Supplementary Materials

Clustering Parameters and Sample Data

They provide additional detail on the text analysis components of the study, including the key parameters used in clustering and examples of public comments from each cluster. This information is provided for transparency and reproducibility.

Clustering Parameters

Embedding Model: KoBERT (Korean Bidirectional Encoder Representations from Transformers).

Clustering Algorithm: k-means (unsupervised clustering).

Distance Metric: Euclidean distance in 768-dimensional embedding space.

Optimal Number of Clusters: 7 (determined via silhouette analysis).

Silhouette Score: 0.621 (average silhouette score across bootstrapped samples, indicating a moderately good cluster separation).

Cluster Size Range: 534 to 912 comments per cluster (clusters were relatively balanced in size).

Keyword Co-occurrence Validation: For each cluster, the top ~15 keywords were extracted using TF-IDF. These keywords were examined to ensure they reflected coherent themes (e.g., one cluster's keywords centered on "housing, jobs, rent, Seoul" etc., indicating a housing cost theme).

Sample Public Comment Excerpts (Translated)

To illustrate the nature of each cluster, below this study provides translated examples of representative public comments for each of the seven identified clusters of citizen sentiment.

(Each quote encapsulates a common viewpoint or theme from that cluster.)

Cluster 1 (Pronatalist Support): *"Government incentives are not enough. We need better housing and job security to consider having children."* (Expresses support for having children but points out material conditions that need improvement.)

Cluster 2 (Policy Skepticism): *"They have been talking about low birth rates for years, but nothing changes. These announcements feel like empty PR."* (Expresses doubt that government actions will have real effects, seeing policy talk as ineffective publicity.)

Cluster 3 (Equity-Oriented Frame): *"Stop blaming women for not having kids. Fix work culture and support child-rearing fairly."* (Advocates for gender equity and better support systems rather than placing burden on women.)

Cluster 4 (Technocratic Appeals): *"AI can help identify which policies work best across cities. We need more data-driven interventions."* (Shows optimism for using technology and data to solve the issue.)

Cluster 5 (Traditionalist Perspective): *"Fewer children means we are losing our cultural identity. This is a crisis for our society."* (Frames low fertility as a threat to cultural or national survival, emphasizing traditional values.)

Cluster 6 (Distrust in Institutions): *"I submitted a petition two years ago and got no reply. How can we trust any of this?"* (Highlights public distrust, referencing personal experience of being ignored by authorities.)

Cluster 7 (Environmental and Economic Trade-offs): *"Maybe we do not need more people. Shouldn't we focus on quality of life and sustainability?"* (Questions the assumption that population growth is necessary, bringing up environmental or quality-of-life arguments.)

These clusters were used to define the initial “belief states” in this quantum probability transition model. Transition probabilities between clusters (states) were then calibrated based on factors like topic salience and sentiment polarity derived from the comment embeddings, as described in the Methods. This approach allowed the simulation to capture how public sentiment might shift from one state to another under various policy framings, including phenomena like opinion reversals or reinforcement of ambivalent attitudes. The clustering and examples above demonstrate the diversity of public views that any successful policy must navigate and address.