DO NOT CIRCULATE

DRAFT FOR SSHA 2026 ONLY

The Invisible Past on the Ballot Box: Latent Structures, Collective Memories, and Voting Preference in Post-Soviet Russia

Abstract

This paper examines how collective memory structures shape voting preference in post-Soviet Russia. While most research treats collective memory as a dependent variable, this study analyzes it as an independent factor influencing political behavior and identify the structures of collective memory with discrete-factor latent class analysis (dfLCA). Using survey data from Schuman and Corning (2000), I find that collective memory is multidimensional rather than organized along a single axis. A discrete-factor model identifies three key dimensions of memory orientation: cultural-social experiences, political historical events, and memories of repression and dissent. I then estimate a weighted multinomial logistic regression predicting voting preferences in the 1993 Russian parliamentary election. The findings show that individuals with stronger political and repression-oriented memory profiles are significantly more likely to support democratic parties and less likely to abstain from political participation. These results demonstrate that collective memory operates as an autonomous and multidimensional influence on political attitudes, highlighting its importance for understanding political behavior in post-authoritarian contexts.

Introduction

Since the "memory turn" of the 1980s, collective memory has become a prominent topic across the social sciences, prompting extensive scholarship on its societal foundations (Erll and Nünning 2010; Olick 1999). Yet, within this growing body of literature, there remains a notable asymmetry between studies of the formation of collective memory and those of its consequences. Most research treats collective memory as a dependent variable, examining how it is shaped by group identity, social context, or institutional frameworks. But can collective memory itself be analytically useful for explaining other social phenomena? While a number of qualitative and comparative-historical studies have explored the role of collective memory in nation-building, state power, and other macro-level processes (Anderson 2016; Hobsbawm and Ranger 2012; LaBranche 2024; Watson 1994; Zubrzycki and Woźny 2020), these belong to what has been termed the "collective" approach to memory research—focusing on the production, semiotics, and reception of public representations (Gerber and Van Landingham 2021; Olick 1999). In contrast, the "collected" approach—dominated by quantitative, survey-based research—treats memory as an independent variable less frequently. It remains unclear how individuals' memory orientations may shape their attitudes, behaviors, or subjective well-being. Can collective memory be used to predict individual-level traits? If so, what methodological strategies are most appropriate for doing so?

In this paper, I argue that analyzing the effects of collective memory requires capturing its latent structure, rather than focusing on recollections of isolated historical events. Latent class analysis (LCA) offers an optimal methodological framework for this task, as it enables researchers to uncover the underlying associations and interactions among multiple memory items. By identifying unobserved patterns of memory orientations, LCA provides a more holistic operationalization of collective memory. Treating these latent memory classes as independent variables allows for a more robust evaluation of the autonomous effects of collective memory on individuals' social and political attitudes.

I revisit and extend a classical study by Schuman and Corning (2000) on generational effects in collective memory. Building on their insights, I refine the analysis of memory patterns and develop one of their proposed research directions. Methodologically, I introduce an alternative strategy for post hoc analysis of discrete latent variables. While relatively coarse, this approach is easy to implement and retains the core logic of the widely used three-step method, offering a pragmatic tool for researchers working with categorical latent constructs. This study thus contributes to both the methodological refinement of latent variable analysis and the substantive understanding of how collective memory shapes political consciousness.

From Collective Memory to Memory Structure

Collective memory is never produced in isolation. Memories of historical events are often entangled—through their temporal or thematic linkages as well as through the social conditions that shape them. Yet, the interactions among collective memories remain underexplored, especially when compared to the extensive literature on memory formation. This gap is partially methodological: when collective memory is treated as a dependent variable, scholars tend to focus on how a single memory is shaped by factors such as demographics or political orientation. In this approach, including other memories as explanatory variables risks redundancy or endogeneity. However, once we shift our perspective and consider collective memory as an independent variable, this lack of attention to the *mnemonic nexus* becomes problematic. As many memories are interconnected, treating one memory as a stand-alone predictor risks introducing conceptual and statistical contamination into regression models.

his concern ties into a deeper theoretical—and even normative—debate within memory studies: what is the relationship between multiple collective memories (Lienen, Eckerle, and Cohrs 2025)? One line of thought follows a *zero-sum* logic, suggesting that memory is competitive and finite (Göpffarth 2021; Rothberg 2019). From this perspective, cognitive limitations constrain individuals to retain only a few salient historical memories, implying that the prominence of one necessarily entails the marginalization of others (Martin 2010; Zubrzycki 2006). Moreover, institutional and political actors—what Fine (1996) terms "reputational entrepreneurs"—compete to promote specific memories for moral, symbolic, and political legitimacy. This dynamic is especially salient in authoritarian regimes, where official and vernacular memories are often locked in perpetual conflict over historical truth and ideological dominance (Jing 1998; Kligman 1990; Watson 1994; Xu 2021). Under a zero-sum framework, we would expect to observe distinct, non-overlapping memory clusters, each representing a coherent and bounded interpretive frame. Analyzing the structure of collective memory in this view requires mapping these boundaries and identifying mutually exclusive memory patterns.

By contrast, the *multidirectional memory* perspective challenges the notion of competition, emphasizing instead the possibility of interaction, borrowing, and mutual reinforcement among different memories (Rothberg 2009). Rather than suppressing other narratives, remembering one historical trauma may activate or deepen awareness of another. Rothberg, for instance, illustrates how Holocaust memory has served as a resource for postcolonial memory projects, enabling groups to articulate their own histories of suffering and claim moral recognition. The multidirectional approach encourages scholars to conceptualize collective memory not as a set of bounded blocs, but as a matrix of interrelated orientations.

Here, the analytical task becomes one of identifying the directions and dimensions within that matrix.

These contrasting theoretical models imply distinct strategies for empirical validation. Latent class analysis (LCA) offers a powerful tool to investigate the unobserved structure of cultural beliefs and ideational systems, including collective memory. For the zero-sum framework, a standard unidimensional LCA can identify discrete and non-overlapping clusters of memory orientations. For the multidirectional model, identifying multiple latent dimensions—or discrete factors—allows us to explore cross-cutting affiliations and overlapping mnemonic fields. In both cases, LCA facilitates a more systematic and statistically rigorous examination of how collective memories cohere and interact in the population. Thus, this paper uses LCA not only as a methodological tool but also as a theoretical adjudicator between competing perspectives on the structure of memory. My analysis suggests a multidirectional memory in postcommunist Russia – supported by empirical interpretation and model specification.

Schuman and Corning (2000) Revisited

Rather than relying on newly collected data, this paper revisits a foundational study by Schuman and Corning (2000) on collective memory and generational effects in post-Soviet Russia. This study was selected for three main reasons. First, their dataset—archived at the Inter-university Consortium for Political and Social Research (ICPSR)—is both publicly accessible and methodologically rigorous, as evidenced by the publication of their findings in the American Journal of Sociology. Second, their analysis offers a comprehensive examination of the social correlates of collective memory, including age, education, gender, and urban–rural residence. Notably, they observed that certain variables, such as age and education, were associated with knowledge of multiple historical events simultaneously. This pattern suggests the presence of a latent structure underlying memory patterns—an implication that warrants further exploration using latent class analysis. Third, although the study collected data on political attitudes and voting preferences, these variables were only briefly discussed. In the conclusion, the authors drew on neo-institutionalist theory to propose a potential link between collective memory and political orientation, noting a statistically significant association ($p = .03$) between knowledge of the Great Purge and self-reported vote choice in the 1993 Russian parliamentary election, after controlling for demographic covariates.

This paper builds directly on their insight by first identifying the latent structure of memory orientations across multiple historical events and then systematically examining their relationship to political attitudes. In doing so, it both extends Schuman and Corning's theoretical proposition and demonstrates the utility of individual-centered approaches for analyzing collective memory as an independent variable.

Data and Method

This study uses the original dataset from Schuman and Corning (2000), with minimal modifications designed to facilitate analysis. The primary adjustment involves recoding respondents' knowledge of historical events into binary indicators. In the original dataset, knowledge scores range from 0 (completely incorrect) to 2 (completely correct), with 1 indicating a partially correct response. However, the distinction between scores of 1 and 2 is not consistently documented across items. To ensure measurement consistency across the eleven historical events and to reduce classification ambiguity, I recode both 1 and 2 as indicating that the respondent possesses "some knowledge" of the event, while 0 is coded as "no knowledge."

able 1 lists the historical events included in the analysis along with their weighted distributions. Beyond measurement consistency, this binary transformation is also motivated by practical considerations related to latent class analysis. With 11 historical items, preserving the full three-level coding would yield $3^{11} = 177147$ possible response patterns, far exceeding the dataset's 2,421 observations and resulting in substantial data sparsity. Collapsing the variables into binary form reduces the number of potential response patterns to $11^2 = 2048$, significantly mitigating estimation complexity and reducing the likelihood of empty or near-empty cells.[1]

Historical Events	Percentage of No Knowledge	Percentage of Some Knowledge
Great Purge	48.92	51.08
Doctor's Plot	69.14	30.86
Virgin Land Campaign	21.57	78.43
20th Congress of CPSU	70.63	29.37
Laika (the dog)	51.87	48.13
Cuban Missile Crisis	77.51	22.49
One Day in the Life of Ivan Denisovich	82.22	17.78
Prague Spring	76.34	23.66
Katya Lycheva	76.32	23.68
Repeatance	72.63	27.37
Little Vera	25.68	74.32

Table 1. Distribution of Collective Knowledge of Historical Events

The latent class analysis includes eight covariates, all of which may influence individuals' memory orientations and were also considered in Schuman and Corning's (2000) original analysis. The most theoretically significant covariate is birth cohort, which captures generational effects in memory formation (Mannheim 1952). Collective memory is often shaped by the sociopolitical context in which individuals come of age, making cohort a crucial variable for distinguishing memory patterns.

[1] I also conducted my analysis based on original scores, and a similar structure of collective memory is observed. It takes much more time to estimate though.

Another key variable is education, which may influence memory orientations through two channels: by enhancing individuals' cognitive complexity and by increasing exposure to, or internalization of, state-sanctioned historical narratives. In line with Schuman and Corning's framework. The remaining covariates—ethnicity, income, sex, and urban/rural residence—serve as controls and were retained in their original analysis. I largely preserve their original coding but make two modifications for analytical clarity: income is recoded into quartiles with an additional category for missing data, and place of residence is simplified by combining Moscow and St. Petersburg into a single category. Table 2 reports the weighted distributions of all covariates.

Covariates		Percentage
Gender		
	Male	39.61
	Female	60.39
Cohort		
	1902-20	3.87
	1921-24	2.94
	1925-28	4.56
	1929-32	6.84
	1933-36	5.26
	1937-40	7.43
	1941-44	4.61
	1945-48	4.88
	1949-52	8.10
	1953-56	8.79
	1957-60	11.78
	1961-64	9.00
	1965-58	6.91
	1969-72	7.92
	1973-76	7.11
Income		
	Bottom Quartile	34.60
	Second Quartile	18.66
	Third Quartile	78.20
	Top Quartile	16.04

DK/NA	5.76
Ethnicity	
Russian	83.42
Non-Russian	16.58
Language	
Russian	93.93
Non-Russian	6.07
Education	
Primary	19.59
Incomplete Secondary	6.55
Incomplete Secondary and Professional Courses	2.37
Secondary Professional-Technical	9.28
General Secondary	27.21
Specialized Secondary (Tekhnikum)	20.38
Incomplete Higher	1.90
Higher	12.74
Place	
Moscow/St.P	29.62
Other Urban	49.52
Rural	20.86
Region[2]	
North	2.8
North-Western	13.71
Volga-Viatsky	5.88
Central	28.46
Central Black Earth	5.76
Volga	11.24
North Caucasian	13.99
Urals	18.16

Table 2. Distribution of Covariates

The analysis proceeds in a quasi 3-step order as many other LCA-oriented paper do (Bonikowski and DiMaggio 2016; Scarborough et al. 2021) with some exceptions. First, I estimate a one-dimensional latent class model with covariates, also known as a *multinomial logit latent class regression*. This approach jointly estimates class membership and its associations with relevant covariates, reducing classification error and improving overall model fit. It also

[2] Only European Russia.

allows for the specification of local dependencies between indicators or between indicators and covariates. Because the ultimate goal of this paper is to use collective memory as an independent variable, incorporating covariates at this stage ensures more accurate and substantively meaningful class assignment. After identifying the optimal class solution, I assess local independence by examining bivariate residuals and introducing additional controls as needed based on both statistical and theoretical considerations.

In the second step, I estimate a multidimensional latent class model using the same procedure. This enables a direct comparison between the one-dimensional (zero-sum) and multidimensional (multidirectional) memory models. The comparison allows me to assess which theoretical framework better fits the memory structure in post-Soviet Russia. The selected model then serves as the basis for subsequent regression analysis.

In the final stage, I examine the relationship between latent memory structure and voting preferences using a quasi–Step-3 approach to distal outcome analysis. Step-3 analysis is designed to account for classification uncertainty by using individuals' posterior class probabilities rather than fixed class assignments (Bakk, Tekle, and Vermunt 2013; Vermunt and Magidson 2021). Due to limitations in Latent Gold 6.1—which does not support Step-3 modeling when discrete factors are used as predictors—I conduct the analysis in Stata. Specifically, I treat the dimensions from the optimal discrete factor model as independent variables and estimate their effects on political preferences using a weighted regression framework. I multiply model parameters by the marginal posterior probabilities of each factor and incorporate joint posterior probabilities as weights. I validate the results using alternative specifications, and the findings remain robust across model types.

Latent Class Structure

Following the analytical strategy outlined above, I estimate a series of one-dimensional latent class models using Latent Gold 6.1. I begin by fitting models without local dependencies to determine the optimal number of classes and subsequently incorporate targeted local dependencies to improve model fit. Model fit statistics are summarized in Table 3. P-values are omitted, as all are effectively zero—indicating that each model captures a significantly different data structure compared to the saturated model. Nevertheless, such models may still yield substantively useful latent classifications.

Model	Npar	BIC(L^2)	L^2	df	Max.BVR	Class.Err.
A. 1-Cluster	11	9328.55	24228.66	1964	452.81	0.00
B. 2-Cluster	60	5478.56	20006.86	1915	55.50	0.04
C. 3-Cluster	109	5013.54	19170.02	1866	57.30	0.06
D. 4-Cluster	**158**	**4769.29**	**18553.95**	**1817**	**33.67**	**0.10**
E. 5-Cluster	207	4827.11	18239.95	1768	28.36	0.12
F. D + Covariates BVR	163	4666.14	18412.86	1812	19.09	0.10
G. F + Events BVR	165	4672.46	18404.01	1810	33.75	0.09
H. F+G	**170**	**4581.80**	**18275.40**	**1805**	**7.79**	**0.09**

Table 3. Latent Class Specification for 1-Dimension Model

Among the unconstrained models, the four-class solution (Model D) yields the lowest BIC value, indicating an optimal balance between model fit and parsimony. However, the maximum bivariate residual (Max. BVR = 33.67) suggests a substantial violation of the conditional independence assumption. To address this, I sequentially introduce local dependencies based on both statistical thresholds (BVR > 5[3]) and theoretical relevance.

In Model F, I specify local dependencies between selected covariates and historical events with high residuals, including gender and memory of the Prague Spring, Cuban Missile

[3] According to Vermunt and Magidson (2021), for two bivariate variables, the ideal control is 3.84, which is the threshold to reject a Chi-square test with a 1 degree of freedom. However, when controlling all items above 3.84, the model will be too complicate to estimate effectively. Therefore, I choose 5 as the threshold and it turns out controlling the highest 7 bivariate residuals will have a better BIC than 8 residuals.

Crisis, and Katya Lycheva; ethnic Russian and the Virgin Lands Campaign; and Russian speakers and the Virgin Lands Campaign. This yields a notable BIC improvement from 4769.29 to 4666.14. In Model G, I introduce local dependencies among historical events with elevated bivariate residuals. Model H combines both sets of local dependencies and achieves the best overall fit (BIC = 4581.80), along with the lowest residual correlation (Max. BVR = 7.79). Nested chi-square comparisons confirm that Model H significantly outperforms both Model F and G.

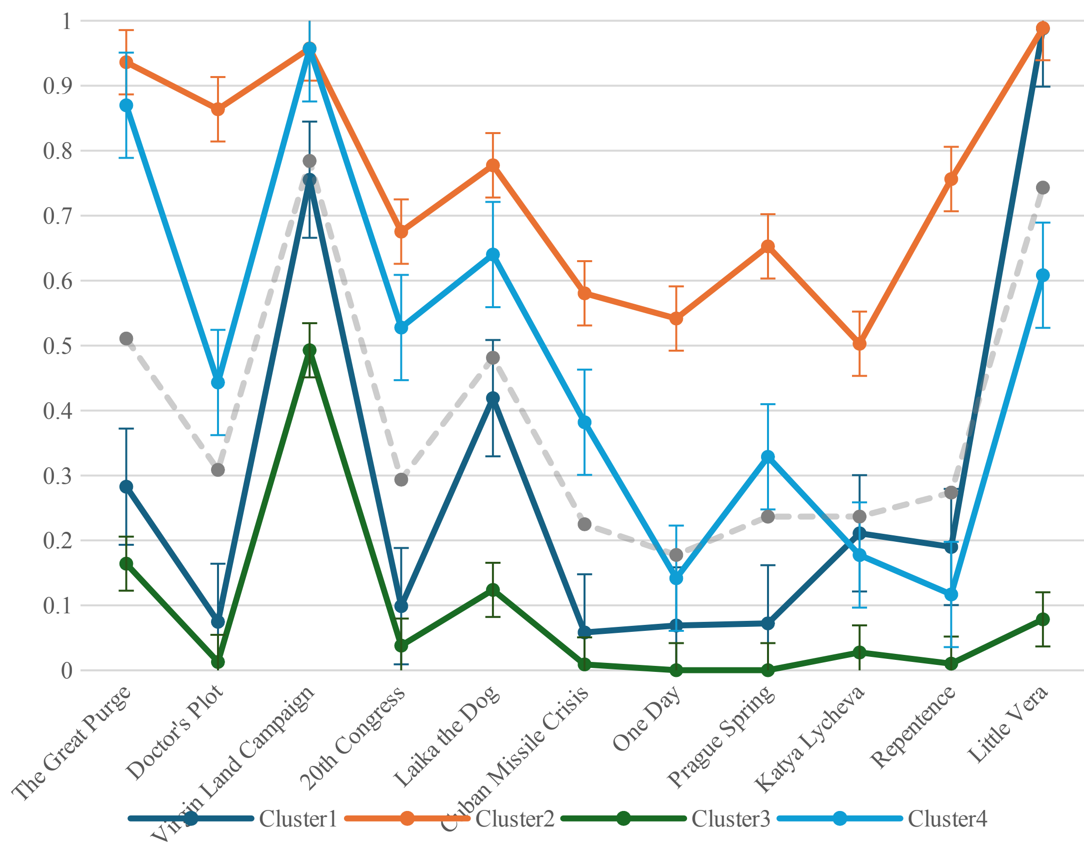

Figure 1. Profile of Latent Class

Figure 1 presents the conditional probabilities of recognizing each historical event by latent class membership. These values represent the proportion of respondents in each class who reported some knowledge of the corresponding event, with standard errors indicated by vertical lines. The overall means across the sample are plotted as a dashed line for comparison. This graphical presentation offers an intuitive overview of memory differentiation across latent classes without sacrificing detail.

Among the four identified classes, Cluster 2 and Cluster 3 are the most readily interpretable. Cluster 2 exhibits uniformly high probabilities across all events, suggesting a *"Comprehensive Memory"* orientation. In contrast, Cluster 3 shows consistently low probabilities, indicative of an *"Amnesic Memory"* profile. These two clusters represent the upper and lower bounds of collective historical knowledge in the sample.

Cluster 1 and Cluster 4, by contrast, reveal more nuanced patterns. Cluster 1 demonstrates relatively low recognition of events prior to the mid-1980s, but substantially higher familiarity with events from the Gorbachev era, including Katya Lycheva, Repentance, and Little Vera. Inversely, Cluster 4 shows stronger recognition of earlier political events but weaker familiarity with late Soviet-era cultural references. This temporal divergence suggests a cleavage between "Depoliticized Recent Memory" (Cluster 1) and "Politicized Past Memory" (Cluster 4). Their contrast is further illustrated by differences on the item One Day in the Life of Ivan Denisovich, which—although originally published in 1962—was widely reintroduced in 1988 during the Glasnost period. The relatively smaller gap between Clusters 1 and 4 on this item supports the interpretation that their distinction centers on Gorbachev-era memory formation.

Notably, the magnitude of difference between Cluster 1 and 4 is most pronounced for explicitly political events, such as the Prague Spring or the Great Purge, while cultural and state-promoted events (e.g., Laika the Dog, Katya Lycheva) show more convergence. This suggests that the differentiation between the two clusters is not merely temporal, but also ideological or political in orientation. Table 4 summarizes the substantive labels and population shares of each latent class:

Cluster	Profile	Cluster Size (Percentage)
Cluster 1	Depoliticalized Recent	39.90
Cluster 2	Comprehensive	23.28
Cluster 3	Amnesic	19.87
Cluster 4	Politicalized Past	16.95

Table 4. Profile and Cluster Size of 4 Latent Classes

Despite the clear distinctions observed between Cluster 1 and Cluster 4, it remains difficult to determine which underlying dimensions—temporal or political—play a more decisive role in their differentiation. Any attempt to decompose this difference into fixed theoretical categories risks imposing a priori assumptions that may distort the inductive value of the latent class model. Relying too heavily on pre-defined dimensions could obscure the possibility that memory orientations emerge from more complex or overlapping structures than existing theories predict. Moreover, while this analysis focuses on the contrast between Clusters 1 and 4, it may inadvertently understate the political relevance of Clusters 2 and 3. Both could also be interpreted through the lens of (de)politicization, albeit in more generalized or disengaged forms. The binary axis implied by the one-dimensional model may thus be too restrictive to fully capture the multidimensional nature of collective memory orientations.To address these limitations, I proceed with a discrete-factor latent class analysis, allowing for the identification of multiple orthogonal dimensions of memory orientation. To ensure comparability, I follow the same modeling strategy used in the one-dimensional case, including the order and threshold of bivariate residual controls. Model fit statistics for the multidimensional specification are presented in Table 5, with the optimal model highlighted in bold.

Model	Npar	BIC(L^2)	L^2	df	Max.BVR	Class.Err.
A. 1-DF (2)	60	5478.56	20006.86	1915	55.50	0.044

B. 2-DF (2, 2)	109	4542.57	18699.05	1866	32.52	0.057
C. 3-DF (2, 2, 2)	**158**	**4392.90**	**18177.56**	**1817**	**18.41**	**0.079**
D. 4-DF (2, 2, 2, 2)	207	4469.59	17882.44	1768	14.73	0.088
E. C + Covariates BVR	161	4358.14	18120.04	1814	13.92	0.092
F. C + Events BVR	160	4387.94	18157.42	1815	17.77	0.080
G. E+F	**163**	**4332.65**	**18079.37**	**1812**	**5.77**	**0.068**

Table 5. Latent Class Specification for n-Dimension Model

A model with three discrete factors is superior given the lowest BIC value. Because of the assumption of independence among discreet factors, a three-factor model is equivalent to a four-class model, which means the discrete factor analysis suggests the same number of the optimal latent class specification factor correlation estimates ($|r| = 0.05–0.09$) confirm the assumption of conditional independence across the three factors. Compared to the best-fitting one-dimensional model (Model H in Table 3), the multidimensional specification provides a superior fit and lower classification error, reinforcing the view that collective memory in post-Soviet Russia is best understood as a *multidimensional* structure.

However, the substantive legibility of latent class/dimension should also be considered. Figure 2-4 present the profile of each discreet factor. Figures 2–4 illustrate the item response profiles for each factor. Preliminary interpretation suggests that discrete Factor 1 appears to capture a cultural-social dimension, with larger differences concentrated on items such as Little Vera, Repentance, Katya Lycheva, and Laika the Dog—all symbolic of late Soviet cultural memory. Discrete Factor 2 displays a temporal orientation, with contrasts structured by the chronological proximity of events; earlier events (e.g., the Great Purge) are distinguished from late-era references. Discrete Factor 3 shows divergence primarily around political events, with particularly sharp contrasts on Prague Spring and Cuban Missile Crisis, but relative similarity on items like the Virgin Lands Campaign.

A key interpretive challenge arises from variation in event salience (Jansen 2007). Some items, such as the Virgin Land Campaign, are widely recognized, while others are obscure. This makes direct comparisons of absolute differences potentially misleading. For example, a 20% gap on a well-known item (80% vs. 60%) may be less substantively meaningful than a 15% gap on a marginally known event (20% vs. 5%). To account for this, I calculate Cohen's D for each item across levels of each discrete factor, allowing for standardized comparisons of effect size. Table 6 and Figure 5 report these results and demonstrate that certain lesser-known events yield disproportionately large factor effects, thereby sharpening our understanding of which memories contribute most to the structuring dimensions.

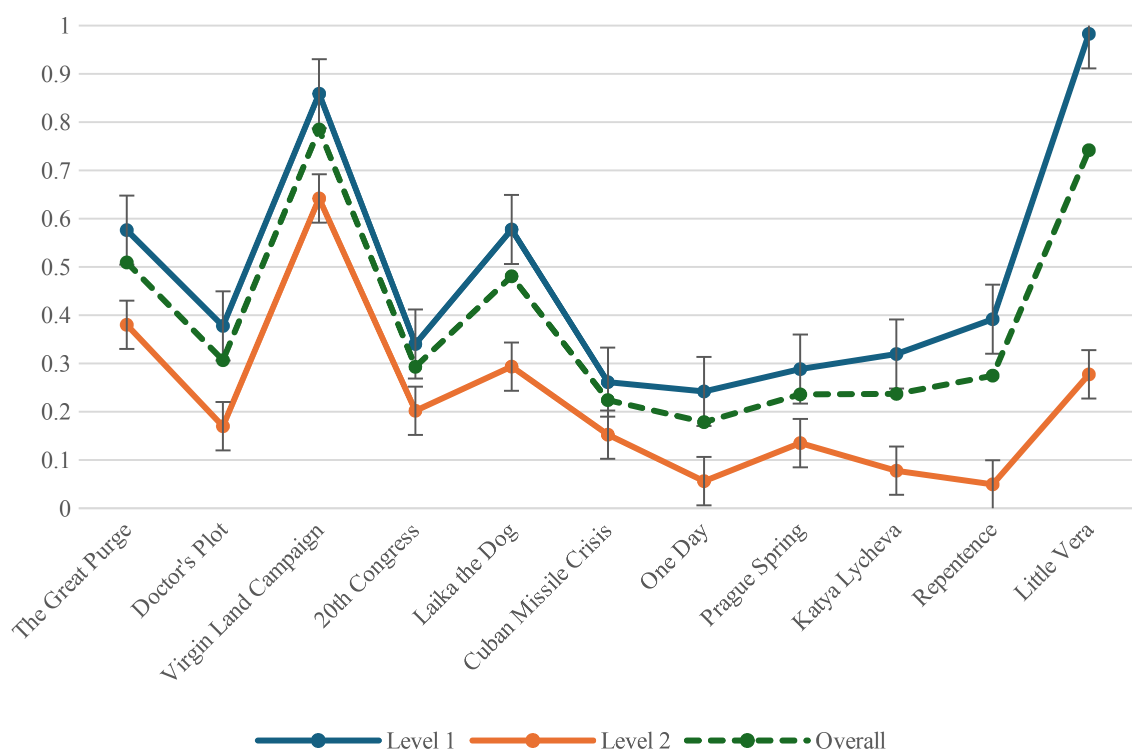

Figure 2. Profile of Discreet Factor 1

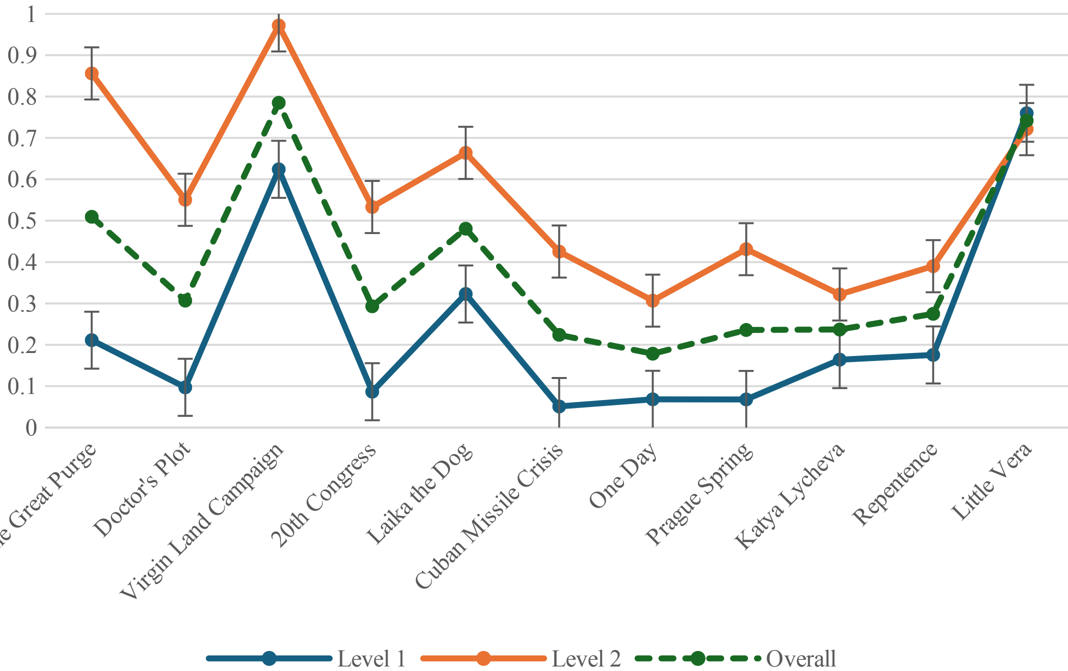

Figure 3. Profile of Discreet Factor 2

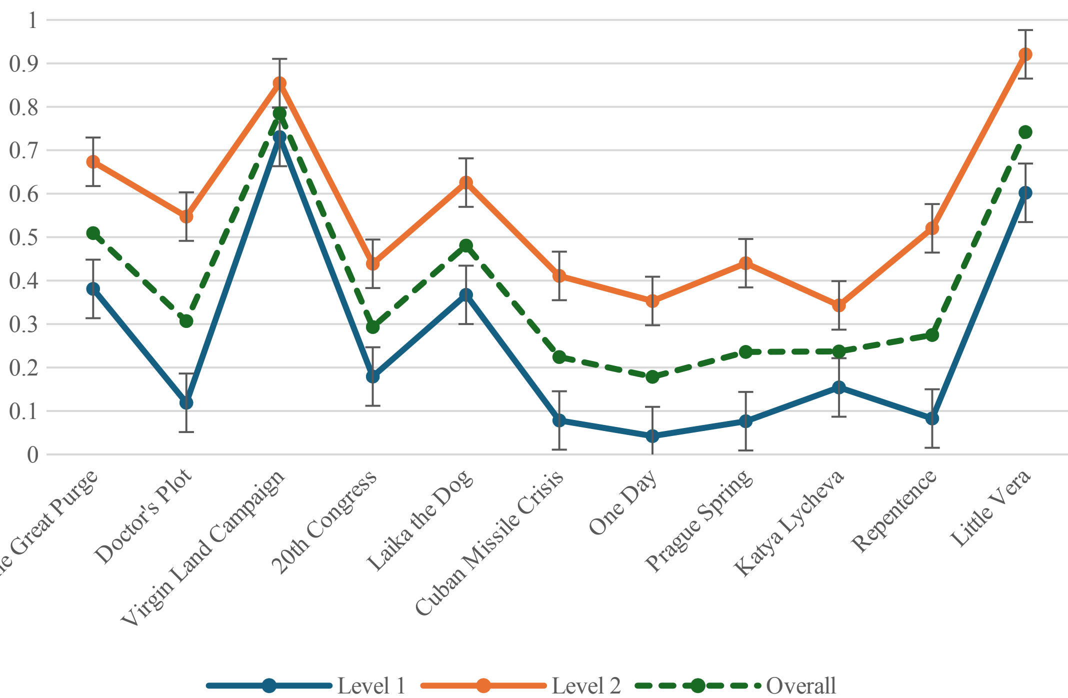

Figure 4. Profile of Discreet Factor 3

The top five Cohen's D values for each factor are used to guide substantive interpretation (Table 6; Figure 5). In Factor 1, the highest Cohen's D values for this factor appear on *Little Vera*, *Repentance*, Katya Lycheva, Laika the Dog, and Virgin Land Campaign. These items are tied to cultural life and late Soviet-era mass experiences, many of which carry emotional resonance without being overtly political. Importantly, both *Repentance* and *One Day*—while critical of Stalinism—exhibit high effect sizes, indicating that this factor does not reflect apolitical memory per se. Instead, it captures **affective engagement with cultural and social narratives**, especially those shaped under the Gorbachev-era discourse.

Events	D-Factor 1	D-Factor 2	D-Factor 3
The Great Purge	0.392	**1.289**	0.585
Doctor's Plot	0.451	**0.983**	**0.929**
Virgin Land Campaign	**0.528**	0.846	0.301
20th Congress	0.304	**0.980**	0.570
Laika the Dog	**0.569**	0.683	0.517
Cuban Missile Crisis	0.261	**0.898**	**0.798**
One Day	0.485	0.622	**0.812**
Prague Spring	0.361	**0.855**	**0.856**
Katya Lycheva	**0.569**	0.371	0.444
Repentence	**0.767**	0.480	**0.981**
Little Vera	**1.612**	-0.088	0.728

Table 6. Cohen's D of Three Discreet Factors on Historical Events

Factor 2 is clearly defined by strong effects on political events: The Great Purge, Doctor's Plot, 20th Congress, Cuban Missile Crisis, and Prague Spring. All of these items relate to major turning points or controversies in Soviet political history. Cultural references and broader social experiences show significantly lower values, reinforcing the interpretation that this factor represents **engagement with formal political history**. Notably, even politically inflected cultural items like *One Day* and *Repentance* exhibit elevated but comparatively lower D-values, further confirming the political orientation of this dimension.

The third factor loads most heavily on *Repentance*, Doctor's Plot, Prague Spring, *One Day*, and Cuban Missile Crisis—all of which involve themes of political violence, dissent, or retrospective re-evaluation. While some of these events were not censored when they occurred (e.g., Prague Spring), they became subjects of critical reinterpretation in the Gorbachev era. This factor thus appears to represent retrospective memory of political repression and alternative narratives, as opposed to either cultural affinity or political orthodoxy. Conversely, the two items with the lowest effect sizes—Virgin Land Campaign and Katya Lycheva—are emblematic of state-promoted narratives, suggesting that the presence of resistant memory does not necessarily imply the absence of official memory.

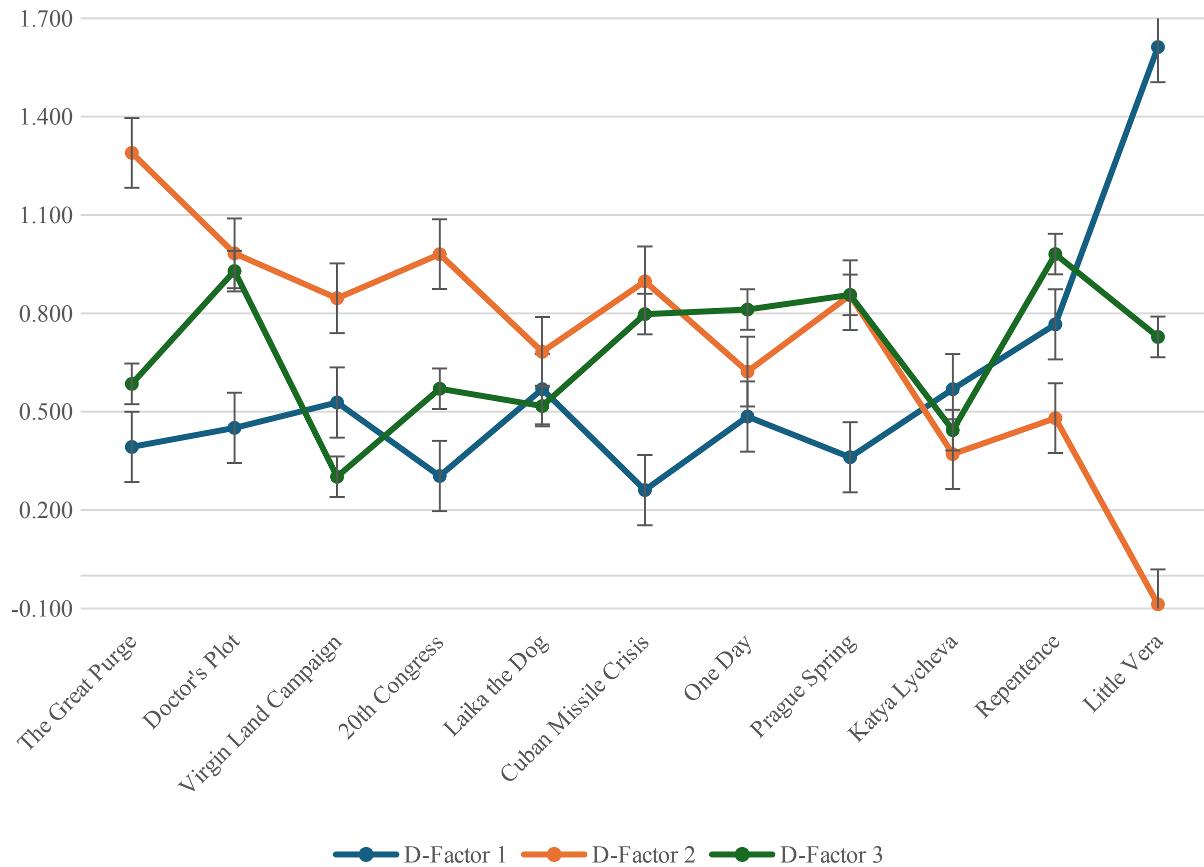

Figure 5. Visualized Comparison of Cohen'D

Discreet Factor	Interpretation	Level	Conditional Prob.
D-Factor 1	Cultural and Social Life		
		High	0.66
		Low	0.34
D-Factor 2	Political Events		

		Low	0.54
		High	0.46
D-Factor 3	Repression and Dissent		
		Low	0.56
		High	0.44

Table 7. Profile and Interpretation of Discreet Factors

Table 7 summarizes the interpretation and estimated distribution of each discrete factor across the sample. All three dimensions show balanced splits, with moderate heterogeneity in population share. These results highlight the multidimensional nature of collective memory in post-Soviet Russia. Rather than existing along a single ideological axis, memory orientations vary across at least three intersecting dimensions—cultural-social, political, and dissent-centered—each capturing distinct mnemonic logics.

Voting and Latent Memory Structure

This section returns to the central premise of the study: treating collective memory as an *independent variable* in explaining political attitudes. A key challenge in this endeavor lies in addressing classification error in the posterior analysis of latent class models. For standard one-dimensional models, Latent Gold 6.1 provides built-in Step-3 procedures that account for this uncertainty by using posterior probabilities as weights. However, no such functionality exists for models estimated using discrete latent factors. There are two potential—but ultimately inadequate—strategies for incorporating discrete factors into Step-3-style analysis: first, treating the joint combinations of discrete factor levels as latent classes. This approach violates the core assumption of conditional independence across dimensions and leads to interpretive complications. In this case, with three 2-level factors, the model yields eight unique combinations—some of which are conceptually ambiguous or difficult to interpret. Another approach is treating each discrete factor independently as a set of binary latent classes. This approach discards the joint structure of the multidimensional model and prevents estimation of the combined effects of memory orientations. It also overlooks interactions among factors that may be theoretically and empirically meaningful. To overcome these limitations, I develop an alternative procedure that incorporates the logic of Step-3 analysis while accommodating the multidimensional structure of memory. Specifically, I estimate a multinomial logistic regression of voting preference on the three discrete factors, using individuals' posterior probabilities as weights. This approach preserves the probabilistic nature of latent classification, accounts for measurement uncertainty, and allows for the simultaneous modeling of multiple memory dimensions.

Building on the multidimensional measurement of collective memory, I now examine how memory structures shape political attitudes—specifically, voting preferences in the 1993 Russian parliamentary election. The key methodological challenge is addressing *classification uncertainty* in posterior analysis. While one-dimensional latent class models benefit from Latent Gold's internal Step-3 functionality, no such option is available for discrete-factor models.
The next step will return to the promise of treating collective memory as independent variables. As discussed earlier, none of the three conventional approaches to Step-3 analysis fully accommodate the logic of discrete-factor modeling. Therefore, I develop a quasi–Step-3 procedure that preserves the multidimensional nature of latent memory while correcting for misclassification bias.

The core idea of Step-3 is to adjust for classification error using ML-based or BCH-based approaches. In this spirit, I construct a probabilistic weight for each respondent based on their posterior probabilities across each *binary latent factor*. For any given factor i, the probability of misclassification is:

$$P = / P(Xi=1) - P(Xi=0) /$$

This quantity captures classification certainty—higher values reflect clearer assignment to one class. Under the assumption of conditional independence among factors, the overall classification confidence is the product across factors:

$$P_{\text{error}} = \prod_{1}^{n} \left| P(X_i=1) - P(X_i=0) \right|.$$

This composite measure ranges from 0 to 1, with higher values indicating greater confidence in factor classification. It is used as a weight in a multinomial logistic regression predicting vote choice.While this method may overweight cases with uneven classification quality across dimensions (e.g., highly certain on one factor, uncertain on others), it remains justified for the goal of estimating the joint effect of memory structure, not the isolated contribution of each dimension.

Using this weighting scheme, I estimate a multinomial logistic regression where the outcome is vote preference in 1993 Russian parliamentary election among five political categories recorded in the original dataset: democrats, mostly Democratic Choice led by Yegor Gaidar; centrists, including the feminist party Women of Russia and the liberal party Yabloko; no party, indicating an abstention or protest vote; communist/left, including CPRF and the Agrarian Party; nationalist, surrounded by the Liberal Democratic Party. The baseline model is

$$Pr(Y_i = k) = \frac{\exp(\alpha_k + Z_i \beta_k + X_i \gamma_k)}{1 + \exp(\alpha_k + Z_i \beta_j + X_i \gamma_j)}$$

Where k is the voting preference on k political bloc (k=1 for democratics, k=2 for centrists, so forth), and α_k is the category-specific intercept. Z_i is the vector of discreet factor indicators capturing the respondent i's memory profile while X_i denotes other covariates such as socio-demographic characteristics. The coefficients matrixes β_k and $\gamma_k$represent the effect of latent memory structure and covariates, respectively, on the log-odds of choosing party category *k* relative to the baseline category. The regression model is weighted. A path model is estimated to exclude compounding effects from covariates as the latent memory structure is estimated jointly with them. Table 8 presents the average marginal effects (AMEs) of each memory dimension on voting preferences, comparing high vs. low levels for each discrete factor. Several notable patterns emerge.

Table 8. Average Marginal Effects of Latent Memory Structure on Voting Preference

Latent Memory Structure	Democrats	Centrists	No Party	Communists	Nationalists
Cultural and Social Life	0.032	0.003	-0.298	0.022	-0.027
Political Events	0.074**	0.002	-0.095**	0.021	-0.025
Repression and Dissent	0.058+	0.029	-0.051	-0.032	-0.005

Note: + P < .10, **P < .01.

The findings offer partial support for Schuman and Corning's (2000) original hypothesis regarding the relationship between memory of Stalin-era repression and liberal-democratic political preferences. While they focused on the Great Purge as a single indicator, my results demonstrate that a broader, multidimensional memory structure is more effective in capturing politically relevant variation. Specifically, individuals with high levels of memory for major political events are significantly more likely to support democratic parties, with an average marginal effect of 7.4%. A similar effect is observed for those with stronger repression- and dissent-oriented memories, who are 5.8 points more likely to support democrats; however, this effect is only marginally significant (p = 0.065). One of the more substantively novel findings is the relationship between memory structure and political disengagement. A strong political memory profile is associated with a 9.5-point reduction in the probability of reporting no party affiliation or abstention—suggesting that political memory may mobilize political participation, rather than merely correlate with partisan identity.

To evaluate the added explanatory value of memory structure, I estimate two additional models. First, a nested multinomial logit model excluding memory variables is compared against the full model. A likelihood ratio test indicates that the inclusion of memory dimensions significantly improves model fit ($p = 0.004$). Second, a path model estimated using structural equation modeling confirms that the effect of latent memory structure is robust, with the previously borderline significant item (repression memory on democrats) becoming significant ($p=0.02$).

These results collectively underscore the *independent and multidimensional role of collective memory* in shaping political attitudes. They further validate the theoretical proposition that memory is not merely a dependent reflection of demographic or institutional structure, but an active and possibly *autonomous* force in political behavior.

Discussion

This paper contributes to the literature on collective memory by demonstrating how latent memory structures, rather than isolated memories of single events (Griffin 2004; Griffin and Bollen 2009), can serve as meaningful predictors of political behavior. This approach allows us to move beyond treating memory solely as a dependent variable and instead conceptualize it as a structuring force in political behaviors and more substantive areas. I do not suggest a causal effect of collective memory on political attitudes and behaviors, and it is extremely difficult to identify any causal relations between two ideational subjects. However, a new path on the classical question how structures of historical knowledge and representation function in cultural schemas is open by this approach (Swidler and Arditi 1994). I also empirically test two theories on interactions among collective memories. The conclusion may not be generalized beyond post-

Soviet Russia, but it suggests that in a transitional and multivocal field of past knowledge, a multi-directional orientation can help us establish a more nuanced structure of collective memory and avoid artificial dichotomies like state memory vs. popular memory.

The paper also discusses two methodological issues. First, in collective memory research, the long debate between two “cultures” can be solved by incorporating them together. The culturalist approach has a strong performance in memory-as-dependent-variable studies – for example, explaining how state-centered narratives emerges. My study, along with some empirical studies in post-Soviet societies (for example, Yurchak 2006), can provide a holistic picture on the zeitgeist of the late-Soviet era. Second, for latent class analysis, I propose an alternative approach to conduct posterior analysis without knowledge of Bayesian statistics.

Reference

Anderson, Benedict. 2016. *Imagined Communities: Reflections on the Origin and Spread of Nationalism*. Revised edition. London New York: Verso.

Bakk, Zsuzsa, Fetene B. Tekle, and Jeroen K. Vermunt. 2013. “Estimating the Association between Latent Class Membership and External Variables Using Bias-Adjusted Three-Step Approaches.” *Sociological Methodology* 43(1):272–311. doi: 10.1177/0081175012470644.

Bonikowski, Bart, and Paul DiMaggio. 2016. “Varieties of American Popular Nationalism.” *American Sociological Review* 81(5):949–80. doi: 10.1177/0003122416663683.

Erll, Astrid, and Ansgar Nünning. 2010. *A Companion to Cultural Memory Studies*. De Gruyter.

Fine, Gary Alan. 1996. “Reputational Entrepreneurs and the Memory of Incompetence: Melting Supporters, Partisan Warriors, and Images of President Harding.” *American Journal of Sociology* 101(5):1159–93.

Gerber, Theodore P., and Michael E. Van Landingham. 2021. “Ties That Remind: Known Family Connections to Past Events as Salience Cues and Collective Memory of Stalin’s Repressions of the 1930s in Contemporary Russia.” *American Sociological Review* 86(4):639–69. doi: 10.1177/00031224211023798.

Göpffarth, Julian. 2021. “Activating the Socialist Past for a Nativist Future: Far-Right Intellectuals and the Prefigurative Power of Multidirectional Nostalgia in Dresden.” *Social Movement Studies* 20(1):57–74.

Griffin, Larry J. 2004. “‘Generations and Collective Memory’ Revisited: Race, Region, and Memory of Civil Rights.” *American Sociological Review* 69(4):544–57. doi: 10.1177/000312240406900404.

Griffin, Larry J., and Kenneth A. Bollen. 2009. “What Do These Memories Do? Civil Rights Remembrance and Racial Attitudes.” *American Sociological Review* 74(4):594–614. doi: 10.1177/000312240907400405.

Hobsbawm, Eric, and Terence Ranger, eds. 2012. *The Invention of Tradition*. Cambridge: Cambridge University Press.

Jansen, Robert S. 2007. “Resurrection and Appropriation: Reputational Trajectories, Memory Work, and the Political Use of Historical Figures.” *American Journal of Sociology* 112(4):953–1007. doi: 10.1086/508789.

Jing, Jun. 1998. *The Temple of Memories: History, Power, and Morality in a Chinese Village*. Stanford University Press.

Kligman, Gail. 1990. “Reclaiming the Public: A Reflection on Creating Civil Society in Romania.” *East European Politics and Societies* 4(3):393–438. doi: 10.1177/0888325490004003002.

LaBranche, Jillian. 2024. “Macro-Micro Interaction in Knowledge Construction: Structural and Communicative Memory in Rwanda and Sierra Leone.” *American Journal of Sociology*. doi: 10.1086/731782.

Lienen, Carmen S., Frank Eckerle, and J. Christopher Cohrs. 2025. “How Do Members of a Perpetrator Group Negotiate Multiple Past Ingroup Transgressions? A German Case Study.” *Memory Studies* 18(1):198–217. doi: 10.1177/17506980241247269.

Mannheim, Karl. 1952. “The Problem of Generations.” Pp. 276–322 in *Essays on the Sociology of Knowledge*, edited by P. Kecskemeti. Routledge.

Martin, John Levi. 2010. “Life’s a Beach but You’re an Ant, and Other Unwelcome News for the Sociology of Culture.” *Poetics* 38(2):229–44. doi: 10.1016/j.poetic.2009.11.004.

Olick, Jeffrey K. 1999. “Collective Memory: The Two Cultures.” *Sociological Theory* 17(3):333–48.

Rothberg, Michael. 2009. *Multidirectional Memory: Remembering the Holocaust in the Age of Decolonization*. Stanford University Press.

Rothberg, Michael. 2019. *The Implicated Subject: Beyond Victims and Perpetrators*. 1st edition. Stanford, CA: Stanford University Press.

Scarborough, William J., Joanna R. Pepin, Danny L. LambouthsIII, Ronald Kwon, and Ronaldo Monasterio. 2021. "The Intersection of Racial and Gender Attitudes, 1977 through 2018." *American Sociological Review* 86(5):823–55. doi: 10.1177/00031224211033582.

Schuman, Howard, and Amy D. Corning. 2000. "Collective Knowledge of Public Events: The Soviet Era from the Great Purge to Glasnost." *American Journal of Sociology* 105(4):913–56.

Swidler, Ann, and Jorge Arditi. 1994. "The New Sociology of Knowledge." *Annual Review of Sociology* 20:305–29.

Vermunt, Jeroen K., and Jay Magidson. 2021. *LG-Syntax User's Guide: Manual for Latent Gold Syntax Module Version 6.0*. Arlington, MA: Statistical Innovations Inc.

Watson, Rubie S., ed. 1994. *Memory, History, and Opposition under State Socialism*. Sante Fe, N.M: School for Advanced Research Press.

Xu, Bin. 2021. *Chairman Mao's Children: Generation and the Politics of Memory in China*. Cambridge: Cambridge University Press.

Yurchak, Alexei. 2006. *Everything Was Forever, Until It Was No More: The Last Soviet Generation*. Princeton University Press.

Zubrzycki, Geneviève. 2006. *The Crosses of Auschwitz: Nationalism and Religion in Post-Communist Poland*. Chicago: The University of Chicago Press.

Zubrzycki, Geneviève, and Anna Woźny. 2020. "The Comparative Politics of Collective Memory." *Annual Review of Sociology* 46(1):175–94. doi: 10.1146/annurev-soc-121919-054808.