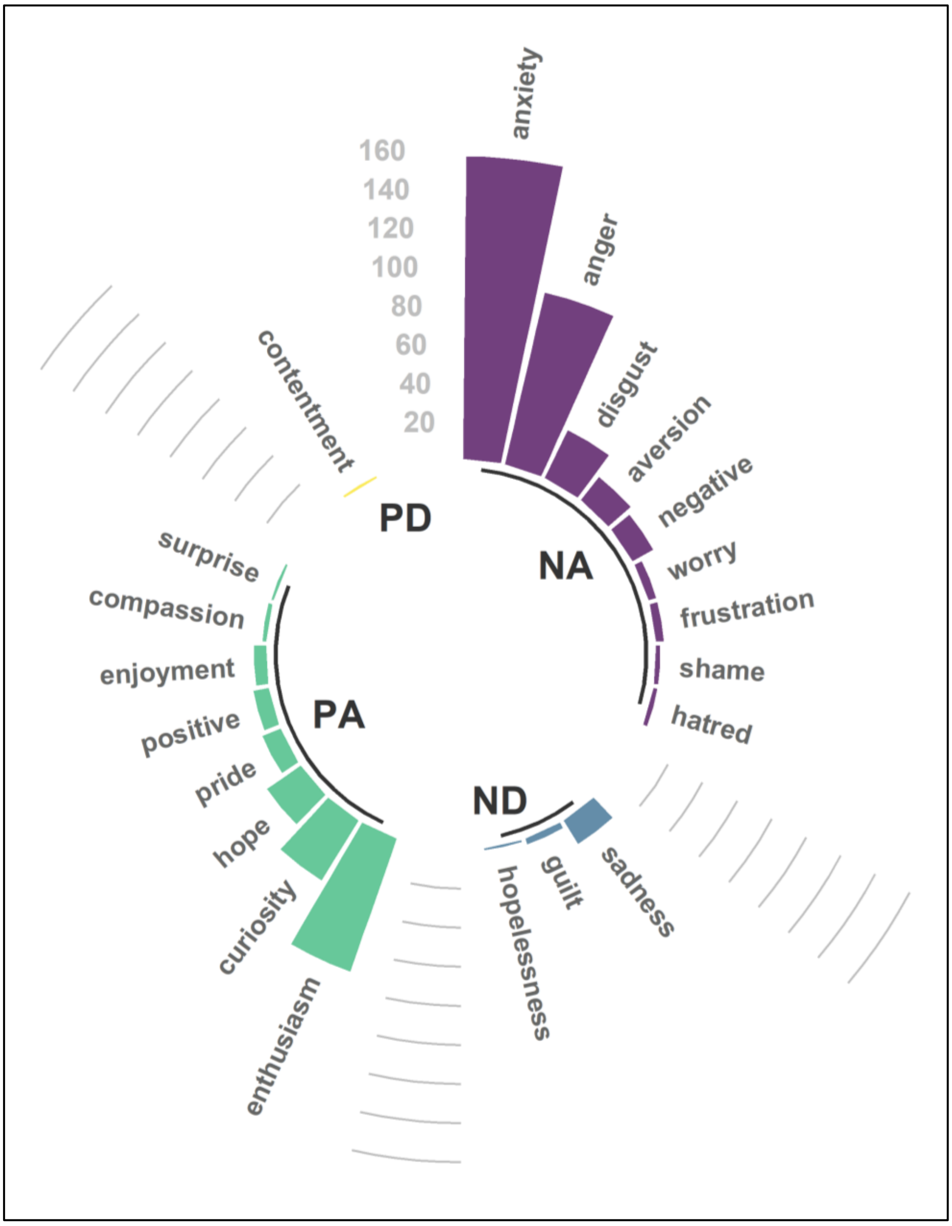


Figure 3

Number of Effect Sizes per Emotion



Note. NA = negative-activating emotions (N = 311), ND = negative-deactivating emotions (N = 18), PA = positive-activating emotions (N = 156) and PD = positive-deactivating emotions (N = 1).