BRATISLAVA UNIVERSITY OF ECONOMICS AND BUSINESS

FACULTY OF ECONOMICS AND FINANCE

SELF-REPORT OF DISSERTATION

Gabriel Procházka

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Self-report of Dissertation

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1. An Overview of the current status of the issues addressed in the dissertation at home and abroad

The dissertation examines the economic and political dimensions of artificial intelligence (AI) and automation as they reshape the nature of work across Europe. It builds on three connected areas of literature: the measurement of occupational and national exposure to AI, the comparative analysis of national AI policy, and text-as-data research on parliamentary discourse. The modern debate on AI and jobs was set off by Frey and Osborne (2017), who estimated that 47% of US occupations were at high risk of automation; a Bruegel analysis by Bowles (2014) applied the same method to EU data and arrived at around 54% of EU jobs. Subsequent research introduced an important qualification by examining the task composition of jobs rather than whole occupations: Arntz, Gregory and Zierahn (2016) found that only about 9% of jobs across OECD countries were highly vulnerable once tasks within jobs are considered. This reframing, formalised in the task-based framework of Acemoglu and Restrepo (2018, 2019), shifted the conversation from occupations being doomed toward identifying which tasks are exposed. Whether AI ultimately displaces or augments labour remains debated (Autor 2015; Susskind 2020; Ilzetzki and Jain 2023): jobs are bundles of tasks, some of which are automated while others are reshaped, so a high exposure score signals that AI could affect many of an occupation's tasks, not that it will replace the people who hold them. High-exposure occupations have so far not shown large employment declines (Albanesi et al. 2023), though firm-level evidence that AI adopters slow their hiring of non-AI staff (Acemoglu et al. 2022) shows the adjustment is uneven.

A growing body of work measures the exposure of jobs to AI. Felten, Raj and Seamans (2018, 2021, 2023) developed the AI Occupational Exposure index by linking advances in AI capabilities to the abilities each occupation relies on; their extension to generative AI finds that highly paid, highly educated white-collar workers are the most exposed group. Webb (2020) constructs exposure from the textual overlap between AI-related patents and job-task descriptions. Prytkova et al. (2024) widen the scope to forty emerging digital technologies, arguing that these technologies are adopted together and that measuring any one in isolation understates the overall employment effect. Oleš (2026) constructs a Europe-specific patent-to-task measure that separates three automation technologies, namely AI and machine learning, software, and robotics. Generative-AI-specific measures use large language models themselves as raters (Eloundou et al. 2023; Gmyrek et al. 2023), and national-level adjustments document a pronounced development gradient in exposure (Lewandowski, Madoń and Park 2025; Cazzaniga et al. 2024). Despite their different foundations, the measures broadly agree: routine cognitive tasks carry high exposure, manual and outdoor work carries low exposure, and advanced economies and knowledge-intensive sectors are on the front line.

On the policy side, European governments have not waited for the labour-market effects to materialise. The first wave of national AI strategies appeared between 2017 and 2019, with Finland, France and Germany among the early European movers, and the European Commission coordinated the activity through its Coordinated Plan on AI (2018, reviewed 2021). A defining feature of the European approach is its progression from soft law, the 2019 Ethics Guidelines for Trustworthy AI, to binding regulation in the AI Act proposed in 2021, whose risk-based approach places AI used in recruitment, task assignment and workplace monitoring in the high-risk category. Reskilling and digital upskilling appear in virtually every national strategy, while the most ambitious redistributive responses have been debated more than implemented: universal basic income pilots produced mixed results, and a robot tax was debated in the European Parliament in 2017 and rejected (Friis 2018). There is a loose pattern in the cross-country data, more documented than tested, that countries with higher AI exposure or stronger digital sectors have tended to respond earlier through policy; establishing whether policy activity tracks measured exposure at all is the task the dissertation takes up in Objective 1.

The political dimension of the question is studied through parliamentary discourse. Plenary speech is a public, on-the-record account of how elected representatives articulate positions, and it has advantages over manifestos, expert testimony, surveys and media coverage: it covers each legislative term in full, preserves the speaker, party, date and procedural context, exposes within-party heterogeneity, and is time-resolved at the level of individual sittings. Harmonised corpora such as ParlaMint (Erjavec et al. 2024, 2025) have recently made comparable cross-national analysis feasible. The methodological reference point is Schwalbach (2023), who shows that government-opposition dynamics continue to structure floor debate across Western European parliaments. Comparative parliamentary-discourse research has, however, concentrated on immigration, climate, austerity and European integration; artificial intelligence and automation have been studied only sporadically, with Suter, Ma, Pöhlmann and Meckel (2025) among the few major comparative analyses to date, even though parliamentary attention to AI has risen sharply since the public release of generative AI systems. This is the substantive gap the dissertation positions itself against.

Methodologically, the dissertation sits in the third generation of text-as-data research in political economy (Hassan et al. 2025). Dictionary-based sentiment scoring and supervised classifiers, the first two generations reviewed by Abercrombie and Batista-Navarro (2020), do not scale to a multilingual parliamentary corpus, because stance in parliamentary debate is rarely expressed through polarity words and labelled training data does not exist across the parliamentary languages of Europe. The current generation uses large language models under constrained prompting, with three refinements that bear on a defensible cross-national classifier: multi-step prompting that separates reasoning from constrained classification, topic-specific stance definitions, and validation against human coding (Wilkerson and Casas 2017; Bestvater and Monroe 2023). The distinction between stance, the position a speaker takes, and sentiment, the tone in which they take it, is conceptually central and often conflated. Finally, the notion of shared prosperity in the dissertation's title connects to the account of pro-worker technology by Acemoglu, Autor and Johnson (2026), which identifies reskilling and education, redistributive taxation and human-centred regulation as the policy levers through which the gains from technology may be steered toward workers, and to evidence that economic exposure to technological change and the political response to it are joint observables on a single underlying process (Bekhtiar 2025).

Domestically, comparative research that would link labour-market AI exposure, national policy activity and parliamentary discourse remains scarce in Slovakia and in Central and Eastern Europe more broadly, and the Slovak National Council is absent from the principal multi-country parliamentary corpus in the field, ParlaMint v5.0. The current state of knowledge thus leaves several questions open: the ideological structure of parliamentary stances on automation, AI and redistribution at cross-national scale; the relative weight of the left-right and government-opposition divisions in organising those stances; the internal consistency of stances across related policy topics; the relationship between stance and sentiment in speech on technology; and whether distinct discursive coalitions form around the shared-prosperity agenda and cross national boundaries. The dissertation addresses these questions in a single integrated empirical framework and, through its custom text infrastructure, contributes independent coverage of the Slovak, German and Irish parliaments.

2. Aim and focus of the dissertation

The primary aim of the dissertation is to characterise how European countries process technology-driven labour-market change. It does so along two complementary research perspectives. The first is economic: the exposure of national workforces to AI capabilities, and the national policy activity that responds to that exposure. The second is political: the language used by elected representatives in national parliaments when they debate robots, AI, automation, and the policies that distribute the gains and losses of technological change. The two perspectives are studied side by side because they are complementary views of a single underlying process: a country may be highly exposed to AI without parliament debating it, and parliament may debate AI intensely in a country that is not yet highly exposed. The dissertation frames its central question around the idea of shared prosperity in the sense of Acemoglu, Autor and Johnson (2026), the question of whether the gains from new technologies accrue broadly among workers and consumers or narrowly to capital and a small set of high-skilled professionals; shared prosperity is used as a reference point that organises the topics under study, not as a hypothesis the dissertation seeks to confirm.

The empirical work is organised into three partial objectives. Objective 1 measures national AI exposure in seventeen European Union Member States across 2012 to 2021 using four occupation-level exposure indices (Felten, Raj and Seamans 2018, 2021, 2023; Webb 2020; Prytkova et al. 2024; Oleš 2026) matched to EU Labour Force Survey microdata, and links the resulting national exposure index to AI policy activity recorded in the OECD.AI Policy Observatory, complemented by a content classification of national policy objectives against the six Responsible AI dimensions of the Stanford AI Index 2025 (Maslej et al. 2025). Objective 2 measures parliamentary discourse on artificial intelligence, automation and shared prosperity across twenty-four national parliaments in the ParlaMint v5.0 corpus over 2015 to 2022, producing a stance and a sentiment classification for each topic-matched speech on ten policy topics. Objective 3 builds and documents a custom multi-country infrastructure for acquiring and extracting parliamentary text from nine national parliaments over 2004 to 2025, providing independent coverage of three parliaments absent from ParlaMint v5.0 (the German Bundestag, the Irish Dáil, and the Slovak National Council), a wider time window, and a modular design built for routine extension; the infrastructure is validated against ParlaMint v5.0 on the three overlapping parliaments.

The dissertation addresses seven partial research questions, distributed across the first two objectives; Objective 3 is a methodological contribution and does not introduce a research question of the same type.

RQ1: How has national-level AI exposure in European Union Member States evolved across 2012 to 2021, and how does the trajectory differ across exposure measures and across countries?

RQ2: Do national governments respond to shifts in AI exposure through more timely or more intensive AI policy activity, and how is that response conditioned by macroeconomic and institutional moderators?

RQ3: How are national AI policy objectives distributed across the six Responsible AI dimensions of the Stanford AI Index 2025 framework (privacy, data governance, fairness and bias, transparency, explainability, security and safety), and does that distribution shift across countries and over time?

RQ4: Do parliamentary stances on automation, AI and redistributive policies align with parties' left-right placement, and how does the strength of any such alignment compare to the institutional government-opposition divide on the same policies?

RQ5: Are stances on related technological topics internally consistent across speakers and parties, and is support for reskilling and education programmes associated with a particular stance on automation and on AI regulation?

RQ6: Does the sentiment of parliamentary speeches on automation differ systematically from the stance the same speeches express, and on which topics is the divergence largest?

RQ7: Do distinct discursive coalitions exist across parties and countries around the shared-prosperity agenda, and how are they composed?

The first three questions form the economic strand of the dissertation: RQ1 is descriptive and methodological, establishing the joint behaviour of four exposure measures that rest on different conceptual foundations; RQ2 is the core empirical question of Objective 1, testing whether policy adoption tracks exposure shifts in the panel with country and year fixed effects and lagged exposure; RQ3 moves from policy intensity to policy content. The remaining four questions form the political strand: RQ4 tests two candidate axes of division, ideological and institutional, in parallel on the same speech sample; RQ5 tests whether positions on linked technological topics cohere into recognisable bundles at the party level; RQ6 separates two attributes of parliamentary speech that the literature often conflates; and RQ7 asks what axes the data themselves reveal when stances on the ten topics are pooled across speakers, parties and countries. Throughout, the design supports claims of association, not causal identification, and the dissertation is explicit about that limit when reporting results.

3. Methodology of work and research methods

National AI exposure and policy activity (Objective 1)

National labour-market exposure to AI is estimated from four occupational exposure indices: the ability-based AI Occupational Exposure index of Felten, Raj and Seamans (2018, 2021, 2023), the patent-task overlap measure of Webb (2020), the TechXposure index of Prytkova et al. (2024) covering a broad set of emerging digital technologies, and the Europe-specific patent-to-task semantic-similarity index of Oleš (2026), which separates AI and machine learning, software, and robotics. All four indices are harmonised to the three-digit occupational classification of the European Union Labour Force Survey (EU-LFS). Country-level exposure is computed in two steps: the share of full-time workers in each three-digit occupational cell is calculated for each country and year using EU-LFS individual weights, and the national exposure index is then the workforce-weighted mean of the occupation-level exposure scores. The Oleš (2026) AI-and-machine-learning dimension serves as the main measure in the regression analysis; the other three indices serve as robustness checks against alternative conceptions of exposure.

National AI policy responses are measured from the OECD.AI Policy Observatory through four indicators per country and year: the count of new AI policies adopted in a given year, the cumulative policy stock, the year of the first national AI strategy, and the share of AI-related publications among all scientific publications. Beyond counting policies, the content of each national policy objective is classified with a large language model (GPT-4) against the six Responsible AI dimensions of the Stanford AI Index 2025 (privacy, data governance, fairness and bias, transparency, explainability, security and safety), in binary, exclusive and multi-dimensional forms, with definitions and examples embedded in every prompt and the output reviewed by hand. The econometric strategy estimates fixed-effects panel regressions on country-year data for seventeen EU Member States over 2012 to 2021. The dependent variables are annual policy counts and the cumulative policy stock; the key explanatory variable is the national exposure index and its annual first difference, entered contemporaneously and at one-, two- and three-year lags. Specifications progressively add year fixed effects and controls drawn from comparative political economy: logged GDP per capita, R&D intensity, the Corruption Perception Index, unemployment, gross fixed capital formation, tertiary education attainment, trade union density, the strictness of employment protection legislation, and the AI publication share. All models include country fixed effects; standard errors are heteroskedasticity-robust and not clustered, because seventeen clusters are too few for reliable cluster-robust inference.

Parliamentary discourse (Objective 2)

The analytical input is the ParlaMint v5.0 corpus (Erjavec et al. 2025), published by CLARIN.SI, which encodes each parliament under a common schema with rich metadata on speakers, parties (coalition or opposition status, a Wikipedia-sourced left-right political-orientation score) and sittings. Excluding the three Spanish regional corpora leaves twenty-six national parliaments with approximately 7.7 million speeches in eighteen languages; Iceland is excluded because the multilingual encoder performed below standard on Icelandic, and Bosnia and Herzegovina yields too few classified speeches, so the reported results cover twenty-four national parliaments over the 2015 to 2022 window. The classification covers ten policy topics in three groups that give the term shared prosperity its concrete content: the emerging technologies themselves (artificial intelligence; technological progress and economic growth), the redistributive and labour-market policies through which societies respond (robot taxation, progressive taxation, universal basic income, reskilling and education), and the wider issues against which technology debate competes for attention (the war in Ukraine, the 2008 financial crisis, cybersecurity, deepfakes and disinformation). The taxonomy deliberately includes overlapping topics so that the consistency of positions across related issues can be measured directly.

The classification procedure turns the corpus into a speech-level dataset of stance and sentiment in three stages. First, every speech is matched against per-language semantic descriptions of the ten topics using a multilingual sentence-transformer encoder, and only speeches whose similarity passes a fixed threshold are carried forward; the production threshold of 0.70 favours precision over recall. Second, within each retained speech, only the passages that are themselves about the topic are kept, so that procedural openings and unrelated material do not dilute the signal. Third, the selected passages are classified by a large language model under a two-step prompt that first elicits free-form reasoning about the speaker's position and then converts it into a structured judgement. Stance takes five categories (supportive, opposing, neutral, mixed, unclear) with topic-specific definitions of the supportive and opposing poles; sentiment is defined separately as the tone of the speech (positive, negative, neutral, mixed). The production classifier is Gemini 2.5 Flash, and a locally hosted open-weight model, Qwen 3 8B, is run as a documented robustness comparator.

The procedure was validated in four pre-specified ways on a stratified 15,000-speech development sample. The production encoder was compared against a parliamentary-domain alternative, which collapsed the range of similarity scores and is not usable on this corpus. The retained speeches were cross-tabulated against the independent Comparative Agendas Project topic codes supplied by ParlaMint, with well-defined policy topics mapping cleanly onto the expected agenda categories. Stance and sentiment were validated against an adjudicated human standard on a stratified sample of 330 speeches coded independently by two annotators: the coders agreed at $\kappa = 0.73$ on stance and $\kappa = 0.78$ on sentiment, and both classifiers agreed with the human consensus about as closely as the two coders agreed with each other, which meets the accepted validity criterion for automated coding. Finally, three production choices were tested by varying one element at a time: the retrieval threshold (0.60, 0.65, 0.70), the classifier model (the two models are statistically equivalent in quality), and the prompt structure (the two-step prompt materially outperforms a single-step alternative, which hedges genuine positions into the neutral category).

The analytical strategy is organised by the research questions. RQ4 uses linear probability models at the speech level on the four redistributive topics, with stance recoded as a binary indicator (supportive = 1, opposing = 0) and a parallel sentiment indicator, country and year fixed effects throughout, and country-clustered standard errors (with party- and speaker-level clustering as robustness checks). Part 1 estimates the left-right gradient with regional interactions (Western and Northern, Central and Eastern, and Southern Europe); Part 2 enters the left-right score and the binary government-opposition indicator jointly and compares their magnitudes through raw coefficients, standardised coefficients, and incremental R-squared. RQ5 is estimated at the party level: party-mean stance and sentiment shares are correlated across parties for five named topic pairs, with bootstrap confidence intervals, within-country versions, and party-level OLS regressions with country fixed effects. RQ6 operates at the speech level on all ten topics with three measures: per-topic Pearson correlations between stance and the continuous sentiment score, regressions of sentiment on stance, and a strict divergence rate. RQ7 uses symmetric correspondence analysis on a party-by-(topic, stance) contingency table (253 parties, 30 columns, 72,077 speeches), followed by k-means clustering with a silhouette scan, a party bootstrap for stability, and two sensitivity analyses, one restricting to the four redistributive topics and one centring party profiles on country means.

Custom multi-country parliamentary text infrastructure (Objective 3)

The infrastructure has two layers. The acquisition layer retrieves plenary transcripts from each parliament's primary source across the 2004 to 2025 window, yielding a raw archive of approximately twelve thousand plenary session documents for nine parliaments: the Czech Chamber of Deputies, the German Bundestag, the Austrian Nationalrat, the Irish Dáil, the Estonian Riigikogu, the Slovak National Council, the Portuguese Assembleia da República, the Belgian Federal Chamber of Representatives, and the Swedish Riksdag. The extraction layer converts the retrieved files, which arrive in many incompatible formats, into a single speech-level dataset with consistent fields (country, source document, order within session, speaker, party affiliation, speech text, term, session, date); each country has a dedicated extractor while a shared core handles segmentation, date parsing and layout handling. Speech-level extraction is complete for five parliaments. The design is modular and built for routine extension as new transcripts are released. A descriptive cross-corpus consistency check validates the infrastructure against ParlaMint v5.0 on the three overlapping parliaments (Czech, Austrian, Estonian), comparing total speech counts, median speeches per session, median unique speakers per session, and total word counts over the common 2015 to 2022 window.

4. Structure of the dissertation

The dissertation is organised into five chapters, preceded by an introduction and followed by references, appendices, and a Slovak-language resumé. The Introduction presents the motivation, identifies the core research problem and outlines the three-objective architecture.

Chapter 1, Literature Review, traces the evolution of thinking on AI's labour-market impact (Section 1.1), surveys occupational and national-level measures of AI exposure (Section 1.2), reviews the European policy response covering national strategies, regulation and labour-market measures (Section 1.3), presents parliamentary discourse as a window onto policy formation (Section 1.4), reviews text-as-data methods in political economy (Section 1.5), focuses on stance and sentiment classification in parliamentary settings (Section 1.6), and turns to discourse on automation, AI and shared prosperity (Section 1.7).

Chapter 2, Aims, states the main aim, the three partial objectives, and the seven research questions with their grounding in the literature. Chapter 3, Methodology and Data, describes the construction of the national AI exposure indices and the measurement of policy activity (Sections 3.1 and 3.2), the ParlaMint v5.0 corpus and sampling (Section 3.3), the custom multi-country text infrastructure (Section 3.4), the three-stage classification procedure with its topic taxonomy and validation protocol (Section 3.5), the summary of data sources (Section 3.6), and the econometric and analytical strategy (Section 3.7).

Chapter 4, Results, reports descriptive statistics and the panel regressions for Objective 1 (Sections 4.1 to 4.3), the analytic dataset and the four question-specific analyses for Objective 2, namely the division structure on redistributive topics by left-right placement and by government-opposition status, the bundling of stances, the stance-sentiment relationship, and the discursive coalitions (Sections 4.4 to 4.9), and the Objective 3 cross-corpus validation (Section 4.10). Chapter 5, Conclusion and Discussion, interprets the findings, situates them within the literature, states the contributions and limitations, and sets out the further-research agenda. Appendices A to F contain the topic taxonomy with stance definitions, the model robustness checks, word clouds, the standard-error robustness tables, an illustrative example of speech extraction, and the detailed description of the classification procedure.

5. The results of the work

National AI exposure and policy activity (Objective 1)

Measured AI exposure rose across the seventeen-country panel between 2012 and 2021 under all four exposure indices, and the rising trend holds in specifications with a linear time trend and with year fixed effects alike, indicating a systematic shift in the composition of national labour forces toward more exposed occupations rather than an artefact of a particular model. In the cross-section, knowledge-intensive economies, Sweden, Denmark, Finland and Germany, sit at the top of the European exposure distribution, while countries with a larger share of manual and less digitised work, Spain, Ireland and Portugal, sit lower. Countries also differ in how evenly exposure is spread across occupations: Hungary and Estonia exhibit wide internal dispersion, whereas Germany and France show more compact distributions.

National AI policy activity grew from almost none in 2012 to a cumulative total surpassing 400 policies by 2021, with the number of newly adopted policies peaking at over 120 in 2019, coinciding with the European Commission's Coordinated Plan on AI and the wave of national AI strategy adoptions; the early adopters of national strategies in 2018 were the digital frontrunners France, Germany, Sweden, Finland and Estonia. The panel regressions show a consistent and statistically significant relationship between lagged changes in AI exposure and the annual number of AI policy initiatives: once time trends or year fixed effects are introduced, the coefficient on the one-year-lagged exposure change is significant at the 1% or 5% level in all specifications, and the two-year lag yields a slightly larger and consistently significant effect, a pattern consistent with the time needed for policy recognition, design and implementation. The inclusion of the full set of macroeconomic and institutional controls does not alter the direction or significance of the exposure variable. The relationship is an association, not a causal claim: the panel is small and identification rests on within-country variation over time.

On policy content (RQ3), the stock of national AI policy objectives diversified across the six Responsible AI dimensions over time, with volume peaking in 2019 and remaining elevated thereafter. Data governance draws the largest share of classified objectives, followed by transparency, fairness and bias, and security and safety, an emphasis that lines up with the wider European regulatory direction set by the GDPR and the AI Act.

Parliamentary discourse (Objective 2)

The production classification run on the full ParlaMint v5.0 corpus produced an analytic dataset of 77,087 speech-topic observations across the ten topics and twenty-four parliaments, with a classification error rate of 0.08% and self-reported high confidence on 91.2% of rows. Stance distributes 50.1% supportive, 39.6% opposing, 6.0% neutral, 3.9% mixed and 0.4% unclear; categorical sentiment distributes 49.9% negative, 22.7% positive, 23.9% neutral and 3.4% mixed. A directional sanity check on the war in Ukraine confirms the construct at full-corpus scale: 96% of speeches classified as supportive of Ukraine are coded sentiment-negative, consistent with pro-Ukraine speech framed as condemnation of aggression.

RQ4, Part 1 (left-right placement). Within-country left-right alignment on the four redistributive topics is small everywhere. On stance, the slope is statistically distinguishable from zero only for robot taxation (about +0.02 per left-right unit) and reskilling and education (about +0.03), in both cases with right-leaning speakers more supportive; progressive taxation and universal basic income show essentially zero left-right alignment on large samples (22,968 and 4,878 speeches respectively), so the null is not a power problem. On sentiment, all four topics show a small positive left-right slope: right-leaning speakers express positive sentiment more often than left-leaning speakers even where they do not differ on policy direction. Country fixed effects span a far wider range than any left-right slope, meaning that whether a parliament is broadly supportive or opposing on a topic is mostly a feature of the country itself. Regional differences are mostly null, with one robust exception: in Southern

Europe, right-leaning speakers are more supportive of universal basic income, a pattern that fits the welfare-chauvinist reading in the populism literature.

RQ4, Part 2 (government-opposition division). The institutional division structures parliamentary speech substantially more strongly than left-right placement. In the joint specification, the Coalition-minus-Opposition gap in the probability of a supportive stance is between +0.35 and +0.37 across all four topics, and the gap on positive sentiment between +0.36 and +0.52, all significant at the 1% level, while a one-unit move along the 0-10 left-right scale shifts the same outcomes by at most about one percentage point. In standardised terms the government-opposition coefficient is roughly four to six times larger than the left-right coefficient on stance and five or more times larger on sentiment, and its unique contribution to explained variance is an order of magnitude greater. Once government-opposition status is held constant, the left-right slopes on progressive taxation and universal basic income emerge as small but significant in the expected redistributive direction (right-leaning speakers less supportive), the robot-taxation slope vanishes, and reskilling and education remains the partial exception, with a mildly positive left-right slope consistent with the social-investment-from-the-right reading in welfare research (Bonoli 2013; Häusermann and Kriesi 2015). The findings hold under standard errors clustered at the country, party and speaker levels.

RQ5 (bundling). Party-level stance correlations are positive on all five literature-named topic pairs, ranging from r = 0.26 (cybersecurity with deepfakes) to r = 0.59 (artificial intelligence with robot taxation), and sentiment correlations are systematically stronger than stance correlations on every pair. The reskilling-and-education with robot-taxation pair shows the strongest combined linkage (stance r = 0.54, sentiment r = 0.74) and is the only pair whose stance correlation strengthens once cross-country variation is removed, the clearest evidence of genuine party-level bundling; the cybersecurity-deepfakes pair, by contrast, collapses within countries. Party-level regressions with country fixed effects confirm the linkage directly: parties that more strongly support robot taxation also more strongly support reskilling and education ($\beta = +0.52$ on stance, $\beta = +0.76$ on sentiment, both $p < 0.001$). Across the full ten-by-ten matrix, all 45 pairwise stance correlations are positive; the four redistributive topics form the densest coherent block, technological progress functions as a hub topic, and the war in Ukraine sits at the opposite extreme. Artificial intelligence, the youngest topic in the set, bundles with robot taxation, technological progress and reskilling about as tightly as any pair in the cluster, indicating that by the end of the corpus window European parties had developed recognisable party-level AI positions.

RQ6 (stance and sentiment). Across the 73,723 eligible speeches, stance and the continuous sentiment score correlate at $r = 0.69$, so roughly half the variance in sentiment is unaccounted for by stance: the two are related but distinguishable signals, neither redundant nor interchangeable. Of the speeches with a clear position and a clearly positive or negative tone, 16.2% point in opposite directions, and the divergence has a striking internal structure: 8,425 of the 8,628 divergent speeches are supportive in a negative tone and only 203 are opposing in a positive tone, a ratio of roughly forty to one. Legislators, in other words, overwhelmingly endorse a course of action while sounding the alarm about the problem the action addresses. The divergence concentrates on the information-integrity and security topics (deepfakes $r = 0.41$, cybersecurity $r = 0.49$, war in Ukraine $r = 0.55$), where the underlying problem is widely acknowledged but the policy response is contested, and alignment is tightest on the fiscal and macroeconomic topics (around $r = 0.72$). The gradient survives within-country recomputation, so it is a property of the topics, not of country composition.

RQ7 (discursive coalitions). The correspondence analysis of the 253-party contingency table extracts two dimensions that together account for 47.9% of the structural variation: the first separates engagement with the security and external-shock topics from concentrated opposition to the redistributive cluster, the second picks up the stance gradient within the redistributive sub-domain. The silhouette-selected partition splits the party landscape into a broad European mainstream spanning 23 of the 24 countries and a small, distinctive cluster of 26 governing parties from 10 countries (mean coalition share 81.6%, mean left-right score 7.0). A finer partition splits the mainstream itself along exactly the line RQ4 identified: an opposition-heavy sub-cluster (110 parties, mean coalition share 15.0%) and a governing-heavy sub-cluster (117 parties, 66.6%) with nearly identical left-right means (5.1 and 5.6), so the within-mainstream division is institutional rather than ideological. A country-residualised sensitivity tempers the cross-national reading: centring party profiles on country means absorbs about 95% of the total inertia, so the structure of parliamentary engagement with the shared-prosperity agenda is predominantly national, with the cross-national coalitions real but operating on the residual.

Cross-corpus validation (Objective 3)

The custom extraction infrastructure produces output structurally comparable to ParlaMint v5.0 on the three overlapping parliaments over the 2015 to 2022 window. Agreement is exact on the Estonian Riigikogu across all four metrics, within one per cent on the Czech Chamber of Deputies, and within three per cent on the Austrian Nationalrat, where the custom extraction returns a small, consistent surplus that points to a minor difference in inclusion rules at the procedural-utterance boundary rather than to substantive divergence. Cross-country differences in absolute speech counts reflect transcript-recording conventions rather than parliamentary activity, which motivates the design choice to anchor the cross-country analysis on stance distributions rather than speech-count aggregates. The check is structural rather than classifier-level; running the Objective 2 classification on both extractions is the priority extension.

6. Conclusion

The dissertation has assembled three things: a national AI exposure index linked to policy activity across seventeen EU Member States from 2012 to 2021; a stance and sentiment classification of parliamentary discourse on the shared-prosperity agenda across twenty-four national parliaments in ParlaMint v5.0; and a custom multi-country parliamentary text infrastructure covering nine parliaments and the 2004 to 2025 window, validated against ParlaMint v5.0 on the three parliaments where they overlap. Together, the three objectives provide an integrated empirical framework, and the resulting datasets and infrastructure, as a foundation for future comparative work on how European societies are adapting to technological change in the labour market.

The main findings are the following. Measured AI exposure has risen across the panel under all four indices, and national policy activity follows exposure with a short delay of one to two years, a result robust to the full set of macroeconomic and institutional controls; the policy stock itself has diversified across the Responsible AI dimensions, with data governance drawing the most attention. On the redistributive technology topics, the institutional position of parties, in government or in opposition, does more to organise plenary discourse than left-right ideology, a pattern that appears both in the direct regression comparison and, independently, in the unsupervised structural analysis; this lines up with the institutional-division reading in comparative parliamentary research (Schwalbach 2023) and carries it over to a new set of topics and a larger group of parliaments. The structure of parliamentary engagement is predominantly national, with cross-national discursive coalitions visible as an interpretable residual once national differences are removed. Stance and sentiment are related but empirically distinguishable signals, diverging most on threat-framed topics, and party positions on linked technological topics bundle on every pair tested, with artificial intelligence integrated into the wider technology cluster by the end of the corpus window.

The theoretical contribution lies in connecting the AI exposure literature, comparative policy analysis, and parliamentary discourse research within one framework organised around the shared-prosperity account of pro-worker technology. The methodological contribution is a three-stage classification procedure, semantic matching, passage selection, and two-step large-language-model classification, validated through a layered protocol combining encoder comparison, external topic cross-validation, human coding and pre-specified robustness checks, together with the documented custom infrastructure that provides independent coverage of the German, Irish and Slovak parliaments. The practical contribution is a set of reusable datasets and tools for researchers and policy institutions monitoring how exposure, policy and discourse co-evolve.

The limitations shape the reading of the results: the design is descriptive and associational by construction; the Objective 2 panel ends in 2022, before the period in which the public profile of generative AI changed substantially; about a third of the country-topic-year cells clear the reporting threshold; the classifier rarely uses the mixed and unclear labels, which slightly overstates how often speakers take a clear position; and the Objective 1 panel of seventeen countries over ten years limits inference. The further-research agenda follows directly: extending the discourse panel past 2022 through the custom infrastructure, completing the extraction layer for the four pending parliaments, running the classifier-level cross-corpus validation, and pursuing research designs that can establish cause and effect where the present work establishes associations.

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9. Summary

This dissertation explores the economic and political dimensions of emerging technologies, mainly artificial intelligence, that are reshaping the nature of work across Europe. As these technologies transform the labour market, policymakers face a dual challenge: harnessing them for productivity while limiting disruption and risk. Empirical research integrating three perspectives on this question, namely what AI exposure looks like at the national level, how governments respond through policy, and how parliaments debate the broader shared-prosperity agenda, remains limited and is usually pursued one perspective at a time. The dissertation brings the three together in a single empirical framework for Europe, organised into three complementary objectives, and offers a foundation and a set of tools that can support similar cross-national comparative research.

Objective 1 assembles a national-level panel of AI exposure and policy activity for seventeen EU Member States over 2012 to 2021, with exposure scores derived from four occupation-level indices matched to EU Labour Force Survey microdata and merged with policy data from the OECD.AI Policy Observatory, and with national policy objectives mapped onto the six Responsible AI dimensions of the Stanford AI Index 2025. Objective 2 classifies parliamentary discourse on ten policy topics spanning emerging technologies, redistribution and related areas of political-economic debate across twenty-four national parliaments in ParlaMint v5.0 over 2015 to 2022, producing a stance and a sentiment classification for each topic-matched speech through a validated three-stage procedure combining semantic filtering, passage extraction and two-step classification with a large language model. Objective 3 builds a custom multi-country infrastructure for extracting parliamentary text from nine national parliaments over 2004 to 2025, providing independent coverage of three parliaments absent from ParlaMint v5.0 (the German Bundestag, the Irish Dáil, and the Slovak National Council), a wider time window, and a modular design built for routine extension, validated against ParlaMint v5.0 with agreement within three per cent on every structural metric.

The main findings are the following. National AI exposure has generally increased across the panel under all four indices, and national policy responses have risen alongside it, more strongly at a lag of one to two years, with data governance the most emphasised Responsible AI dimension. On the topics studied, parliamentary stance and sentiment are more closely connected to the government-opposition division than to left-right ideology: the coalition-opposition gap in supportive stance is several times larger than the left-right gradient on the same speeches, and the same institutional division re-emerges in an unsupervised structural analysis of party discourse profiles. Stance and sentiment bundle across pairs of related topics, most strongly between reskilling and automation-related taxation; stance and sentiment are related but empirically distinguishable, diverging most on threat-framed topics where legislators support policies while sounding the alarm; and the structure of parliamentary engagement is predominantly national, with cross-national discursive coalitions visible as an interpretable residual. All results are reported as associations, and the design does not support causal interpretation.

The dissertation does not claim definitive conclusions on the relationship between exposure, policy and discourse; it offers an integrated empirical framework, and the resulting datasets and infrastructure, as a foundation for future comparative work on how European societies are adapting to current technological change in the labour market. The natural extensions, reaching past the 2022 corpus cut-off, completing the extraction of the four pending parliaments, and running the classifier-level cross-corpus validation, form the post-doctoral research agenda.

10. Extended abstract in the Slovak language

Technologická zmena spojená s rozvojom umelej inteligencie a automatizácie predstavuje jednu z ústredných výziev súčasnej politickej ekonómie. Nastupujúce technológie pretvárajú pracovný trh, vlády štátov Európskej únie reagujú regulačnými a strategickými politikami a parlamenty sú priestorom, kde sa tieto politiky formulujú, komunikujú a legitimizujú. Empirický výskum, ktorý by prepájal tri pohľady súčasne, teda mieru vystavenia pracovného trhu umelej inteligencii na národnej úrovni, politické reakcie vlád a obsah parlamentného diskurzu o zdieľanej prosperite, je však limitovaný; väčšina štúdií analyzuje tieto dimenzie oddelene. Predložená dizertačná práca ponúka integrovaný empirický rámec pre Európu, ktorý tieto tri pohľady spája. Jej ambíciou nie sú definitívne kauzálne závery, ale dátová základňa, metodologická infraštruktúra a analytické nástroje pre ďalší komparatívny výskum.

Práca sleduje tri komplementárne ciele a spolu zodpovedá sedem výskumných otázok. Cieľ 1 zostavuje panel vystavenia umelej inteligencii a politickej aktivity pre sedemnásť členských štátov EÚ za obdobie 2012 až 2021: skóre vystavenosti AI sú odvodené zo štyroch indexov na úrovni povolaní (Felten, Raj a Seamans; Webb; Prytkova a kol.; Oleš), napojených na mikrodáta EU-LFS a na politiky z databázy OECD.AI Policy Observatory; obsah politík je klasifikovaný podľa šiestich dimenzií zodpovednej umelej inteligencie (Stanford AI Index 2025). Cieľ 2 klasifikuje parlamentný diskurz na desiatich témach naprieč dvadsiatimi štyrmi národnými parlamentmi v korpuse ParlaMint v5.0 za obdobie 2015 až 2022, pričom pre každý priradený prejav produkuje klasifikáciu postoja a sentimentu. Cieľ 3 buduje vlastnú infraštruktúru na extrakciu parlamentných textov z deviatich parlamentov za obdobie 2004 až 2025 a validuje ju oproti ParlaMint v5.0.

Národná miera vystavenia je konštruovaná ako vážený priemer expozičných skóre povolaní s váhami podľa ich podielu na pracovnej sile; hlavným meradlom je index Oleša (2026), ostatné slúžia ako kontroly robustnosti. Regresná analýza využíva panelové regresie s fixnými efektmi krajín a rokov, oneskoreniami expozičného indexu a kontrolnými premennými z komparatívnej politickej ekonómie. Klasifikácia diskurzu prebieha v troch krokoch: sémantické priradenie prejavov k témam v jazyku prejavu, výber relevantných pasáží a dvojkroková klasifikácia veľkým jazykovým modelom. Desať tém pokrýva najmä oblasti spojené s aktúalnymi technológiami, redistribučnými politikami a širšie témy slúžiace ako komparatívny kontext. Infraštruktúra Cieľa 3 nezávisle pokrýva nemecký Bundestag, írsky Dáil a slovenskú Národnú radu, ktoré v ParlaMint v5.0 absentujú.

Merané vystavenie umelej inteligencii rástlo v rokoch 2012 až 2021 naprieč celým panelom pod všetkými štyrmi indexmi; na vrchole distribúcie sú znalostne intenzívne ekonomiky (Švédsko, Dánsko, Fínsko, Nemecko). Počet politík vzrástol z takmer nuly v roku 2012 na vyše 400 kumulatívne do roku 2021, s vrcholom v roku 2019. Koeficient oneskorenej zmeny vystavenia je kladný a štatisticky významný pri jednoročnom aj dvojročnom oneskorení (dvojročný efekt je o niečo väčší); kontrolné premenné výsledok nemenia. Vzťah je asociatívny, nie kauzálny. V obsahu politík dominuje správa dát, nasledovaná transparentnosťou.

Produkčná klasifikácia vytvorila dataset so 77 087 pozorovaniami prejav-téma. Ústredným zistením je, že na štyroch redistribučných témach sa postoje aj sentiment viažu podstatne silnejšie na inštitucionálne rozdelenie vláda-opozícia než na os ľavica-pravica: rozdiel v pravdepodobnosti podporného postoja medzi koalíciou a opozíciou dosahuje 0,35 až 0,37 (na sentimente až 0,52), zatiaľ čo posun o jednotku po škále ľavica-pravica mení tie isté premenné len o niekoľko percentuálnych bodov. Postoje strán sa zhlukujú na všetkých piatich testovaných dvojiciach tém; najsilnejšou väzbou je rekvalifikácia so zdanením robotov (postoj $r = 0{,}54$, sentiment $r = 0{,}74$). Postoj a sentiment korelujú na úrovni $r = 0{,}69$, sú teda príbuzné, no nezameniteľné signály: takmer všetky nesúladné prejavy sú podporné v negatívnom tóne, rečníci presadzujú politiku a súčasne signalizujú znepokojenie z problému, ktorý ju motivuje.

Korešpondenčná analýza 253 strán extrahuje dve dimenzie vysvetľujúce 47,9 percenta štrukturálnej variability a oddeľuje široký európsky hlavný prúd od malého zhluku vládnych strán; jemnejšie členenie rozdeľuje hlavný prúd na opozičný a vládny podzhluk s takmer identickou ideologickou pozíciou, vnútorný predel je teda inštitucionálny, nie ideologický. Centrovanie profilov na priemer krajiny absorbuje približne 95 percent variability: štruktúra angažovania je prevažne národná. Medzikorpusová kontrola potvrdila zhodu vlastnej infraštruktúry s ParlaMint v5.0 do troch percent na všetkých metrikách.

Prínosom práce je deskriptívna evidencia v rozsahu dvadsiatich štyroch krajín, že na redistribučných technologických témach je inštitucionálna pozícia strán aktívnejšou deliacou silou diskurzu než ideológia, zistenie, že štruktúra angažovania je prevažne národná, validovaný trojstupňový klasifikačný postup a vlastná infraštruktúra pokrývajúca aj slovenský parlament. Obmedzeniami sú deskriptívna orientácia, koniec panelu v roku 2022 a malý panel Cieľa 1; pokračovaním do ďalšieho výskumu je rozšírenie pozorovaní po roku 2022, dokončenie extrakcie zostávajúcich parlamentov a validácia na úrovni klasifikátora. Agenda zdieľanej prosperity nie je oblasťou, v ktorej by európske parlamenty hovorili jednotným hlasom; hlavným organizujúcim prvkom diskurzu je inštitucionálna pozícia strán a národný kontext, v ktorom pôsobia.