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ABSTRACT

This paper presents MORESPulse, a freely available, theory-grounded, and expert-validated multilingual large language model based on XLM-RoBERTa that detects the textual manifestation of five primary emotions (anger, fear, sadness, joy, and disgust) in political texts across seven European languages. We illustrate its scientific potential through a longitudinal analysis of the Hungarian Parliamentary Corpus from 1998 to 2022, covering more than five million sentences across six electoral cycles. Emotional language has increased steadily since 2010, driven primarily by opposition Members of Parliament (MPs) and smaller party representatives, while government MPs show a comparatively stable and more restrained emotional tone. Anger and joy are the most prevalent emotions across the corpus, while disgust remains negligible. Emotional intensity also varies systematically by policy topic: macroeconomics, immigration, and health generate higher levels of emotional language, while foreign trade consistently produces the lowest. These findings suggest that emotionalization is a consistent and enduring feature of Hungarian parliamentary discourse rather than an episodic rhetorical response, with implications for how scholars understand affective dynamics in democratizing and backsliding political contexts.

KEYWORDS

Emotion analysis; LLM; large text corpora; political science; XLM-RoBERTa

Introduction

How has the emotional language of parliamentary debate evolved over the past quarter-century, and what tools enable us to trace it across decades and linguistically diverse legislatures? Political debates have long served as forums for exchanging ideas and negotiating visions on collective futures (MacKenzie, 2021). In recent decades, however, they have undergone a marked emotionalization: emotional appeals, affect-rich rhetoric, and personal attacks increasingly overshadow factual analysis and rational argumentation (Cepernich & Novelli, 2018; Szabó, 2020). More than a stylistic shift, emotionalization signals a transformation in political communication where emotions not only color but fundamentally steer public discourse, shaping how issues are framed and alliances formed, and how citizens engage with politics (Halperin & Schwartz, 2010). Its consequences are far-reaching: emotionalization can intensify polarization and negative campaigning, reduce tolerance for opposing views, and reorient political engagement toward affective reactions rather than deliberati (Beichelt, 2022; Nai et al., 2022). Modern political communication exploits emotional narratives with unprecedented scale and sophistication (D'Ambrosio, 2022; Richards, 2004; Szabó, 2020). Politicians deploy evocative stories, emotionally charged language, and symbolic imagery to mobilize supporters, demonize opponents, and shape public perception (Marcus et al., 2000). These strategies are neither static nor uniform: they evolve alongside social crises, institutional changes, and changes in party competition (Bramsen & Poder, 2018; Leach & Bou Zeineddine, 2021). This underscores the need for a longitudinal perspective, as only by tracking emotional patterns across electoral cycles and key political events can scholars grasp continuity, episodic surges, or transformations in the emotional tone of political communication (see Valentim & Widmann, 2023; Widmann, 2021).

Despite this, longitudinal emotion research remains rare, explicable by gaps. First, available tools are predominantly trained on English texts, leaving low-resource Central and Eastern European languages underrepresented. Translation pipelines are an unreliable substitute, since affective cues often hinge on language-specific idioms and

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morphological markers. Second, most quantitative emotion analyses rely on dictionary or polarity-based methods that miss negation, irony, and context-dependent meanings central to political rhetoric (Boukes et al., 2019; Rheault et al., 2016). Third, where emotion classification does exist, it tends to reduce affect to broad valence categories rather than the theory-grounded primary emotions that political-communication research increasingly treats as functionally distinct (Brader, 2006; Widmann, 2021).

This paper addresses these gaps by introducing MoresPulse, a multilingual, expert-validated large language model fine-tuned to detect five primary emotions – anger, fear, sadness, joy, and disgust – in political texts across seven Central European languages. To illustrate its scientific potential, we apply MoresPulse to Hungary's parliamentary speeches from 1998 to 2022 and trace the evolution of emotional dynamics of democratic discourse across six electoral cycles and a populist-illiberal turn.

The study contributes to the literature in four ways. Theoretically, it operationalizes primary emotions for longitudinal political analysis, distinguishing episodic emotional surges from affective routines. Methodologically, it offers a fine-tuned, multilingual transformer-based tool that overcomes the limitations of dictionary methods and English-centric pipelines. Empirically, it presents the first quarter-century-spanning, sentence-level analysis of emotional expression in the Hungarian Parliament. Infrastructurally, the model and code are released openly, lowering the entry barrier for cross-national replication in low-resource language settings.

The paper proceeds as follows. Section 2 outlines the conceptual challenges of measuring emotional displays in political discourse and defines the primary emotions targeted by MoresPulse. Section 3 reviews computational approaches to emotion detection in political texts and identifies the methodological gaps the tool fills. Section 4 details design: model architecture, training data, fine-tuning, and expert validation. Section 5 applies MoresPulse to the Hungarian parliamentary corpus and presents longitudinal findings. Section 6 discusses the results in light of existing literature, and Section 7 concludes with implications and directions for future research.

The challenge of measuring emotional displays in political discourse

Emotions are both evolutionarily ingrained and culturally constructed, which makes their measurement in political discourse exceptionally complex (Ahmed, 2013). Primary emotions form the basic elements of more complex ones: joy is a component of pride, and can be transformed through political discourse (Griffiths, 2003; Majeed, 2024). While primary emotions are universal human responses (Ekman, 1992a, 1992b), their expression is heavily shaped by cultural norms that dictate how individuals should feel and how they should display feelings publicly (Hochschild, 1979, 1983). These internal expectations, known as "feeling rules," and outward social conventions, or "display norms," vary across gender, social groups, and contexts, which add substantial challenges to analyses of emotional expression (Boler & Davis, 2018; Penić et al., 2024). This variability is vividly illustrated by expectations for emotional displays among political leaders across cultures (Masters et al., 1986). In many Western societies, leaders are encouraged to show strong emotional reactions, such as anger or empathy, during crises, which are often interpreted by audiences as signs of authenticity and decisive leadership (Gardner et al., 2009). Emotions in political communication simultaneously reflect a speaker's internal state and act as deliberate rhetorical tools to influence audiences (Bitzer, 2020). Complex emotions like outrage or pride blend several emotional elements and moral evaluations, resisting simple classification into discrete categories (TenHouten, 2006). For instance, labeling an opponent's policy as "outrageous" conveys both an emotional reaction and moral condemnation designed to sway public opinion (Macagno & Walton, 2010). This dual function is especially pronounced in politics, where emotional appeals not only reflect individual feelings but shape collective perceptions, reinforce in-group identities, and delegitimise opponents (R. C. Solomon, 1993; T. Solomon, 2026).

Emotional displays are further complicated by their evolving cultural and political meanings: what is considered appropriate or effective emotional expression changes over time and across political contexts. Emotionalization thus simultaneously reflects and shapes micro-level expectations (how individuals should feel) and macro-level feeling structures (shared societal attitudes) (Koschut, 2020; Lerner & Rivkin-Fish, 2021).

The emotionalization of political discourse is largely shaped by political elites, with Members of Parliament playing a central role (Salgado & Bos, 2024). Politicians frequently harness emotional language to forge a connection with audiences (Valentim & Widmann, 2023; Widmann, 2021). Emotional cues make political messages more memorable, therefore more persuasive.

Emotional appeals operate through peripheral persuasion routes, shaping collective moods, influencing policy support, and ultimately affecting the dynamics of democratic life (Frevert et al., 2022; Metz & Plesz, 2025; Petty & Cacioppo, 1986). Reliable analysis therefore requires sensitivity to political-cultural contexts and awareness of how emotions are strategically deployed, a complexity that conventional dictionary-based methods are ill-equipped to handle (Fink et al., 2023; Wilce, 2009).

Dictionaries identify emotions by matching words in a text to predefined lists of emotion-related terms (for example, words denoting fear). While this approach is computationally straightforward, it has substantial limitations. First, dictionaries lack understanding of the indirectness of emotional manifestation: they evaluate words in isolation, failing to account for how meaning shifts based on surrounding words or sentence structure – such as distinguishing whether "sick" refers to illness or excitement. Second, they offer limited nuance, often missing complex or subtle emotional cues, idiomatic expressions, sarcasm, or phrases where emotional meaning only emerges at the sentence level. Third, dictionaries require manual compilation per target language, posing significant challenges for low-resource or morphologically rich languages. Finally, dictionary-based approaches rely on static word lists, making them ill-equipped to adapt to the dynamic evolution of language. In contrast, a multilingual large language model like MoresPulse, can be fine-tuned for emotion detection to overcome these shortcomings.

Measuring emotion manifestation in political texts: the conceptual background of MoresPULSE

MoresPulse is a fine-tuned multilingual Large Language Model for emotion detection in political texts. By processing entire sentences, it captures context, negations, irony, and implicit emotional cues that dictionary-based methods miss, including in underrepresented languages like Hungarian. It does not outsource academic work to AI; it is a human-guided tool to enhance research. The initial human intervention is defining emotions and their manifestations, which form the foundation of the model.

MoresPulse focuses on primary emotions: deeply rooted responses like anger, fear, joy, sadness, and disgust, which play a central role in political communication. Surprise was excluded from the final taxonomy because its manifestations in political discourse are often highly context-dependent and ambiguous: expressing surprise frequently functions not as standalone emotional category but as a mechanism that destabilizes established interpretations and activates new affective states (Depraz, 2025). Moreover, because surprise lacks strongly prototypical and consistently recurring linguistic manifestations in political discourse, constructing reliable annotated training data proved substantially more difficult than for other primary emotions, which made distinguishing surprise from the emotional reactions it triggers analytically less reliable in longitudinal parliamentary corpora.

Importantly, politicians and media actors leverage emotions to simplify complex realities, connect with audiences on an intuitive level, and craft resonating narratives. Because primary emotions are visceral and immediate, they can override rational deliberation, encouraging snap judgments aligned with existing biases or group identities. This makes them a double-edged sword: while they can energize democratic participation, they can also distort debate, deepen divisions, or legitimize exclusion. Understanding how primary emotions operate in political communication is therefore essential for scholars, practitioners, and citizens, shedding light on how leaders persuade, how narratives shape public opinion, and how emotions strengthen or undermine democratic dialogue and cohesion. In the following sections, we outline the definitions of the emotions that underpin MoresPulse.

Fear

Fear appeals are among the most researched tools in political rhetoric, employed to heighten perceived risks and bolster support for policies or candidates promising safety (Robin, 2004: Valentino et al., 2011; Wodak, 2015). By framing issues like immigration as threats, using terms like "invasion," politicians amplify public anxiety and push audiences toward risk-averse, conservative policies (Huddy et al., 2005; Kinder & Sanders, 1990; Lakoff & Johnson, 1980). Fear appeals can deepen polarization by exaggerating threats, eroding institutional trust, and reinforcing in-group /out-group divisions (Füredi, 2007; Iyengar & Westwood, 2015; Mason, 2018).

Anger

Anger arises from perceived injustices, often targeting specific individuals, groups, or institutions (Lazarus, 1991). It transforms dissatisfaction into demands for change, mobilizing protests, voting, and advocacy (Jasper, 1998), and allows politicians to identify scapegoats and rally support through moralistic language emphasizing the righteousness of their cause (Crawford, 2013). Indignation – a moral form of anger prototypical in politics – responds to perceived norm violations (R. C. Solomon, 1993), enabling actors to claim the moral high ground while delegitimizing opponents (Haidt, 2012) and appealing to audiences' sense of fairness (Goodwin et al., 2001). While anger-family emotions energize political participation, they also deepen polarization and can foster radicalism when grievances go unaddressed (Mason, 2018; Müller, 2016). In political texts, anger manifests across a range of rhetorical forms – including irony, sarcasm, verbal aggression, and grievance framing – and frequently blurs into related affects like indignation, contempt, and ressentiment (Beichelt, 2022; Capelos et al., 2022; Feldman, 2023).

Sadness

Sadness arises from loss, decline, disappointment, or perceived injustice, motivating reflection and a call for consolation rather than immediate action (Eng & Kazanjian, 2003; Lazarus, 1991), and may be triggered by collective losses of self-worth, economic security, political influence, or identity (Demertzis, 2020). Political actors use it to humanize abstract issues through personal stories of suffering, evoking compassion – as in social justice movements where sadness over systemic injustice highlights its human consequences (Goodwin et al., 2001; McIvor, 2016). Sadness can unite communities by emphasizing shared grief, strengthening communal bonds and promoting solidarity (Durkheim, 1912), while also enhancing the moral authority of politicians who express concern (Nussbaum, 2001). During crises like the COVID-19 pandemic or armed conflict, stories of loss underscore severity and advocate for humanitarian responses (Murthy & Lakshminarayana, 2006; Wardman, 2020). Sadness also operates as a component of more complex states – nostalgia, disappointment, pessimism – expressed through framings like broken promises and collective decline (Gotlib, 2018).

Joy

Politicians use joy to inspire, unify, and galvanize public support through positive visions of the future, celebrating successes, and building shared purpose (Isen, 2004; Nussbaum, 2013). Joyful rhetoric is connected to optimism and celebration about collective achievements that reinforce shared values, goals, and identity (Brader, 2006; Goodwin et al., 2001), while public commemorations leverage joy to strengthen national pride and unity (Smith, 1992). Politicians use joyful expressions to boost morale, establish political legitimacy by linking past accomplishments to future aspirations (Enjalbal, 2024), and counterbalance negative emotions during crises to maintain morale (Fredrickson, 2001; Marcus et al., 2000). However, joy-based rhetoric can slip into "toxic positivity" silencing critique and obscuring structural problems (Gruber et al., 2011; Held, 2004).

Disgust

Disgust originally evolved as a protective response to physical contamination but has become moralized and increasingly deployed in sociopolitical contexts, extending to behaviors, ideologies, and groups deemed morally or culturally impure (Haidt, 2012; Jasper, 1998; Rozin et al., 2009). Referencing filth, disease, or contamination appear in rhetoric aimed at delegitimizing opponents; phrases like "rotten democracy" or "putrid policy" serve as emotional cues evoking collective moral decay. Disgust functions as a boundary-setting device, drawing lines between the "pure" in-group and the "impure" out-group and reinforcing moral hierarchy (Hodson & Costello, 2007). Migrant populations depicted as a "scabies-infested threat" or LGBTQIA+ communities as "deviant lifestyles" exemplify how disgust frames difference as contagion (Grinan-Moutinho, 2022; Mason, 2018), making it potent in polarized environments where opponents are rendered not merely wrong but repulsive.

None of them

This category encompasses neutral statements that do not exhibit the five primary emotions – factual reporting, procedural language, technical explanations, and routine administrative content that serves informational rather than emotional purposes (Van Dijk, 2003). Neutral language includes statistical presentations, legislative procedures, budget allocations, and objective policy descriptions (Proksch & Slapin, 2015); however, the absence of detectable emotion does not necessarily indicate complete neutrality, as political actors may employ strategic restraint to convey authority, or expressions may be too subtle or culturally specific to be captured (Chilton, 2004). By identifying emotionally neutral content, MoresPulse enables researchers to distinguish between heightened emotional discourse and routine communication, providing baseline measurements for understanding when and why political language becomes emotionally charged.

Complex or non-primary emotions like hope, pride, nostalgia, or contempt are not treated as separate analytical categories. Depending on their linguistic construction, they may partially overlap with one primary emotion (e.g. some hope expressions may overlap with joy) or remain uncoded within "none of them."

Computational approaches to emotion detection in political discourse

Computational research on political emotion has progressed along three methodological generations, each addressing the limitations of the previous one. Dictionary-based approaches like NRC (Mohammad & Turney, 2013) and the Lexicoder Sentiment Dictionary (Young & Soroka, 2012) – match texts against pre-defined emotion-term lists. While computationally cheap and easy to interpret, they evaluate words in isolation, miss negation and sarcasm, and require manual compilation for each language, which makes them ill-suited for morphologically rich, low-resource languages such as Hungarian (Boukes et al., 2019; Rheault et al., 2016). Classical machine learning (e.g., SVM, naïve Bayes) improved cross-domain performance but still relied on hand-crafted features and large in-domain training sets (Balahur, 2013).

The third generation builds on transformer-based language models (Devlin et al., 2019), which encode context-sensitive meaning and can be fine-tuned for sentence-level emotion classification. Multilingual variants like XLM-RoBERTa (Conneau et al., 2020) extend this advantage to under-resourced languages by jointly pre-training on parallel corpora, enabling cross-lingual transfer without translation loss. Recent applications to political texts illustrate this turn: Wicke and Bolognesi (2025) use contextual embeddings to contrast lexical and emotional choices in the Trump–Harris 2024 presidential debate, while

Berthele (2026) and Berthele and Shafer (2025) analyze sentiment, subjectivity, and the foreign-language effect in Swiss multilingual parliamentary debates. These studies confirm the methodological maturity of LLMs for political discourse but remain limited to specific events, single legislatures, or narrow time windows.

Longitudinal evidence on emotionalization is correspondingly scarce. Wyss, Beste, and Bächtiger (2015) trace the cognitive complexity of Swiss immigration debates across five decades through semi-automated indicators; Bartscherer (2023) combines automated dictionary analysis with qualitative discourse analysis to examine more than a century of British party speeches. Both studies underscore the value of long time horizons yet are constrained by the methodological compromises of dictionary or hybrid designs. Work on polarizing language (Donohue & Hamilton, 2022) further argues that emotional valence and identity-loaded vocabulary must be analyzed jointly, a requirement existing tools rarely meet at scale.

Three gaps emerge from this literature. First, most fine-tuned LLM tools for political emotion remain monolingual or English-centered, leaving Central and Eastern European languages largely uncovered. Second, the few longitudinal designs available rely on dictionary or hybrid approaches with shallow semantic coverage, which compromises the validity of inferences about long-term emotionalization. Third, available emotion classifiers tend to reduce affect to polarity (positive/negative) or broad valence categories, missing the theory-grounded emotion repertoire (anger, fear, sadness, joy, disgust) that political-communication research increasingly identifies as functionally distinct (Brader, 2006; Valentim & Widmann, 2023; Widmann, 2021). MoresPulse is designed to address all three gaps simultaneously: it is multilingual, fine-tuned on expert-coded political training data across seven Central European languages, applicable to decades-long corpora, and grounded in primary-emotion theory.

Methodology design of MoresPulse

The model employs a theory-driven framework grounded in primary emotion theory to ensure classifications align with established psychological and political communication research rather than generic commercial applications. Its multilingual architecture, built on XLM-RoBERTa, provides robust performance across smaller Central European languages, with native-speaking political communication experts validating performance in each language for cultural and linguistic accuracy (Salmerón-Ríos et al., 2024). Critically, MoresPulse captures six distinct manifestation types of emotional expression – from direct acknowledgment to figurative expressions and emotive descriptions of events – enabling detection of subtle semantic cues, irony, and implicit emotional displays that conventional dictionary-based methods ignore (Overbeck et al., 2023).

Model architecture

For MoresPulse, we selected the XLM-RoBERTa multilingual architecture, pre-trained on data from all target languages. Compared to monolingual alternatives, this simplifies maintenance, increases cross-lingual consistency, and leverages knowledge from resource-rich languages to improve performance for low-resource ones, a critical advantage for Central European languages. We opted for the Large variant of the model (355 M parameters), which captures more nuanced contextual relationships than the Base model, making it particularly suitable for the complex emotional expressions in political discourse.

Fine-tuning and training data development

MoresPulse was developed to analyze political speeches across seven languages (Czech, English, French, Hungarian, German, Polish, and Slovak) using a sentence-level approach. Expert-coded training data was developed for German, Hungarian, and Polish using double-blind coding, for the remaining languages, machine translation via the Google API extended coverage. Initial fine-tuning using only the German dataset produced unsatisfactory results due to class imbalance, so underrepresented emotion categories were augmented with synthetic data generated by GPT-4-turbo, following an established methodology (Üveges & Ring, 2025). Training data counts by language and emotion category are reported in Appendix A (Table A1).

Model performance

Rather than developing separate language-specific models, we created a single pooled model trained on all available data, fine-tuned on a single NVIDIA A100 GPU using stratified 80/20 train-test splits. Model performance was evaluated using the weighted mean F1 score (macro F1), which provides a balanced measure that mitigates the inflation issues common to simple accuracy metrics. MoresPulse achieved consistent results across all seven target languages, with weighted average F1 scores ranging from 0.81 to 0.82 – a variation of less than one percentage point. Detailed language-specific results are provided in Appendix B (Figure B1).

Expert validation

Expert validation is crucial to ensure that LLM outputs are accurate and reliable for cross-linguistic emotion detection. We conducted comprehensive validation across all target languages through iterative rounds of expert review and model refinement. Native speakers were recruited as validators wherever possible, including German, Hungarian, and Polish native speakers with expertise in political communication. For languages where native speakers were unavailable, we engaged validators with advanced proficiency and demonstrated competence in emotion analysis. In each validation round, reviewers examined model outputs, identified inaccuracies, and provided corrections; the model was subsequently retrained until satisfactory performance was achieved.

We established a minimum threshold of 75% accuracy for each emotion category; lower performance triggered additional rounds of validation and model adjustment. The process continued until all emotion categories in all languages met or exceeded this standard, ensuring cross-linguistic reliability.

Illustrating the MoresPulse: analysis of Hungarian Parliamentary Corpora

The Hungarian context

Between 1998 and 2022, Hungary's National Assembly underwent significant institutional and political transformations. Hungary's unicameral legislature historically comprised 386 members elected every four years through a mixed electoral system combining single-member districts and party lists. In 2011, the new Fundamental Law reduced the number of seats from 386 to 199 starting with the 2014 elections – a reform that intensified the stakes of each seat and combined with a 5% electoral threshold, contributed to growing party consolidation and Fidesz–KDNP 's structural dominance.

Politically, the period saw dramatic shifts. From 1998 to 2002, the conservative Fidesz party led by Viktor Orbán, governed in coalition. Between 2002 and 2010, the Hungarian Socialist Party (MSZP), often allied with the liberal SZDSZ, held power – an era marked by political instability, economic challenges, and widespread disillusionment that eroded trust in left-liberal leadership. In 2010, Fidesz–KDNP won a supermajority, enabling constitutional reform and sweeping institutional changes. From 2010 onward, Fidesz adopted increasingly nationalist, anti-elite, and anti-migration rhetoric, securing supermajorities in 2014, 2018, and 2022. Over these cycles, the Hungarian political landscape polarized sharply, with growing concerns over democratic backsliding, media freedom, and rule of law, while opposition forces struggled to mount an effective challenge.

Research questions and hypotheses

Our analysis addresses the following research question: What are the emotional patterns of parliamentary speeches over time, by policy topic, by emotion type, and by the political identity of the speaker (governing or opposition party)? Although primarily explorative, we formulated three hypotheses.

H1: *The emotionality of political discourse is increasing over time.*

Previous research has demonstrated that emotional language in parliamentary debates is neither random nor merely stylistic, but reflects broader political, economic, and institutional dynamics (Shah, 2022). Longitudinal analyses of political corpora suggest that emotional tone changes over time and responds to periods of political conflict, economic hardship, and shifting institutional roles (Caiani & DiCocco, 2023; Rheault et al., 2016; Verduyn et al., 2009). These findings support the expectation that emotionalization constitutes a measurable and evolving feature of parliamentary communication rather than an episodic anomaly.

Recent large-scale analyses of parliamentary debates demonstrate that emotive rhetoric is systematically associated with political competition and institutional position. For example, Yildirim (2025) shows that electorally vulnerable, junior, and opposition MPs in the UK House of Commons use higher levels of emotive rhetoric, especially anger, fear, disgust, and sadness, than electorally safer or government-affiliated representatives. These findings support the expectation that emotionalization constitutes a strategic communicative resource in parliamentary politics rather than a spontaneous feature of political speech. We therefore test in H2 and H3 whether opposition and government MPs differ systematically in their use of emotional language and whether opposition speeches contain higher levels of negative emotional expressions.

H2: *Speeches of opposition MPs use more emotions than those of governing party MPs.*

H3: *Speeches of opposition MPs use more negative emotions than those of governing party MPs.*

Data and methods

To conduct a longitudinal study, we rely on the ParlText dataset (Sebők et al., 2025) of texts and metadata for parliamentary speeches, with 361,043 unique parliamentary speeches (comprising 5,178,783 sentences) from 1998–2022.

Policy content was classified using the Comparative Agendas Project (CAP) methodology (Baumgartner & Jones, 1991; Bevan, 2019), facilitated by the Babel Machine application (Sebők et al., 2024) using fine-tuned multilingual transformer models available on Hugging Face. Each text received a mutually exclusive CAP major topic classification covering 21 policy areas, including macroeconomics, immigration, health, and foreign trade.

We analyzed both the presence of emotional expressions and the specific emotions conveyed. Our dependent variables included a binary measure capturing whether any of five core emotions were detected in each speech segment and a categorical outcome specifying which particular emotion was present among the most frequent types (anger, fear, joy, sadness).

We examined a range of independent variables to understand which individual, party-level, and contextual factors influenced emotional expression. Speaker-level predictors included the gender of MPs, their parliamentary position (government or opposition), and their party's seat share. Party-level characteristics included ideological orientation, with categories representing party families such as socialist, religious, agrarian, or green. This classification enabled us to explore whether ideological affiliation influences emotional rhetoric. The categorization of parties into these families was based on data from the Comparative Political Data Set (Armingeon et al., 2025).

To analyze the presence of emotional content, we employed logistic regression models, estimating the probability that a given text segment contains any primary emotional expression versus none. We then applied multinomial logistic regression models to investigate which factors predict the appearance of specific emotions – anger, fear, joy, or sadness – since these outcomes are categorical and mutually exclusive. This two-step approach captures both the general tendency toward emotional language and nuanced differences in emotional tone across political, temporal, and contextual conditions.

Findings

To address our research question, we first examined the proportion of emotions across the entire corpus. As illustrated in Table 1, joy and anger are the most prominent emotions in Hungarian parliamentary speeches, followed by fear and sadness, with disgust almost negligible. The data reveal a gradual increase in emotional content over time, with a roughly 7-percentage point decrease in "none of them" from its peak to the latest cycle, a trend that becomes more pronounced from 2010 onward (Figure 1).

Table 1. Count of emotions identified over parliamentary cycles.

Cycle	Anger	Fear	Disgust	Sadness	Joy	None of them	Total
1998–2002	219471	13117	632	7010	75691	488145	804066
2002–2006	259902	14494	597	7892	96769	591737	971391
2006–2010	210662	12269	550	6979	73618	481027	785105
2010–2014	321399	16474	1033	10489	100010	604178	1053583
2014–2018	267136	12679	914	8936	89161	478769	857595
2018–2022	218875	14376	953	8973	79968	383898	707043
Total	1497445	83409	4679	50279	515217	3027754	5178783

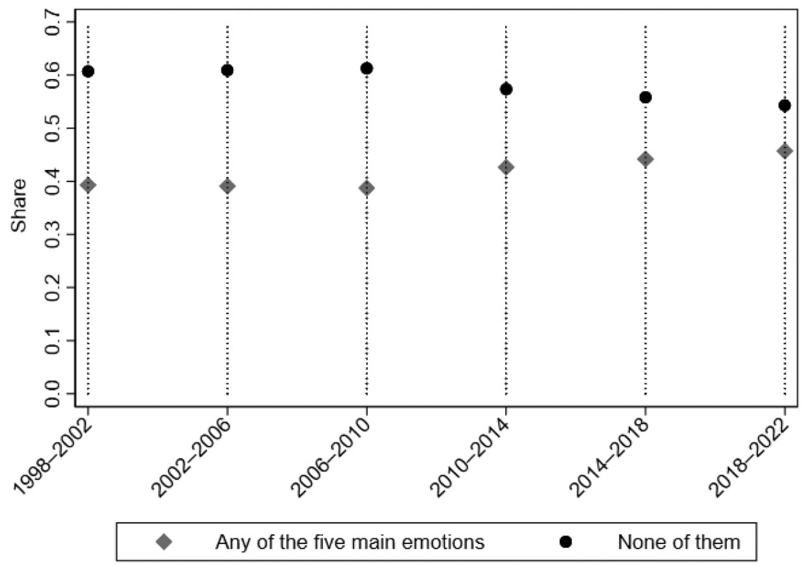

Figure 1. Share of speeches containing any of the five main emotions versus none, by parliamentary cycle.

The comparison between opposition and government MPs' speeches reveals distinct emotional tendencies. The growing emotionalization of parliamentary discourse is primarily driven by opposition MPs from 2010 onward, while the emotional tone of government speeches remained relatively stable – following a slightly decreasing trend between 1998 and 2018. Anger emerges as the most prominent emotion in both groups, though more intense in opposition speeches reflecting their critical stance. Fear and disgust are also more prevalent in opposition rhetoric, suggesting a more confrontational tone. Government speeches, meanwhile, tend to exhibit slightly higher levels of joy in recent periods, possibly projecting optimism or success (Figure 2).

Turning to the multivariate regressions, we examine the factors associated with the likelihood that a parliamentary speech contains any emotional tone, using speeches with no primary emotion as the reference category. Model 1 includes only speeches for which a major policy topic was identified. Odds ratios above one indicate higher odds of emotional expression relative to the reference group, while odds ratios below one indicate lower odds; confidence intervals crossing one indicate non-significance.

Government–opposition status and party size emerge as the strongest predictors. Government speakers have substantially lower odds of using emotional tone than opposition speakers (OR = 0.59, $p < .001$), while as a party's seat share increases, the odds of emotional expression decrease sharply (OR = 0.58, $p < .001$). These effects are large in magnitude and highly significant. Across policy topics, most categories show odds ratios below one, indicating that emotional expression is less likely than in the reference topic (Macroeconomics). The strongest reductions occur in Energy (OR = 0.78), Environment (OR = 0.81), Foreign Trade (OR = 0.76), Defense (OR = 0.81), and Domestic Commerce (OR = 0.85), all highly significant. Only Immigration shows an odds ratio above one (OR = 1.06), but this effect is not

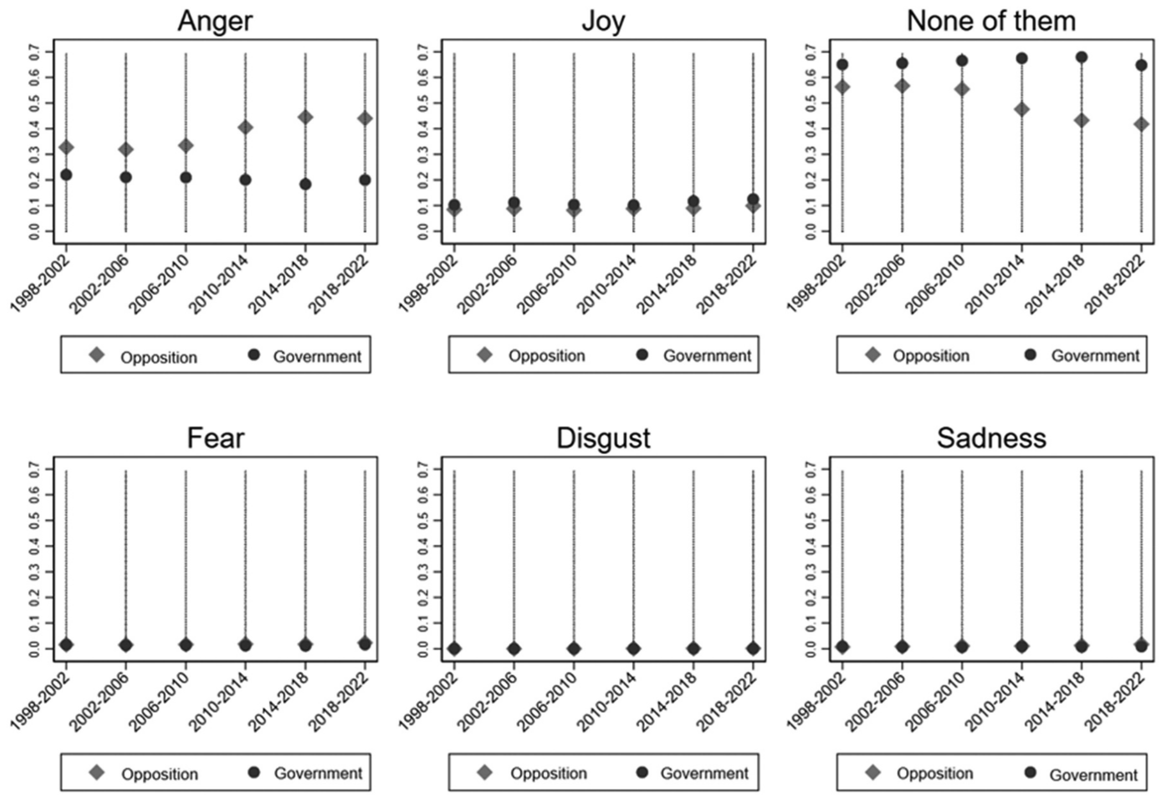

Figure 2. The proportion of each emotion in government and opposition MPs' speeches over parliamentary cycles.

statistically significant ($p = .242$). The temporal pattern is clear. Beginning with the 2010–2014 cycle, the odds of emotional expression increase significantly, with ORs of 1.17 (2010–2014), 1.16 (2014–2018), and 1.26 (2018–2022), all $p < .001$. This aligns with the descriptive evidence of a rise in emotionalization from the 2010 cycle. Differences across party types are modest. Socialist (OR = 1.15), Conservative (OR = 1.17), Agrarian (OR = 1.22), and Green (OR = 1.18) parties all show significantly higher odds of emotional expression relative to Religious parties, although differences are significant only on a $p < .05$ level.

Overall, Figure 3 displays the odds ratios from Model 1, showing that party position (government vs. opposition), party size, and parliamentary cycle exert the strongest and most consistent effects on emotional expression in parliamentary speeches.

The role of gender and government-opposition affiliation of the speaker, and seat share of speakers' party

Having examined the likelihood of any emotional expression, we turn to the multinomial model (Model 2) which focuses on the four most frequently used emotions: anger, fear, joy, and sadness. This enables us to assess the factors associated with the occurrence of four distinct emotions relative to no emotional expression. In the multinomial models, reported odds ratios are relative risk ratios from a multinomial logit with "none of them" as the base, interpretable as odds ratios conditional on the outcome being either that main emotion or none of them. Key speaker characteristics emerge as significant predictors (Figure 4): male MPs are significantly more likely to use anger and joy, whereas female MPs to express fear and, especially, sadness. Gender has a modest overall effect, though it is more pronounced for policy-relevant content, where men tend to use somewhat more emotional language than women. Political affiliation also plays a crucial role: opposition MPs are significantly more likely to use emotions in general, and especially negative emotions compared to government MPs. While opposition MPs also tend to use joy more frequently, this difference does not reach statistical significance. That is, H2 and H3 are both corroborated. Among the predictors, the seat share of the MP's party has the strongest relative

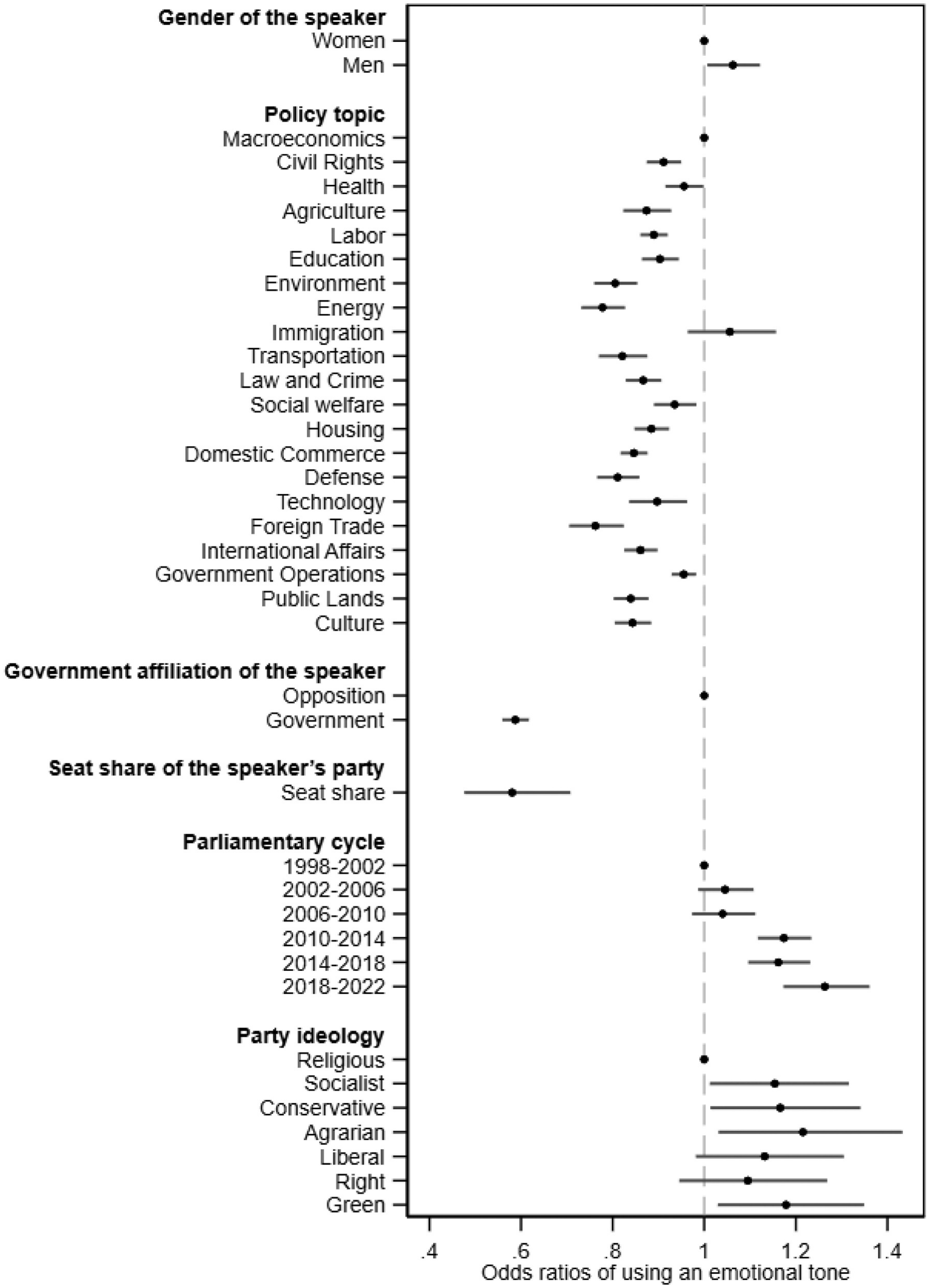

Figure 3. Odds ratios of speeches containing an emotional tone (Model 1).

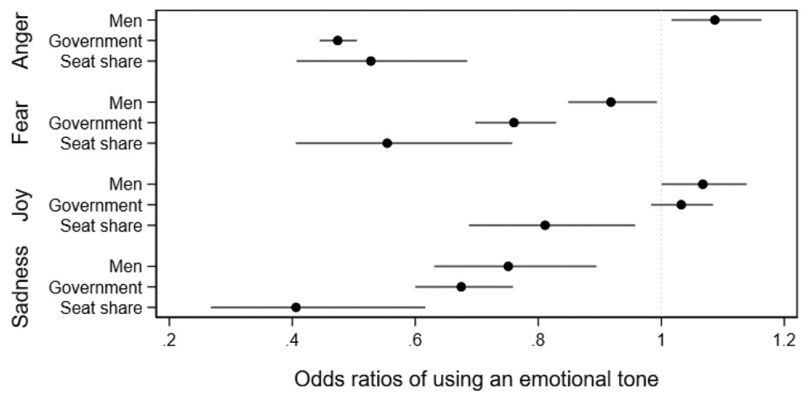

Figure 4. Odds ratios of using an emotional tone in parliamentary speeches across gender of the speaker, their government-opposition status, and their parties' seat share, in model 2.

effect. MPs from larger parties are consistently less likely to use emotional language, especially when it comes to negative emotions, with sadness showing the most pronounced estimated difference. The smallest difference we observed lies in the use of joy, though even this MPs from smaller parties are more likely to express.

The role of time

Consistent with the descriptive statistics as well as the logistic regression model, the results reveal a trend of increasing emotionalization across emotion types over successive parliamentary cycles. The most recent cycle (2018–2022) exhibits the highest positive coefficients for all four emotions. Therefore, our first hypothesis is corroborated. For anger, joy, and sadness, the increase appears gradual and steady across cycles (Figure 5). In contrast, fear remained relatively stable during the first four cycles, experienced a notable decline between 2014 and 2018, and surged significantly in the 2018–2022 cycle. A finer-grained specification (Model 4, Figure 6), replacing cycle indicators with year dummies, confirms the upward trend for anger, joy, and sadness, while fear shows a sudden and substantial spike in 2020.

Discussion

The findings confirm our three hypotheses. The emotionalization of parliamentary discourse has increased over time (H1), with the most

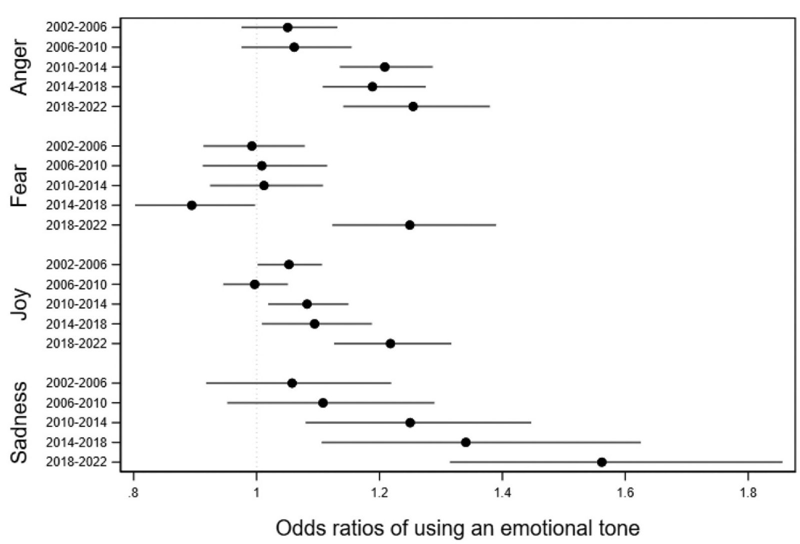

Figure 5. Odds ratios of using an emotional tone in parliamentary speeches across cycles, based on model 3.

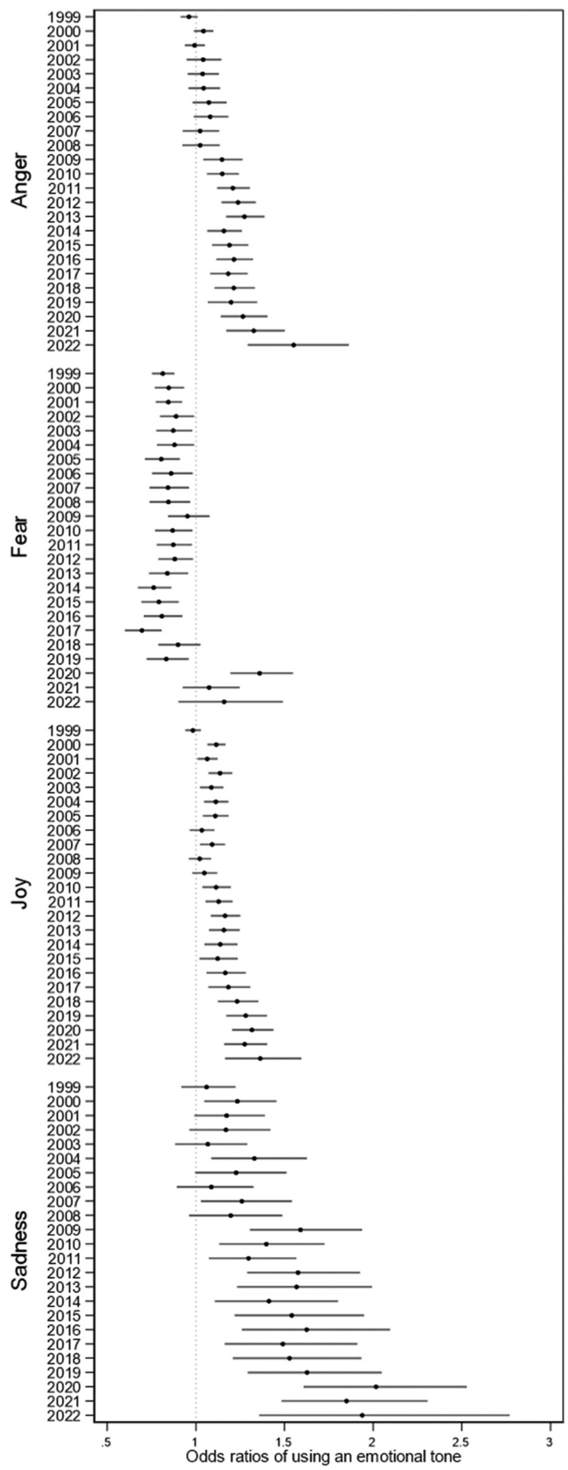

Figure 6. Odds ratios of using an emotional tone in parliamentary speeches across years, based on model 4.

pronounced rise occurring from the 2010 cycle and continuing through the most recent period. Opposition MPs consistently display higher levels of emotional expression than government MPs (H2) and particularly negative emotions – anger, fear, and sadness (H3). The use of joy is more even, but slightly higher in government speeches in recent periods. The seat-share effect operates in parallel: smaller parties consistently use more emotional language than larger ones, with the strongest difference observed for sadness.

Taken together, these patterns suggest that emotionalization is institutionalized in parliamentary debate rather than being an episodic response – a conclusion convergent with Bartscherer's (2022) analysis of British parliamentary speeches. The consistent use of anger, fear, and sadness by the opposition reflects their role in holding government accountable, whereas government MPs more often deploy joy to project confidence and success.

Our results also speak to the role of policy context. The likelihood of emotional expression varies systematically with topic: macroeconomics, immigration, and health are associated with higher levels of emotional language, while foreign trade is associated with the lowest. The pattern indicates that emotional rhetoric is unevenly distributed across the parliamentary agenda, with certain policy domains drawing more affective engagement.

These findings advance the theoretical understanding of political emotionalization in three respects. First, the longitudinal design moves the analysis beyond snapshots of single campaigns or crises and traces patterns of continuity and change. Individual emotions may be episodic, but at the collective level, their repeated invocation can normalize repertoires (such as anger in parliamentary debate) so that they become a consistent and enduring feature of political discourse rather than a fleeting rhetorical device. This temporal dimension contributes to theories of political communication by showing how emotions diffuse and sediment into discursive routines. Second, by comparing governing and opposition parties across multiple cycles, the analysis sheds light on the institutionalization of affective styles: institutional position interacts with time to shape the emotional tone of communication. Third, emotions are not merely psychological states but culturally and historically situated practices, and tracking their manifestation across decades shows how broader transformations (e.g. democratic backsliding, party-system change, rising populism) reshape the emotional grammar of politics.

Several limitations should be acknowledged. While the model performs robustly across languages and emotion types, detecting (sub)culturally specific metaphors, highly ambiguous statements, or blends of one or more primary emotions remains challenging. The focus on primary emotions excludes other affects like envy or hope, which are also potentially salient in political speech. Although expert validation improves accuracy, the risk of misclassification cannot be fully eliminated. As with all supervised NLP models, changes in display norms necessitate continuous retraining as political language evolves. The empirical scope of the present analysis is also restricted to Hungary's parliamentary record; broader generalizations require cross-national replication, which MoresPulse's multilingual coverage makes feasible.

Future research could address these limitations by expanding the model's emotion taxonomy and applying MoresPulse in comparative cross-national settings. Examining emotional patterns beyond parliamentary discourse – party manifestos, campaign speeches, or social media posts – would explore emotionalization in different arenas of political communication.

Conclusion

This study presented MoresPulse, a multilingual, expert-validated large language model designed to detect five primary emotions – anger, fear, sadness, joy, and disgust – in political texts across seven Central European languages. By applying it to Hungarian parliamentary speeches from 1998 to 2022, we showed how a single, coherent computational framework can illuminate long-term affective dynamics in low-resource language settings while preserving conceptual rigor in emotion classification. The analysis revealed a steady rise in emotional expression since 2010, driven primarily by opposition MPs and smaller parties, with anger and joy dominating the spectrum and fear surging in 2020.

The contribution of the work is fourfold. Theoretically, it operationalizes primary emotions for longitudinal political analysis and treats emotional repertoires as historically situated practices rather than static rhetorical tools. Methodologically, it offers a fine-tuned, transformer-based classifier validated through expert review across seven languages that overcomes the limitations of dictionary methods and English-centric pipelines. Empirically, it presents the first quarter-century-spanning, sentence-level analysis of emotional expression in the Hungarian Parliament, covering over five million sentences across six electoral cycles. Infrastructurally, the model and accompanying code are released openly, lowering the entry barrier for cross-national replication in low-resource language environments.

In line with Lynggaard's (2019) call for methodological pluralism and context-sensitive strategies in studying political emotions, MoresPulse operationalizes this vision by combining computational precision with interpretive transparency. It empowers researchers to trace patterns of emotional expression across time and arenas without reducing them to word counts, thereby contributing to a deeper understanding of how affective dynamics shape democratic discourse.

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Appendices

Appendix A. Training data details

Our primary foundation was a freely available German dataset containing political texts annotated for emotions (Widmann & Wich, 2022), which had been validated by German-speaking political communication experts. The optimal fine-tuning approach for this dataset has been previously established and published (Üveges & Ring, 2025). To this core dataset, we added manually labeled Hungarian and Polish data, employing double-blind coding and conducting comparisons at multiple stages to ensure consistency across languages and coders. For languages where manual coding resources were unavailable, we utilized machine translation through the Google API to extend training data coverage.

Initial fine-tuning attempts using only the German dataset (Model version ger_01) produced unsatisfactory results, likely due to imbalanced training data across emotion categories. To address this, we augmented underrepresented classes with synthetic data generated using GPT-4-turbo. Research has shown that GPT-4-generated synthetic data significantly improves classification performance for minority emotion categories in German political texts while maintaining overall model stability (Üveges & Ring, 2025). Although synthetic data exhibit reduced lexical diversity compared to original data, they successfully preserve fundamental syntactic structures and provide valuable training diversity for underrepresented categories. We validated that the synthetic data provided similar but non-repetitive content compared to the original training data using SBERT (Sentence-BERT) architecture (Reimers & Gurevych, 2019).

Table A1. Number of training sentences.

Emotion/Language	German	Hungarian	Polish	In Sum
Anger	7129	1170	1001	9300
Fear	3784	1287	995	6066
Disgust	945	1004	–	1949
Sadness	2998	1200	–	4198
Joy	3569	1425	985	5979
None of them	14584	2534	661	17779
In Sum	33009	8620	3642	45271

Appendix B. Model performance details

Model performance was evaluated using the weighted macro F1 score, which mitigates class imbalance and provides a more balanced measure than simple accuracy. The model was evaluated on language-specific test sets and achieved nearly identical performance across all languages. MoresPulse achieved consistent results across the seven target languages (German, Polish, Slovak, Czech, French, Hungarian, and English), with weighted average F1 scores ranging from 0.8076 to 0.8169. English achieved the highest weighted average F1 score (0.8169), while French showed the lowest but still robust performance (0.8076). The relatively small performance variation (approximately 0.9% points) across all languages demonstrates the model's ability to maintain high accuracy regardless of the target language. These results confirm that the multilingual pooled model approach successfully leverages cross-lingual transfer learning, enabling robust emotion detection across diverse Central European languages without significant performance degradation.

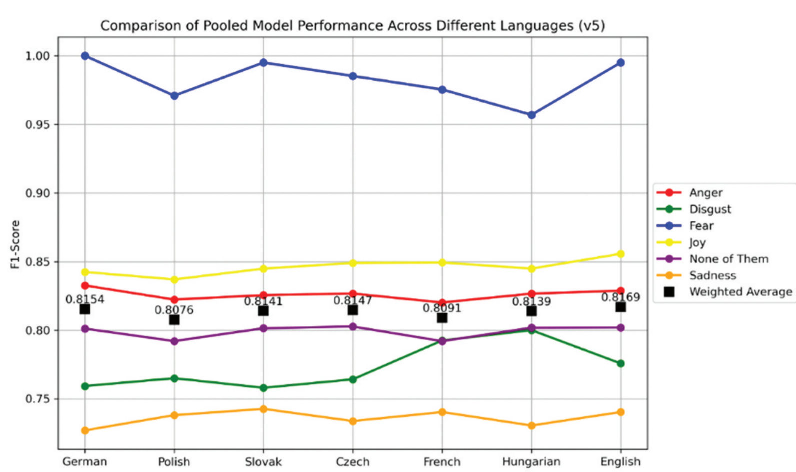

Figure B1. MoresPulse model performance.