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META-ANALYSIS

The Associations Between Discrete Emotions and Political Learning: A Cross-Disciplinary Systematic Review and Meta-Analysis

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Abstract

In recent decades, researchers' interest in the role of emotions in individual political learning has grown. However, it is still unclear whether and how discrete emotions are associated with political learning. Through a cross-disciplinary systematic review and multilevel meta-analysis, we reviewed which discrete emotions have been analyzed in the context of political learning so far and meta-analytically synthesized how these emotions relate to political learning. We addressed this question by synthesizing 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 (65%; mainly anxiety, 32%, and anger, 19%) and positive-activating emotions (32%; mainly enthusiasm, 15%), while studies on positive-deactivating emotions (e.g., contentment) and negative-deactivating emotions (e.g., sadness) are largely lacking. We uncovered small positive associations ($r = .05$ to $.13$) for activating emotions, of both negative (especially anger) and positive valence (e.g., enthusiasm, only in cross-sectional designs), but no associations for negative-deactivating emotions. We discuss theoretical implications and recommend future research to include previously unconsidered emotions in order to extend existing findings.

Keywords Emotions · Political learning · Political knowledge · Meta-analysis · Systematic review

This study was registered with Prospero (Registration ID: CRD42020211220) on November 5, 2020. Data, accompanying analysis scripts, and supporting information are available via OSF.

Extended author information available on the last page of the article

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Introduction

Emotions undoubtedly play a role in political activism, political campaigns, and political learning (Brader & Marcus, 2013). It has been speculated that emotions may even trump rationality in politics, with Westen (2007) remarking that "In politics, when emotion and reason collide, emotion invariably wins" (p. 35). 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). The increased research attention may be due to the emotionally laden political events of recent years, with studies examining emotions regarding the Brexit referendum (Nadeau et al., 2021; Vasilopoulou & Wagner, 2022), the Trump election campaigns (Ford et al., 2019; Hoewe & Parrott, 2019), and public threats caused by pandemics (Albertson & Gadarian, 2015; Wang & Ahern, 2015) and climate change (Chadwick, 2015; Furlong & Vignoles, 2021).

Particularly, there is a great number of studies addressing questions on whether and how emotions are related to different aspects of political learning, such as 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 emphasize 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). This is quite surprising, as the relevance of emotions for learning and its pedagogical consequences has been emphasized among civic education researchers, while systematic empirical evidence is still missing (Keegan, 2021; Sheppard & Levy, 2019).

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 of emotions and political learning 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, for example, 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 contexts is the control-value theory of achievement emotions (Pekrun, 2006). This theory details what factors may contribute to the experience of emotions during learning, and how these emotions affect learning processes and corresponding outcomes. Though the control-value theory was initially developed to explain emotions in achievement settings, it has also been applied to epistemic emotions experienced during cognitive processing (Muis et al., 2015) and informal learning settings (Beymer et al., 2022). According to the universality assumption, structural associations between emotions and learning are similar across domains (Pekrun, 2018). 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.

The aims of this study were twofold: First, we reviewed which emotions have been analyzed in the context of political learning. Second, we aimed to analyze whether and how discrete emotions are related to political learning by using meta-analytic methods to synthesize reported associations between discrete emotions and 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 & 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). Knowing which emotions can catch students' interest to engage with political matters is highly relevant for civic education teachers, who often make pedagogical decisions based on emotions perceived in classrooms (Sheppard & Levy, 2019). 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; Pekrun et al., 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 election day, reading a newspaper article about a recent corruption scandal, or when running into a protest of climate activists on the street. They can be conceptualized as situational, short-term responses to stimuli (i.e., state emotions) or trait-like measures similar to personality traits (Crigler & Just, 2012).

Generally, theories applied to 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 & 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 is experienced negatively (i.e., unpleasant) and is activating (i.e., high arousal), and boredom is experienced negatively (i.e., unpleasant) and deactivating (i.e., low arousal).

The intertwined nature of emotion and cognition (Dreisbach, 2022) suggests that emotions play a crucial role in 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 in learning is the control-value theory (Pekrun, 2006; Pekrun et al., 2023), which primarily focuses on achievement emotions in academic settings and aims to explain their antecedents and effects on learning. Similar to the aforementioned 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 versus 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. For example, enjoyment, hope, and pride as positive-activating emotions typically relate positively to motivation, engagement, and achievement, while boredom and hopelessness as negative-deactivating emotions show directionally opposite associations (Graf et al., 2024; Pekrun et al., 2011).

Observations about positive-deactivating and negative-activating emotions are more complex (Pekrun, 2006). Positive-deactivating emotions are generally understudied and might undermine, but also reinforce, learning effort and motivation (Pekrun et al., 2023). For negative-activating emotions, variable associations to learning have been reported. For example, while anxiety experienced in achievement situations relates negatively to intrinsic motivation, effort, and achievement, it relates positively to extrinsic motivation (Pekrun et al., 2011). Similarly, in the context of civic education at schools, anger experienced during political discussions at school shows negative associations with political knowledge, while revealing positive associations with students' extrinsic motivation and political engagement (e.g., talking with parents; Graf et al., 2024). Additionally, studies have observed diverging effects of anxiety and anger — both typically classified as negative-activating emotions — on news consumption (Huddy 2007).

Learning about Politics

Political learning is a complex and multi-faceted construct. Like politics itself (e.g., see Hay, 2002), it can be conceptualized broadly (e.g., including a variety of political competencies and attitudes on societal topics) or more narrowly (e.g., focusing on specific competencies, core political themes). In our work, we define political learning as the process of acquiring political knowledge. We focus on political knowledge as it is highly relevant to other civic competencies, like participation (Schlozman et al., 2018). Political knowledge impacts not only whether one participates or not, but also "the quality of political decision making, and thus … the quality of citizenship" (Delli Carpini, 2009, p. 41). To conceptualize political learning as a process of knowledge acquisition, it is important to specify the contexts in which political learning occurs (i.e., where and when), describe the specific learning processes involved (i.e., how), and identify the content of political learning (i.e., what).

Where and when do we usually observe political learning? Learning about politics is a lifelong process and takes place in various contexts. Basic foundations are settled in early childhood via socialization through family and peers and civic education at schools (Schlozman et al., 2018). Thereby, schools play a major role in citizens' political development, on the one hand directly through civic education, but also indirectly through fostering knowledge and skills relevant to lifelong political learning (Ichilov, 2003; Niemi & Junn, 1998). Civic education can be conceptualized as an institutional form of political knowledge acquisition (Ichilov, 2003) which includes both formal (i.e., lessons specifically aimed to teach about political matters) and informal political learning, such as learning by discussing politics in class (Deimel et al., 2020; Galston, 2001; Losito et al., 2021). During adulthood, informal political learning continues to be highly relevant. Specifically, citizens learn across their lifespan through incidental and self-directed (i.e., intentional) exposure to political information (Schugurensky & Myers, 2003).

Thus, political information processing is often used as an umbrella term to describe processes (the "how") of political learning (e.g., Funck et al., 2023). Political learning across all these contexts occurs when citizens pay attention to mass media (Barabas et al., 2014), actively seek political information (Redlawsk et al., 2007), or engage in political discussions with friends (Moeller & de Vreese, 2019). Finally, the content of political learning can be defined based on dimensions of political knowledge. Essential aspects of political knowledge are what the government is (i.e., political structures) and does (i.e., policy issues on which public decisions are made), knowledge about political actors and their positions (e.g., political leaders and parties), as well as knowledge about related fields like political history (Delli Carpini & Keeter, 1993).

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, 2013; Marcus et al., 2000). 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 (e.g., sadness or curiosity).

Political learning is often investigated in the context of (mock) election campaigns or focused on specific policy issues. In line with the aforementioned 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 relation (Huddy et al., 2007), while further ones found a negative relation between anxiety and political attention (Otto et al., 2020). These discrepancies might be explained by the differing object focus of the emotions (e.g., election candidates versus specific policy issues) or focusing on trait emotions (Marcus et al., 2000) versus state emotions (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 neighbors (Huddy et al., 2007). The most consistent findings have been shown 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, there is a need 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 account is the only available 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 that they can foster or even prevent us from learning related processes, there is no extensive overview on political emotions and their associations with political learning.

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

With this study, we attempt to fulfill various objectives. First, we aimed to gather a sufficient overview of which emotions are included in existing studies on political learning. 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. Thereby, we include both cross-sectional and experimental designs, as both investigate the main research question, but from different angles. While cross-sectional studies are able to catch possible recursive effects, experimental designs are able to identify causal mechanisms involved. We apply a theoretical framework novel for this context by analyzing 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) should be related to less political learning and weaker learning outcomes. Using this theory thus allows us to combine multiple discrete emotions to these categories with uniform expectations regarding their associations with learning. 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 (e.g., Huddy et al., 2007; Pekrun et al., 2011).

Based on control-value theory, we hypothesised 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, in exploratory analysis, we tested how negative-activating emotions (e.g., anger and anxiety) are related to learning. We added analyses for discrete emotions if sufficient empirical information for these emotions was available. Differentiating between discrete emotions is especially relevant for negative-activating emotions, where often varying effects have been found in prior studies (Graf et al., 2024). Though we did not know in advance for which emotions this would be possible, models for emotions that fall into one of the categories stated in Hypotheses 1 and 2 can be viewed as subtests of the hypotheses. Finally, we took an exploratory approach to test for possible moderators. According to Lipsey (2009), study descriptors such as extrinsic matters, study methods and procedures, and substantive matters are typically considered as moderators in meta-analyses. First, in addition to publication status, we included country and discipline as extrinsic matters. Effect sizes might differ depending on the political systems and associated roles of citizens in a country. Disciplinary affiliation might indirectly affect effect sizes through applied theoretical frameworks and methods common within a discipline (Lipsey, 2009), which is of special relevance for the current meta-analysis due to its cross-disciplinary approach. Regarding study methods and procedures, we included sample size, sampling method, type of measurement, and target population. Third, as substantive aspects, we included central emotion characteristics addressed in prior studies utilizing the control-value theory (state vs. trait emotions; Bieg et al., 2014; object focus; Muis et al., 2018; type of discrete emotion; Pekrun et al., 2023). Finally, as we subsumed multiple learning categories to one effect-size measure, the learning category itself was used as a moderator, as well as a dummy for whether the learning measure focuses specifically on attitude-(in)congruent information (see emotions and motivated reasoning, e.g., confirmation bias during information seeking; Wollebæk et al., 2019).

Open Practices

We preregistered this study on PROSPERO on November 5, 2020. Data and accompanying analysis scripts are available via OSF. Data were processed and analyzed in R (R Core Team, 2022), utilizing the following packages: revtools (Westgate, 2019) for identifying and removing duplicates after the literature search, 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 pema (Van Lissa et al., 2023) 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 were 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 observational 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 about politics throughout the lifespan and its most important concepts in the literature.

Specifically, we included studies on political information seeking, attention to politics, 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 that did not supply adequate measures (e.g., non-bivariate, partial effects; Aloe, 2014), or that did not measure emotion and learning at the same time point, were excluded. These studies seemed not to be comparable, as effect sizes highly depended on the other predictors included or the respective time spans between measures. A detailed description of the concepts and inclusion and exclusion criteria is available in the Supplementary Information, Section 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 in English and German that included a large number of discrete emotions, combined with phrases used for the defined learning concepts and the word ‘politics’ (see Supplementary Information, Section 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), American Educational Research Association (AERA), Society for Empirical Educational Research (GEBF), and the Society for Civic Education Didactics and Civic Youth and Adult Education (GPJE), and the Biannual Meeting of the 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 Supplementary Information, Section A.

Deviation from the Preregistration

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, and discipline).

Study Selection

Search results ($k = 358$) 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% ($\kappa_w = 0.74$), which increased to 85% ($\kappa_w = 0.63$) 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 (e.g., journal article, book, dissertation, etc.), and main theoretical approach at the publication level. Whereas publication type and discipline were coded in predefined categories (see Supplementary Information, Section B), the aim and theoretical approach was openly coded and only used for the qualitative synthesis. On the study level (relevant if one publication reports several studies), data source (if not using primary data), study design (e.g., experimental), sampling (e.g., random, convenience), 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, e.g., behavioral or self-report; number of 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 authors. The agreement rate for most of the variables was satisfying (Krippendorf's $\alpha > 0.70$ for 71% of the variables, $M = 0.73$, $SD = 0.45$). Disagreement was discussed to clarify underlying reasons for the remaining variables and if necessary, coding revised. Emotions were categorized to positive-activating (e.g., curiosity), positive-deactivating (e.g., contentment), negative-activating (e.g., anxiety), and negative-deactivating (e.g., sadness) based on the literature (see Appendix B in the Supplementary Information, Sect. 6.1.). The full codebook with a detailed description of each variable can be found in the Supplementary Information (Section B), and the corresponding agreement rates for double coding are displayed in Table C1 in the Supplementary Information (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; Moosbrugger & Kelava, 2012; 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 Supplementary Information for details of categorization).

Summary Measures

In order to calculate effect sizes, all statistics were converted to correlation coefficients. We standardized effect sizes into Pearson correlation coefficients and, for analysis, applied Fisher's z conversion to these. The R script used for effect-size calculation is available via OSF.

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). We categorized studies as experimental if either the emotions themselves were induced, or if the study included an experimental condition and emotions were measured after the manipulation, thus if reported emotions depend on the experimental condition (e.g., threat manipulation). Furthermore, we conducted separate analyses focusing on the discrete emotions enthusiasm, anger, and anxiety, as these are studied more frequently in the context of politics (Brader & Marcus, 2013) and a sufficient number of effect sizes was 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 sample). Specifically, we added random effects for effect size-ID and data-ID, the latter corresponds to the study level (with the exception of one study pair,[1] where the same data, but different measures, were used and therefore assigned the same data-ID). This allows us to differentiate three levels of effect-size variances in our models: (1) sampling variance, (2) variance within studies, and (3) variance between studies (Assink & Wibbelink, 2016). 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 compared 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 possible explanations for the observed variance.

[1] Valenzuela & Bachmann, 2015 and Valenzuela, 2011; Valentino et al., 2009 and Valentino et al., 2008 also used the same data but were excluded from the quantitative synthesis due to missing bivariate effect sizes measures.

As no a priori hypotheses concerning moderators were formulated in our preregistration, we took an exploratory 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, Bayesian regularized meta-analysis (BRMA) is a suitable method to identify relevant moderators while avoiding overfitting. It allows to select relevant moderators by shrinking small regression coefficients towards zero using regularization priors (Van Lissa et al., 2023). We use the R package pema (Van Lissa et al., 2023) to estimate three-level mixed effects models with a minimum of 4000 iterations and a horseshoe prior for each emotion group and design. We slightly increased regularization to avoid high numbers of divergent transitions (Van Lissa et al., 2023). We included the variables' sample size, publication status (0 if coded as conference paper, dissertation, or thesis, 1 if coded as journal article, book, or book chapter), discipline, target population, country, sampling, type of emotion measure, state vs. trait emotion measure, object focus of emotion measure, type of discrete emotion, learning category, a dummy for whether the learning measure focuses on attitude-(in)congruent information, and type of learning measure in the model (for coding details, see Supplementary Information, Appendix B). Models were checked for convergence according to their Rhat, effective sample size, and using parameter trace plots (Van Lissa et al., 2023).

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 when using correlations as effect size (Viechtbauer, 2020). Due to the low number of studies available for models on negative-deactivating emotions, analyses of publication bias were not applied to this emotion group.

Results

Study Selection

From the systematic literature search, 358 publications were screened for inclusion and exclusion criteria, of which 80 were coded and 66 included in the final dataset. Thus, this study included 66 publications reporting 78 studies and 486 effect sizes, of which 36 publications (42 studies, 259 effect sizes) could be used for the quantitative synthesis and calculation of overall effects (for details, see Fig. 1, PRISMA flow chart).

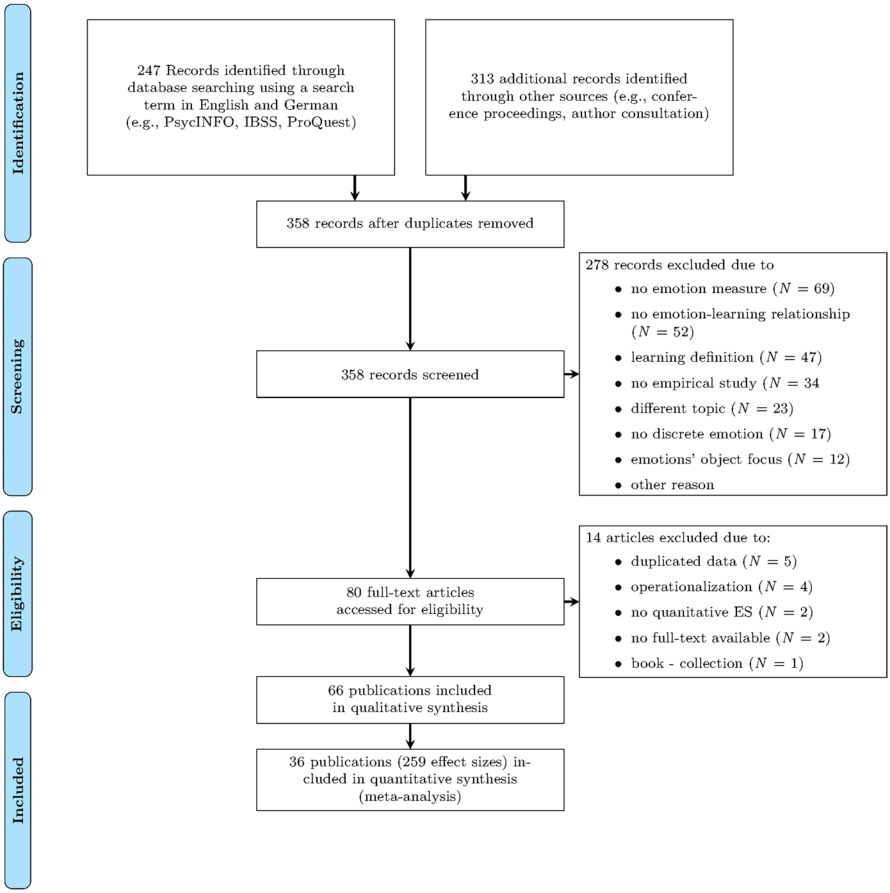


Fig. 1 PRISMA flow chart of the number of studies resulting from the literature search

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 Fig. 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 USA (71%) and mainly focused on adults (53%) or university and college students (32%). Table E1 in the Supplementary Information (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

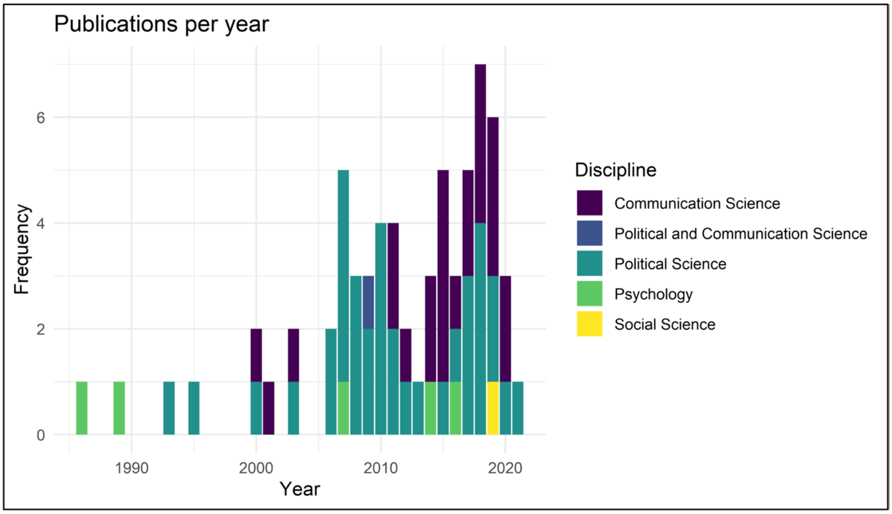
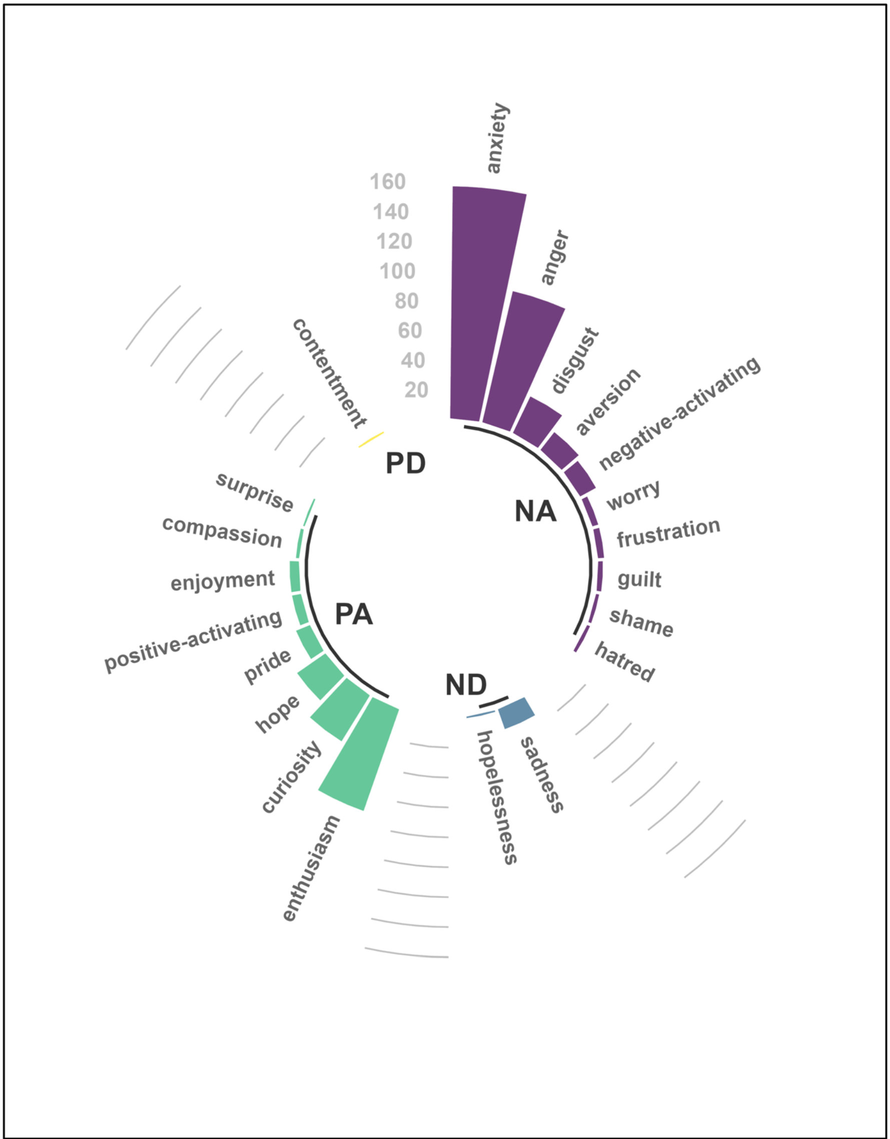


Fig. 2 Number of publications per year and discipline

of the studies utilized experimental designs (54%), followed by cross-sectional studies (27%), and longitudinal studies (17%), 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 in the studies (see Fig. 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 elections, 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%). These emotions were largely assessed with self-report measures (78% of effect sizes). In experimental designs, authors either used self-report emotion measures after the experimental manipulation (62%), the assignment to the experimental groups (35%), or a combination of both to calculate the effect sizes. To manipulate emotions, researchers utilized texts in combination with images (e.g., Clifford & Jerit, 2018; Lamprianou & Ellinas, 2019; Ryan, 2012) and videos (e.g., Kim, 2016) or videos alone (e.g., Brader, 2006; Sirin et al., 2011). Brader (2006), for example, created professional political ads including images and music to induce enthusiasm or fear, which additionally varied in how evocative they were. Others utilized prompts with a task to recall and describe in detail an emotional situation or list thoughts, for example describing something during a campaign that made one feel angry or enthusiastic (Ditonto et al., 2017; Valentino et al., 2008,



Note. NA = negative-activating emotions (N = 314), ND = negative-deactivating emotions (N = 15), PA = positive-activating emotions (N = 156) and PD = positive-deactivating emotions (N = 1)

Fig. 3 Number of effect sizes per emotion

2009), or a prompt to list worries about a specific policy issue (e.g., immigration; Albertson & Gadarian, 2015; Gadarian & Albertson, 2007).

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 11% each on knowledge and knowledge gain.[2] Studies utilized various methods to assess learning, ranging from self-report questions (63%), behavioral measures (17%; especially with information seeking), to knowledge tests (21%) either based on general political knowledge or specific information provided during the studies.

Results of Individual Studies

The results of individual studies are summarized in Table E1.

Synthesis of Results

For synthesizing effect sizes, we first conducted multilevel random-effects models for each group of emotions (positive-activating, negative-deactivating, negative-activating), and for the discrete emotions 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 ($r = 0.13$, 95% *CI* [0.06, 0.19]). Enthusiasm showed a small positive association with learning in cross-sectional designs ($r = 0.10$, 95% *CI* [0.01, 0.19]; see Figure F1 in Section F of the Supplementary Information).

Negative-Deactivation Emotions

Our second hypothesis, which assumed negative associations between negative-deactivating emotions and learning, was not supported ($r = 0.03$, 95% *CI* [−0.16, 0.22]), but results should be interpreted with caution as the model is based on only three effect sizes.

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

Table 1 ML-random-effects model results

Model	k	N	r	CI	t (df)	p	% Variance (I^2)		
							Level 1	Level 2	Level 3
Cross-sectional designs									
Pos.-Act. Emotions	12	42	0.128	[0.061, 0.194]	3.846 (41)	0.000	5.768	**38.251**	**55.981**
Enthusiasm	6	19	0.101	[0.008, 0.191]	2.288 (18)	0.034	4.918	**60.576**	34.506
Neg.-Act. Emotions	22	83	0.049	[0.009, 0.089]	2.407 (82)	0.018	7.279	**32.795**	**59.926**
Anxiety	19	45	0.027	[−0.019, 0.072]	1.188 (44)	0.241	7.692	**27.607**	**64.702**
Anger	12	32	0.061	[0.006, 0.116]	2.257 (31)	0.031	8.370	**49.334**	42.296
Neg.-Deact. Emotions	2	3	0.032	[−0.160, 0.222]	0.721 (2)	0.546	28.143	0.000	71.857
Experimental designs									
Pos.-Act. Emotions	6	16	0.057	[−0.120, 0.231]	0.685 (15)	0.504	5.810	**10.982**	**83.207**
Enthusiasm	5	10	0.002	[−0.064, 0.068]	0.054 (9)	0.958	60.333	39.667	0.000
Neg.-Act. Emotions	19	107	0.060	[0.013, 0.107]	2.536 (106)	0.013	12.270	**51.528**	**36.202**
Anxiety	16	45	0.055	[−0.036, 0.146]	1.219 (44)	0.230	7.017	0.787	**92.196**
Anger	13	25	0.109	[0.029, 0.188]	2.797 (24)	0.010	20.060	0.000	**79.940**
Neg.-Deact. Emotions	3	7	0.008	[−0.244, 0.259]	0.076 (6)	0.942	16.910	0.000	**83.093**

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 sample), and level 3 to the variance between studies (using different samples). Significant variability in the variance between effect sizes and studies is displayed in bolt

Negative-Activating Emotions

The overall correlation between negative-activating emotions and learning was small and positive ($r=0.05$, 95% *CI* [0.01, 0.09]). However, as shown in Figure F2, there was a great variation of effect sizes. The model on anxiety did not reveal a significant overall association between anxiety and learning ($r=0.03$, 95% *CI* [−0.02, 0.07]). In contrast, anger revealed a small positive overall correlation with learning ($r=0.06$, 95% *CI* [0.01, 0.12]).

Associations Between Emotions and Learning from Experimental Studies

Positive-Activating Emotions

Our model, including effect sizes from positive-activating emotions and experimental designs, did not reveal a significant overall correlation ($r=0.06$, 95% *CI* [−0.12, 0.23]. The same finding holds for the model on enthusiasm ($r=0.00$, 95%

CI [−0.06, 0.07]). For this model, only five publications including ten effect sizes about enthusiasm were included (see Figure F3 in the Supplementary Information, Section F).

Negative-Deactivating Emotions

Again, we could use only few effect sizes to test Hypothesis 2 on negative-deactivating emotions, which was not supported ($r = 0.01$, 95% *CI* [−0.24, 0.26]).

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 ($r = 0.06$, 95% *CI* [0.01, 0.11]). Regarding discrete emotions, no significant association could be found for anxiety ($r = 0.06$, 95% *CI* [−0.04, 0.15]), but a small positive effect for anger ($r = 0.11$, 95% *CI* [0.03, 0.19]).

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 Supplementary Information, Section G [Table G1 and G2]). We therefore proceeded to moderation analysis with these models. All estimated BRMA models indicated convergence, with Rhat close to 1, sufficient effective sample sizes and well-mixed parameter trace plots for all moderators. As shown in Table H1, we could not identify any relevant moderator from the included variables. In order to verify whether results differ depending on the type of learning outcome (cognitive versus behavioral), we conducted an additional moderator analysis. Here, the included dummy variable differentiating between cognitive (knowledge, knowledge gain) and behavioral learning categories (information seeking, attention to politics, discussions) did not reveal any significant effects (see Supplementary Information, Section H, Table H2).

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 Supplementary Information). 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

Table 2 Moderator analysis of publication status

Model	Predictor	*k*	*N*	Estimate	*SE*	*t* (df)	*p*	95% *CI*
Cross-sectional designs								
Pos.-Act. Emotions	Intercept	12	42	0.134	0.071	1.882 (40)	0.067	[− 0.01, 0.277]
	Status			− 0.005	0.082	− 0.064 (40)	0.950	[− 0.171, 0.161]
Enthusiasm	Intercept	6	19	0.115	0.141	0.82 (17)	0.423	[− 0.182, 0.413]
	Status			− 0.015	0.150	− 0.102 (17)	0.920	[− 0.331, 0.301]
Neg.-Act. Emotions	Intercept	22	83	0.072	0.040	1.782 (81)	0.079	[− 0.008, 0.152]
	Status			− 0.031	0.047	− 0.658 (81)	0.513	[− 0.124, 0.062]
Anxiety	Intercept	19	45	0.012	0.052	0.237 (43)	0.814	[− 0.092, 0.117]
	Status			0.018	0.058	0.309 (43)	0.759	[− 0.099, 0.134]
Anger	Intercept	12	32	0.090	0.110	0.819 (30)	0.419	[− 0.135, 0.315]
	Status			− 0.031	0.114	− 0.273 (30)	0.787	[− 0.264, 0.202]
Experimental designs								
Pos.-Act. Emotions	Intercept	6	16	− 0.125	0.205	− 0.61 (14)	0.552	[− 0.566, 0.315]
	Status			0.218	0.225	0.972 (14)	0.348	[− 0.264, 0.7]
Enthusiasm	Intercept	5	10	− 0.130	0.109	− 1.189 (8)	0.269	[− 0.381, 0.122]
	Status			0.141	0.113	1.251 (8)	0.246	[− 0.119, 0.402]
Neg.-Act. Emotions	Intercept	19	107	− 0.024	0.088	− 0.274 (105)	0.785	[− 0.199, 0.150]
	Status			0.091	0.091	0.996 (105)	0.321	[− 0.090, 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

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 I1 in section I of the Supplementary Information). Thus, studies with lower precision (i.e., smaller sample size) had smaller effect sizes. For experimental designs, the same occurred in models of positive-activating emotions and anxiety (see Figure I2).

Table 3 Results of Egger's regression test

Model	Predictor	*k*	*N*	estimate	*SE*	*t* (df)	*p*	95% *CI*
Cross-sectional designs								
Pos.-Act	Intercept	9	36	0.067	0.076	0.886 (34)	0.382	[−0.087, 0.222]
Emotions	Inverse of N			32.458	31.403	1.034 (34)	0.309	[−31.361, 96.277]
Enthusiasm	Intercept	5	18	0.130	0.099	1.32 (16)	0.205	[−0.079, 0.339]
	Inverse of N			−14.209	40.905	−0.347 (16)	0.733	[−100.923, 72.505]
Neg.-Act	Intercept	16	69	0.082	0.030	2.709 (67)	0.009	[0.022, 0.143]
Emotions	Inverse of N			−26.206	12.438	−2.107 (67)	0.039	[−51.032, −1.38]
Anxiety	Intercept	15	38	0.073	0.034	2.147 (36)	0.039	[0.004, 0.142]
	Inverse of N			−27.111	13.826	−1.961 (36)	0.058	[−55.152, 0.93]
Anger	Intercept	11	31	0.105	0.041	2.553 (29)	0.016	[0.021, 0.19]
	Inverse of N			−25.044	16.229	−1.543 (29)	0.134	[−58.236, 8.148]
Experimental designs								
Pos.-Act	Intercept	5	13	0.371	0.114	3.269 (11)	0.007	[0.121, 0.621]
Emotions	Inverse of N			−64.448	23.702	−2.719 (11)	0.020	[−116.615, −12.28]
Enthusiasm	Intercept	4	9	0.111	0.091	1.216 (7)	0.264	[−0.105, 0.326]
	Inverse of N			−20.476	17.836	−1.148 (7)	0.289	[−62.652, 21.7]
Neg.-Act	Intercept	17	103	0.090	0.036	2.546 (101)	0.012	[0.020, 0.161]
Emotions	Inverse of N			−4.871	5.292	−0.920 (101)	0.360	[−15.368, 5.626]
Anxiety	Intercept	14	43	0.182	0.061	2.980 (41)	0.005	[0.059, 0.306]
	Inverse of N			−22.494	8.430	−2.645 (41)	0.012	[−39.319, −5.269]
Anger	Intercept	12	24	0.087	0.069	1.265 (22)	0.219	[−0.056, 0.23]
	Inverse of N			5.673	8.510	0.667 (22)	0.512	[−11.976, 23.323]

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

Discussion

We present the first cross-disciplinary systematic review and meta-analysis 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 a decade ago already noted an increase in interest in the topic. This trend appears to have continued since then, particularly in the age of emotionally laden political events such as public health crisis (e.g., the H1N1 swine flu epidemic, the Covid-19 pandemic) or 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 which emotions have been investigated in the literature on political learning (systematic review) and analyze how they are associated with learning in the context of politics (meta-analysis). Our hypotheses based on control-value theory (Pekrun, 2006) were partially supported, and informative results regarding negative-activating emotions in our exploratory analysis were observed. 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 had no predefined hypotheses, as relations often have varied depending on the specific emotion and specific facet of learning (Pekrun et al., 2011). Interestingly, negative-activating emotions (e.g., anger) were positively related to learning in both experimental and cross-sectional study designs. In contrast to studies in the field 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. Ryan (2012) and Kim (2016), for example, found positive effects of anger on information seeking and knowledge, and consequently discuss the "the democratic value of anger" (Kim, 2016, p. 18). Kim (2016) thereby refers to the feeling-as-information model. Emotions like anger might signal that an action is needed and increase citizens' cognitive alertness. 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 (e.g., Goetz et al., 2016) and its mobilizing effect for political participation (Elliot et al., 2013; Redlawsk & Mattes, 2022).

On the other hand, anger during the learning process might lead to focus on information and arguments with respect to defending one's own political attitudes (Redlawsk & Mattes, 2022). Some in our meta-analysis included studies reported positive associations between anger and learning particularly when considering information congruent to their opinion (e.g., for information seeking: Wollebaek et al., 2019, for attention to politics: Song, 2017). Given that the majority of our effect sizes are based on outcomes like information seeking and attention to politics, less is known about breadth and depth of knowledge actually acquired. Thus, results of negative-activating emotions might only relate to shallow, in contrast to more detailed, information processing (Muis et al., 2015).

The hypothesis on negative-deactivating emotions was not supported, but models were based on just a 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. A recent study has already revealed negative associations 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., 2024). Therefore, 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 Literature 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 studies is based on the US (70%), only 12% of the studies are including non-western countries. Predominance of western, educated, 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 citizens' 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., 2024) 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. Relatedly, future studies are encouraged to analyze whether the role of emotions differs between formal civic education at schools and informal learning settings.

Implications for Theory, Practice, and Future Studies

Overall, results are partly in line with 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 to 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 increasing 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 suggested that models of 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.

What do these small, positive effects of negative-activating emotions mean for the control-value theory and the affective intelligence theory? Similar results, meaning positive effects for both anxiety and anger, were found in a recent review on emotions and information seeking (Funck & Lau, 2023). The authors argue that given the contradictions to affective intelligence theory, there is a need for a new theory about emotions for the context of politics. In control-value theory, positive effects of negative-activating emotions are possible, but far from common (e.g., Pekrun et al., 2011). One explanation might be the object focus of the emotions. In contrast to typical achievement emotions, which for example, focus on taking a test, emotions in our current study were mainly focused on political topics or activities during which political information was processed. It might be that activating topic emotions mainly increases the focus and attention, and, if the context allows, learning. However, learning could still depend on the intensity of experienced emotions and the difficulty of the learning task, but also type and the quality of learning. Additionally, characteristics of the learning context might be important, especially in the complex situations where political learning usually takes place. Future studies are encouraged to further develop the control-value theory with respect to its assumptions related to negative-activating emotions. For example, it should be analyzed whether there are systematic differences between discrete emotions of this category, learning contexts, and the quality of learning.

Our classification and analysis of emotions is built on Pekrun's (2002, 2018) cognitive motivational model as part of his control-value theory. In this model, emotions are categorized along the dimensions of valence and arousal, consequently resulting in four emotion groups (positive-activating, positive-deactivating, negative-activating, and negative-deactivating). These two dimensions are broadly supported by studies using judgments of faces, words, and self-report ratings of experiences (Barrett & Bliss-Moreau, 2009). Categorization, however, always comes along with a reduction of complexity and information, which would be available with more fine-grained metrics. Additionally, there is still a lack of cumulative evidence on the associations of emotions and physiological arousal (Horvers et al., 2021). While in this meta-analysis, the categorization allowed us to include as much information as possible while still differentiating between core dimensions relevant for learning, there is a need for future studies to validate the classification of discrete emotions.

Similarly, we did not find moderating effects of the learning category. However, this might be explained by the relatively low number of effect sizes per category in each estimated model. When more studies will exist in the future, it would be of great interest to further inspect whether associations between emotions and learning differ depending on the learning category or the quality of learning. Further, the learning categories could be combined into a path model (e.g., with paths from emotions to knowledge gain mediated by attention, information seeking, and discussion) and tested with a meta-analytic structural equation model (Jack & Cheung, 2020).

According to Lupia (2016), civic educators[3] 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 by our results on associations of negative-activating emotions (particularly anger) and 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 when trying to enhance learning through emotions. For example, anger has been shown to negatively relate to institutional trust (e.g., Erhardt et al., 2021) and positively to populist attitudes (e.g., Rico et al., 2017). Further, anxiety was identified as a driver of believing in misinformation (Freiling et al., 2023). Given that the effects we observed were relatively small, there is a need to carefully weigh the positive impacts of emotions against any potentially unfavorable side effects.

Though we could not identify moderators to the overall effects in this meta-analysis, we found considerable variation in the effects. This might still be explained by the relatively low number of effect sizes and variation in moderators per model. 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. Additionally, characteristics of the learning outcomes, such as the quality of discussions, type of knowledge, or the breadth of information searched for might be possible moderators to consider in future when investigating the association between emotions and learning.

[3] While Lupia (2016) refers to various stakeholders who can serve as civic educators (e.g., teachers, issue advocates, journalists), we primarily define civic educators as teachers in educational settings (e.g., schools, universities, adult education).

Finally, a great challenge for the cross-disciplinary synthesis were diverging reporting standards. Many effect sizes had to be excluded, as only unstandardized regression coefficients from multiple regression models were reported. We recommend future studies to include descriptive and bivariate measures, no matter whether published or unpublished, and to make their data openly accessible. 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 aim of this cross-disciplinary systematic review and meta-analysis was to synthesize current research on the associations between emotions and political learning. Small positive associations for positive-activating emotions (e.g., enthusiasm) and negative-activating emotions (e.g., anger) imply that these emotions might help to raise attention and keep citizens informed about current political matters. Still, more research is needed to investigate systematic heterogeneity in the effect sizes, particularly focusing on the contexts and the quality of political learning.

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Data Availability Data and accompanying analysis scripts are available via OSF.

Declarations

Conflict of Interest The authors declare no competing interests.

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