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Explaining Consumer Inaction in Boycott Movements: A Psychological Framework of Passivity During Periods of Social Change

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ABSTRACT

Research on collective action has primarily focused on participation, while the mechanisms underlying non-participation remain less understood. This study examines why individuals remain inactive in boycott movements despite holding negative attitudes toward targeted companies, focusing on animosity toward firms associated with Israel. Using a quantitative design, data from 212 Indonesian participants were analyzed using partial least squares structural equation modeling (PLS–SEM) and artificial neural network–neural network regression (ANN–NNR). The PLS–SEM approach was employed to examine explanatory relationships leading to purchasing behavior (PB). The results indicate that several hypothesized predictors do not exhibit significant direct effects on PB, while indirect effects are partially supported through mediating mechanisms. To complement the explanatory model, ANN–NNR results identified out of sight as the most important predictor of PB, followed by boycott attitude and urge of freedom. This divergence suggests that psychological mechanisms differ between explanatory and predictive frameworks, with ANN capturing potential nonlinear relationships. Overall, the study highlights the value of integrating PLS–SEM and ANN–NNR to better understand boycott-related inaction in a non-Western context.

Key words: *boycott, collective action, non-participation*

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1. INTRODUCTION

We will not go down. In the night, without a fight. You can burn up our mosques and our homes and our schools. But our spirit will never die. We will not go down. In Gaza tonight - Michel Heart

Research on collective action has extensively examined why individuals participate in social movements, with influential frameworks—most prominently the Social Identity Model of Collective Action (SIMCA)—emphasizing social identity, group-based emotions, and perceived efficacy (Louis et al., 2020; van Zomeren et al., 2018). More recent work has extended these models to account for digital and networked forms of participation, illustrating how online environments reshape processes of collective engagement (Chen et al., 2021; Li, 2025; Mongo, 2025).

Subsequent extensions, including EMSICA (Louis et al., 2020) and ESIM (Thomas et al., 2009), have further elaborated the psychological mechanisms underlying participation. Despite these advances, the decision not to participate remains theoretically underdeveloped. From a decision-making standpoint, individuals must first choose between action and inaction (Wright et al., 1990), rendering inaction a fundamental yet

understudied component of collective action dynamics. Recent work in behavioral decision-making further indicates that inaction is not merely passive but reflects systematic cognitive tendencies such as inaction bias and omission effects (Fillon et al., 2023).

Scholars have likewise argued that non-participation is not merely the absence of action but reflects distinct psychological processes (Stekelenburg & Klandermans, 2017). More recent work conceptualizes inaction as an active psychological stance shaped by cognitive and contextual factors (Diesburg & Wessel, 2021; Elliot et al., 2024). As Verba et al. (1995) put it, individuals may refrain from collective action because they do not want to, cannot, or are not mobilized.

Mobilization processes—both consensus mobilization and action mobilization—further shape whether individuals engage in or withdraw from collective action (Klandermans, 1988). Empirical work examining these mechanisms, however, remains scarce, particularly in the context of consumer-based collective action such as boycotts.

Within the boycott domain, prior research has identified several psychological barriers to participation. Yuksel (2013) distinguishes three such factors—out of sight, urge of freedom, and counterarguments—as the principal explanations of inaction. Subsequent work in political consumerism corroborates the presence of analogous barriers in contemporary boycott movements (Copeland & Boulianne, 2022; Hino, 2022).

While this qualitative evidence offers important insights, it does not permit formal testing of predictive relationships among these constructs. Moreover, the bulk of research on collective action and inaction has been conducted in Western, Educated, Industrialized, Rich, and Democratic (WEIRD) contexts, constraining its generalizability to non-Western settings (Atari et al., 2025; Henrich et al., 2010). Recent commentary continues to underscore this limitation and calls for broader cultural representation in psychological science (Kryś et al., 2025; Üskül et al., 2024).

Recent geopolitical tensions involving Israel and Palestine have catalysed widespread consumer boycotts across multiple countries, including Indonesia, furnishing a particularly apt context for examining collective action and non-participation in real-world settings (e.g., Amalia et al., 2025; Anwar et al., 2025; Banjaransari, 2025; Evelyn & Sekarasih, 2025; Faizi et al., 2025; Hino, 2022; Husaeni & Ayoob, 2025; Kristiningsih et al., 2025). Within this setting, public responses extend beyond participation in boycott actions and encompass varying degrees of inaction even among individuals who hold negative attitudes toward targeted companies.

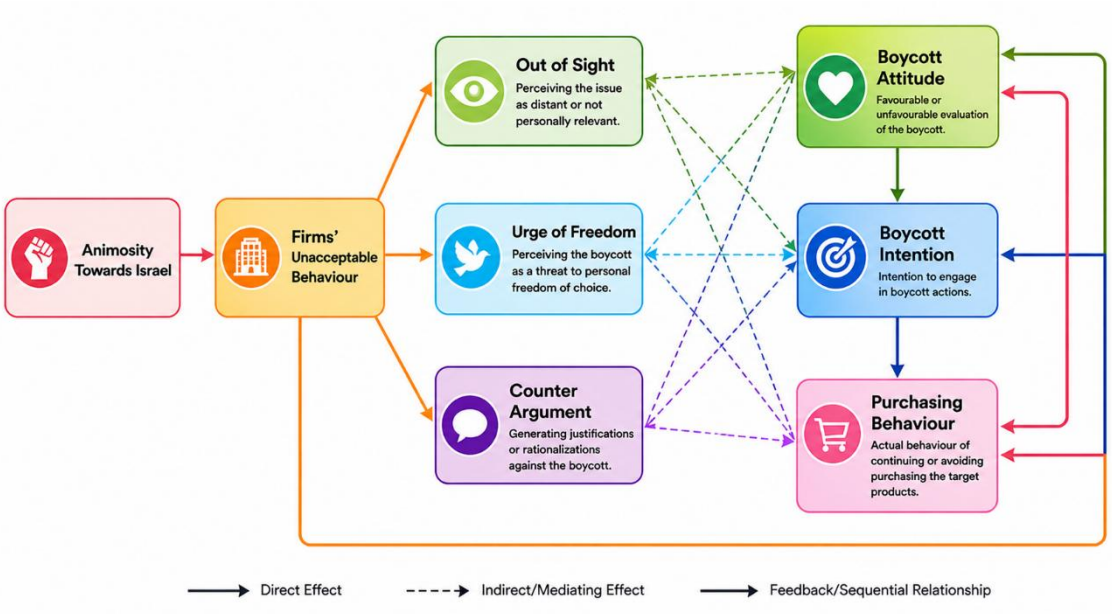


Figure 1. Proposes a model (Source: Researcher, 2025)

The present study addresses these gaps by examining non-participation in boycott actions within the Indonesian context. Drawing on collective action theory and the political consumerism literature, recent integrative approaches emphasize the interplay among emotional, cognitive, and identity-based processes in shaping consumer activism (Ateş, 2025; Narayanan & Singh, 2025; Ulfah et al., 2025).

Building on this perspective, the present study proposes that animosity toward Israel predicts perceptions of firms' unacceptable behavior, which in turn shapes boycott attitudes, intentions, and purchasing behavior. Crucially, this pathway is theorized to be mediated by three internal psychological barriers—out of sight, urge of freedom, and counterarguments (see Figure 1).

By formally testing this model, the study extends the collective action literature by demonstrating that inaction reflects distinct and measurable psychological processes. In so doing, it advances a more comprehensive understanding of consumer behavior in boycott movements, particularly in non-Western contexts.

2. METHOD

2.1. Procedure and Participants

Data were collected through an online survey. After providing informed consent, participants completed a brief demographic questionnaire followed by eight measurement scales and received a debriefing statement upon submission.

The final sample comprised 212 respondents (M_{age} = 23.92, SD = 4.38), predominantly male (71.7%), Muslim (95.8%), and holding a bachelor's degree (52.4%); 67.9% reported participating in boycott actions. Full demographic breakdown is reported in Table 1.

2.2. Measures

Unless otherwise specified, all multi-item scales used a 5-point Likert response format ranging from strongly disagree to strongly agree, and reliability coefficients (Cronbach's α) are reported alongside each scale.

2.2.1. Animosity Towards Israel

Animosity toward Israel was measured using an adapted scale from (C. Kim, Yan, et al., 2022). An example item is, "I feel angry about the actions taken by Israel against Palestine" (α = 0.817).

2.2.2. Firms' Unacceptable Behavior

Perceptions of firms' unacceptable behavior were measured using a scale adapted from Abdul-Talib et al. (2016), which taps participants' evaluations of companies affiliated with Israel. A sample item reads, "Companies affiliated with Israel deserve to have their products boycotted" (α = 0.734).

2.2.3. Out of Sight

Out of sight was operationalized using binary (yes/no) single-item measures adapted from Hoffmann (2013) to capture proximity to boycott-related impacts. A sample item reads, "Is the city you live in close to a company affiliated with Israel that is subject to boycott?"

Table 1. Characteristics of the survey respondents (N = 212)

Characteristic	Frequency	Percentage (%)
Age (18 – 39 years old, M = 23.915, SD = 4.377)		
Gender		
Male	152	71.700%
Female	60	28.300%
Education		
High school	82	38.700%
Bachelor's degree	111	52.400%
Master's degree	19	9.000%
Religion		
Islam	203	95.800%
Christian	4	1.900%
Catholic	4	1.900%
Buddhist	1	0.500%
Boycott Status		
Non-Boycott	68	32.100%
Boycott	144	67.900%

Source: Personal research data, 2025.

2.2.4. Urge of Freedom

Urge of freedom was assessed using a scale adapted from Dillard & Shen (2005), A sample item reads, "Messages about boycott calls interfere with my freedom to choose" (α = 0.893).

2.2.5. Counterargument

Counterargument was measured using a scale adapted from (Abdul-Talib et al., 2016). A sample item reads, "Boycotting will harm Indonesia's economy" (α = 0.903).

2.2.6. Boycott Attitude

Boycott attitude was measured using a scale adapted from (C. Kim, Yan, et al., 2022). An example item is, "It is beneficial to boycott products from companies affiliated with Israel" (α = 0.888).

2.2.7. Boycott Intention

Boycott intention was measured using a scale adapted from (C. Kim, Yan, et al., 2022). An example item is, "I plan to boycott products from companies affiliated with Israel" (α = 0.693).

2.2.8. Purchasing Behavior

Purchasing behavior was assessed using a single-item measure adapted from (C. Kim, Yan, et al., 2022). Participants indicated changes in their purchasing behavior over the past year on a 10-point scale ranging from 1 (*not at all changed*) to 10 (*very much changed*). The item read: "Compared to your average purchases before the boycott campaign began on October 7, 2023, how have your purchases changed over the past year?"

2.3. Data Analysis

Data analysis proceeded in several stages. First, descriptive statistics summarized participants' demographic characteristics and main study variables, followed by Pearson correlation analyses to examine bivariate relationships (Dancey & Reidy, 2020) and preliminary bias checks in IBM SPSS Statistics version 22. To test the proposed hypotheses, Partial Least Squares Structural Equation Modeling (PLS–SEM) was employed for its suitability in predictive modeling, theory development with complex models (Hair et al., 2022), and robustness under non-normal data (Hair, Risher, et al., 2019), using SmartPLS version 3.2.9 (Henseler et al., 2015). Following current methodological recommendations, both structural and measurement models were evaluated through explanatory power (R^2), construct cross-validated redundancy (Q^2), fit indices (SRMR, d_G, d_ULS, RMSθ, NFI), the goodness-of-fit index (GoF), and robustness assessments for linearity, endogeneity, and heterogeneity (Hair et al., 2021, 2022).

To complement PLS–SEM and enhance predictive performance, an Artificial Neural Network (ANN; Orrù et al., 2020)—specifically Neural Network Regression (NNR; Kovač et al., 2024)—was implemented within a broader machine learning framework (Ghosh, 2022; Jacobucci et al., 2023; Pargent et al., 2023; Vélez, 2021). A multilayer perceptron model was specified with animosity toward Israel (ATI), firms' unacceptable behavior (FUB), out of sight (OS), urge for freedom (UF), counterargument (CA), boycott attitude (BA), and boycott intention (BI) as inputs, and purchasing behavior (PB) as the output. Latent variable scores from PLS–SEM served as inputs to account for measurement error and indicator loadings. Data were normalized prior to estimation, and performance was evaluated via RMSE, MAE, and R^2. ANN analyses were conducted in R version 4.5.0 (Team, 2025) within the Positron environment (Posit Software, 2025). Integrating ANN-based NNR with PLS–SEM aligns with recent methodological developments emphasizing hybrid machine learning approaches to improve predictive accuracy and assess variable importance in complex behavioral models (Baban & Baban, 2024). Further methodological details appear in the supplementary materials.

3. RESULT

3.1. Descriptive Statistics and Correlations

Normality assessment was conducted using skewness values to ensure data quality (Appelbaum et al., 2018), although the PLS approach remains robust to non-normal distributions (Hair, Risher, et al., 2019). All variables fell within the acceptable range (-3 to +3), indicating no severe deviations from normality (Heidary et al., 2022).

Pearson correlations (Table 2) revealed expected patterns: ATI, FUB, BA, BI, and PB were positively interrelated (rs = 0.348 to 0.765, all ps < 0.001), whereas urge of freedom (UF) and counterargument (CA) were

negatively associated with all boycott-related variables (*r*s = -0.367 to -0.746). Out of sight (OS) showed only a weak negative correlation with UF (r = -0.138, p = 0.045) and was otherwise unrelated to study variables. These patterns suggest that boycott attitudes and intentions are tightly coupled with purchasing behavior, while perceived freedom and counter-argumentative tendencies are systematically linked to boycott disengagement.

Table 2. Descriptive statistics and correlation between variables

Variables	ATI	FUB	OS	UF	CA	BA	BI	PB
ATI	1	0.501**	0.009	-0.380**	-0.451**	0.514**	0.537**	0.348**
FUB		1	-0.125	-0.367**	-0.520**	0.561**	0.581**	0.371**
OS			1	-0.138*	-0.054	0.019	-0.009	0.069
UF				1	0.634**	-0.548**	-0.541**	-0.441**
CA					1	-0.746**	-0.724**	-0.499**
BA						1	0.765**	0.535**
BI							1	0.505**
PB								1
Minimum	1	1	1	1	1	1	1	0
Maximum	5	5	2	5	5	5	5	10
Mean	4.677	4.339	1.125	2.021	2.095	4.174	4.274	7.174
SD	0.544	0.732	0.251	0.945	0.848	0.748	0.715	2.389
Skewness	-2.413	-1.167	2.001	0.717	0.586	-0.652	-0.888	-1.288
Kurtosis	7.952	1.716	3.145	-0.313	-0.230	-0.205	0.328	1.595

Note. *p < 0.05. **p < 0.01. ***p < 0.001. ATI: animosity towards Israel. FUB: firms' unacceptable behavior. OS: out of sight. UF: urge of freedom. CA: counterargument. BA: boycott attitude. BI: boycott intention. PB: purchasing behavior. Source: Personal research data, 2025.

3.2. Common Method Variance (CMV)

As all constructs were measured using a single data collection method, common method variance (CMV) was evaluated to ensure that the results were not biased by the measurement approach (Chin et al., 2012). Harman's single-factor test indicated that the first factor accounted for 42.05% of the total variance, below the conventional 50% threshold (Comrey, 1978). Thus, common method bias is unlikely to be a substantive concern in this study.

3.3. Measurement Model Evaluation

The measurement model was evaluated via variance-based CFA (Table 3). All loadings exceeded 0.40, composite reliability values exceeded 0.70, and AVE values exceeded 0.50, demonstrating adequate reliability and convergent validity (Hair, Black, et al., 2019; Hair et al., 2022).

Model fit was acceptable based on SRMR (0.068 < 0.08; Hu & Bentler, 1999); SRMR was prioritized over RMS theta given the latter's known sensitivity to sample size and complex models (Maydeu-Olivares et al., 2017).

Discriminant validity was supported by HTMT values below 0.85 (Henseler et al., 2015) and cross-loadings (Table S1), confirming that constructs are empirically distinct. The measurement model thus demonstrates adequate reliability and validity for subsequent structural analysis.

Table 3. Measurement model evaluation

Indicator	LF	VIF	α	ρ_c	AVE	Overall model fit measurement			
						SRMR	d_G	d_ULS	Rms theta
Animosity towards Israel									
Animo1	0.925	3.266	0.852	0.911	0.773	0.068	1.643	0.608	0.156
Animo2	0.923	3.198							
Animo3	0.783	1.571							
Firms' unacceptable behavior									
Firms1	0.612	1.245	0.769	0.864	0.685				
Firms2	0.925	2.357							
Firms3	0.909	2.437							
Out of sight									
Distance1	0.613	1.317	0.675	0.808	0.588				
Distance2	0.855	1.262							
Distance3	0.810	1.488							

Indicator	LF	VIF	α	ρ_c	AVE	Overall model fit measurement			
						SRMR	d_G	d_ULS	Rms theta
Urge of freedom									
Freedom1	0.828	2.202	0.899	0.929	0.766				
Freedom2	0.844	2.447							
Freedom3	0.910	3.451							
Freedom4	0.916	3.721							
Counterargument									
Counter1	0.769	1.900	0.904	0.926	0.678				
Counter2	0.870	2.838							
Counter3	0.732	1.781							
Counter4	0.884	3.150							
Counter5	0.785	2.092							
Counter6	0.886	3.068							
Boycott attitude									
Attitude1	0.912	3.615	0.894	0.927	0.763				
Attitude2	0.935	4.342							
Attitude3	0.717	1.545							
Attitude4	0.912	3.352							
Boycott intention									
Intention3	0.946	2.812	0.891	0.948	0.901				
Intention4	0.953	2.812							
Purchasing behavior									
Behaviour	1.000	1.000	1.000	1.000	1.000				

Note. *p < 0.05. **p < 0.01. ***p < 0.001. LF: loading factor. VIF: variance inflation factor. α: cronbach's alpha. ρ_c: composite reliability. AVE: average variance extracted. Source: Personal research data, 2025.

3.4. Structural Model Evaluation

Prior to hypothesis testing, structural-level collinearity was assessed. All variance inflation factor (VIF) values fell below the threshold of 10, indicating no multicollinearity issues (Field, 2024); the structural model was therefore deemed appropriate for hypothesis testing.

Table 4. Path coefficient for direct effect

Hypothesis	Path	*B*	*t*	95% Confidence Interval		*p*	f^2	VIF
				Lower	Upper			
H1	ATI ➔ FUB	0.557	8.327	0.446	0.666	< 0.001	0.450	1.000
H2	FUB ➔ OS	-0.140	1.046	-0.306	0.117	0.148	0.020	1.000
H3	FUB ➔ UF	-0.406	5.542	-0.532	-0.292	< 0.001	0.197	1.000
H4	FUB ➔ CA	-0.586	8.490	-0.696	-0.469	< 0.001	0.523	1.000
H5	FUB ➔ BA	0.297	3.965	0.186	0.436	< 0.001	0.156	1.572
H6	OS ➔ BA	0.015	0.350	-0.065	0.077	0.363	0.001	1.044
H7	UF ➔ BA	-0.117	1.845	-0.222	-0.015	0.033	0.021	1.790
H8	CA ➔ BA	-0.506	6.597	-0.621	-0.369	< 0.001	0.317	2.244
H9	FUB ➔ BI	0.173	2.464	0.068	0.300	0.007	0.063	1.818
H10	OS ➔ BI	0.024	0.723	-0.030	0.076	0.235	0.002	1.045
H11	UF ➔ BI	-0.032	0.630	-0.110	0.052	0.264	0.002	1.828
H12	CA ➔ BI	-0.244	3.372	-0.357	-0.120	< 0.001	0.077	2.956
H13	BA ➔ BI	0.512	5.872	0.373	0.663	< 0.001	0.358	2.777
H14	FUB ➔ PB	0.059	0.697	-0.066	0.209	0.243	0.003	1.932
H15	OS ➔ PB	0.040	0.473	-0.096	0.179	0.318	0.002	1.047
H16	UF ➔ PB	-0.166	1.524	-0.339	0.022	0.064	0.023	1.831
H17	CA ➔ PB	-0.072	0.506	-0.301	0.168	0.306	0.002	3.182
H18	BA ➔ PB	0.219	1.516	-0.005	0.474	0.065	0.019	3.772
H19	BI ➔ PB	0.164	1.314	-0.043	0.368	0.094	0.011	3.800

Note. *p < 0.05. **p < 0.01. ***p < 0.001. VIF: variance inflation factor. f^2: f–square. ATI: animosity towards Israel. FUB: firms' unacceptable behavior. OS: out of sight. UF: urge of freedom. CA: counterargument. BA: boycott attitude. BI: boycott intention. PB: purchasing behavior. Source: Personal research data, 2025.

Results (Table 4) show that animosity toward Israel (ATI) significantly and positively predicted firms' unacceptable behavior (FUB; B = 0.557, t = 8.327, p < 0.001), with a large effect size (f^2 = 0.450). However, FUB did not significantly predict out of sight (OS; B = -0.140, t = 1.046, p = 0.148).

FUB significantly and negatively influen–

Table 5. Path coefficient for indirect effect

Hypothesis	Path	B	t	95% Confidence Interval		*p*	v
				Lower	Upper		
H20	FUB ➔ OS ➔ BA	-0.002	0.258	-0.012	0.014	0.398	0.000
H21	FUB ➔ OS ➔ BI	-0.003	0.495	-0.016	0.004	0.310	0.000
H22	FUB ➔ OS ➔ PB	-0.006	0.304	-0.044	0.014	0.380	0.001
H23	FUB ➔ UF ➔ BA	0.047	1.717	0.006	0.096	0.043	0.002
H24	FUB ➔ UF ➔ BI	0.013	0.601	-0.022	0.047	0.274	0.000
H25	FUB ➔ UF ➔ PB	0.067	1.474	-0.010	0.141	0.070	0.005
H26	FUB ➔ CA ➔ BA	0.297	6.904	0.225	0.366	< 0.001	0.088
H27	FUB ➔ CA ➔ BI	0.143	3.298	0.070	0.213	< 0.001	0.020
H28	FUB ➔ CA ➔ PB	0.042	0.494	-0.102	0.179	0.311	0.002

Note. *p < 0.05. **p < 0.01. ***p < 0.001. VIF: variance inflation factor. v: upsilon (v). ATI: animosity towards Israel. FUB: firms' unacceptable behavior. OS: out of sight. UF: urge of freedom. CA: counterargument. BA: boycott attitude. BI: boycott intention. PB: purchasing behavior. Source: Personal research data, 2025.

ced urge for freedom (UF; B = -0.406, t = 5.542, p < 0.001) and counterargument (CA; B = -0.586, t = 8.490, p < 0.001), suggesting that higher perceived unacceptable behavior weakens psychological resistance factors. Conversely, FUB positively predicted boycott attitude (BA; B = 0.297, t = 3.965, p < 0.001) and boycott intention (BI; B = 0.173, t = 2.464, p = 0.007), though its direct effect on purchasing behavior (PB) was non-significant (B = 0.059, t = 0.697, p = 0.243).

Among mediators, CA exerted strong nega–

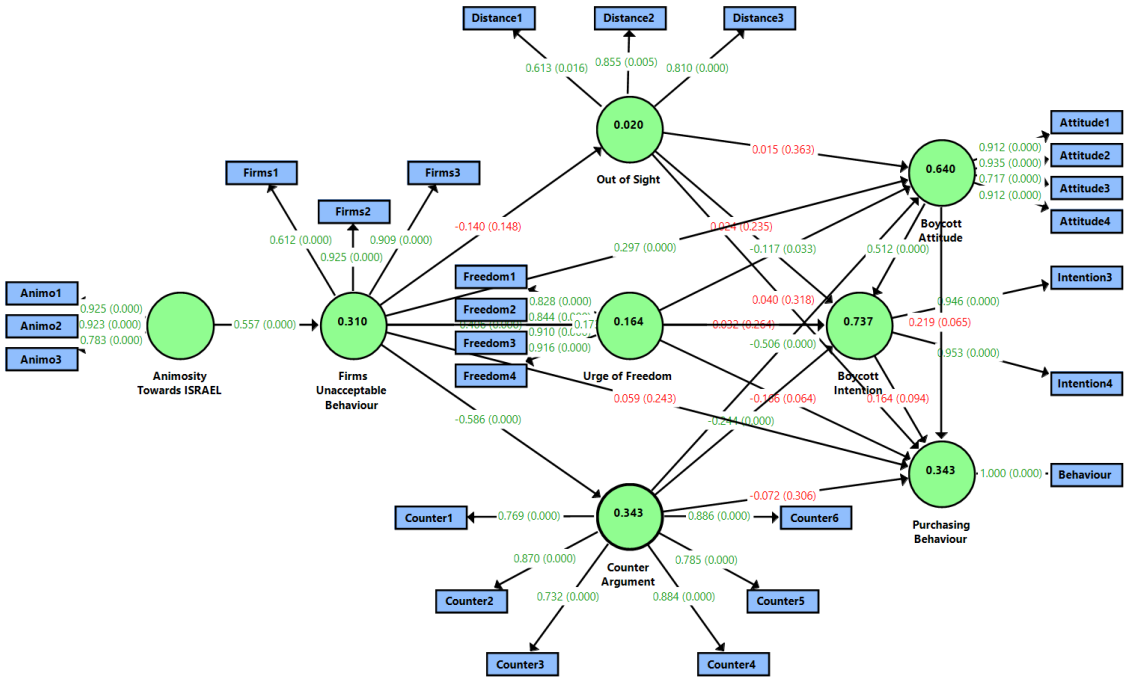


Figure 2. Structural model (Source: Authors' elaboration using SmartPLS)

tive effects on BA (B = -0.506, t = 6.597, p < 0.001) and BI (B = -0.244, t = 3.372, p < 0.001), whereas UF showed a weaker negative effect on BA (B = -0.117, t = 1.845, p = 0.033) and no significant effect on BI or PB. OS did not significantly predict BA, BI, or PB. BA strongly predicted BI (B = 0.512, t = 5.872, p < 0.001), while neither BA nor BI significantly influenced PB.

Mediation analysis (Table 5) revealed that counterargument significantly mediated the relationship between FUB and BA (B = 0.297, t = 6.904, p < 0.001) and between FUB and BI (B = 0.143, t = 3.298, p < 0.001), indicating substantively meaningful indirect effects. Mediation through OS and UF, by contrast, was generally weak or non-significant. These findings position counterargument as the

central mechanism explaining nonparticipation in boycott behavior (see Figure 2).

3.5. Quality of Model Predictive

The coefficient of determination (R^2) indicates that firms' unacceptable behavior (FUB) exhibits moderate explanatory power (R^2 = 0.310), whereas boycott attitude (BA) and boycott intention (BI) show substantial explanatory strength (R^2 = 0.640 and R^2 = 0.645, respectively). In contrast, out of sight (OS) presents a very low explanatory level (R^2 = 0.020). In terms of predictive relevance, Q^2 values suggest that most constructs possess adequate predictive capability, with the exception of OS (Q^2 = -0.005), indicating a lack of predictive relevance for this variable (Hair et al., 2021; Hair, Risher, et al., 2019).

PLSpredict (Table 6) indicated moderate overall predictive performance, with most indicators showing slightly higher RMSE/MAE values than the linear-model benchmark (Shmueli et al., 2019). Overall fit indices were acceptable (SRMR = 0.068; GoF = 0.520; Klesel et al., 2019; Wetzels & Odekerken, 2009), indicating adequate explanatory capacity (see Table S3).

3.6. Robustness Check

Robustness checks confirmed model stability. Linearity tests revealed mostly linear structural relationships (ps > 0.05), with only a few quadratic exceptions (Figure 3; Table S4), supporting model robustness against nonlinearity (Hair, Risher, et al., 2019). FIMIX-PLS analysis identified a two-segment solution as optimal based on information criteria (AIC, BIC, CAIC) and entropy (EN = 0.773 > .50), indicating well-separated segmentation (Hair, Black, et al., 2019; Matthews et al., 2016) and notable structural differences across segments—evidence of latent heterogeneity within the sample (Table S5; Table 7).

Table 6. Predictive power

Indicator	Model PLS			Model LM			Different (PLS – LM)		
	RMSE	MAE	Q^2 pred	RMSE	MAE	Q^2 pred	ΔRMSE	ΔMAE	ΔQ^2 pred
Firms' unacceptable behavior (RMSE = 0.855, MAE = 0.656, Q² pred = 0.293)									
Firms1	1.065	0.779	0.062	1.069	0.789	0.056	-0.003	-0.009	0.006
Firms2	0.734	0.601	0.279	0.742	0.604	0.265	-0.007	-0.003	0.014
Firms3	0.623	0.454	0.253	0.633	0.457	0.227	-0.010	-0.003	0.025
Out of sight (RMSE = 1.033, MAE = 0.662, Q² pred = -0.021)									
Distance1	0.362	0.259	-0.009	0.365	0.259	-0.026	-0.003	-0.001	0.017
Distance2	0.204	0.082	-0.012	0.207	0.084	-0.041	-0.003	-0.002	0.029
Distance3	0.392	0.303	-0.015	0.394	0.302	-0.026	-0.002	0.001	0.010
Urge of freedom (RMSE = 0.947, MAE = 0.774, Q² pred = 0.112)									
Freedom1	1.142	0.910	0.052	1.161	0.910	0.021	-0.019	0.000	0.031
Freedom2	1.171	0.945	0.064	1.175	0.928	0.058	-0.004	0.017	0.006
Freedom3	0.918	0.722	0.135	0.901	0.711	0.168	0.017	0.011	-0.033
Freedom4	0.903	0.713	0.112	0.896	0.709	0.126	0.007	0.004	-0.014
Counterargument (RMSE = 0.908, MAE = 0.730, Q² pred = 0.191)									
Counter1	0.850	0.676	0.116	0.852	0.679	0.112	-0.002	-0.002	0.004
Counter2	0.905	0.699	0.177	0.898	0.703	0.190	0.007	-0.003	-0.013
Counter3	1.019	0.785	0.044	1.039	0.795	0.005	-0.021	-0.011	0.039
Counter4	0.972	0.763	0.157	0.963	0.779	0.172	0.009	-0.016	-0.015
Counter5	1.084	0.925	0.077	1.078	0.914	0.087	0.006	0.012	-0.009
Counter6	0.963	0.768	0.188	0.947	0.772	0.214	0.016	-0.005	-0.027
Boycott attitude (RMSE = 0.877, MAE = 0.718, Q² pred = 0.245)									
Attitude1	0.780	0.643	0.204	0.769	0.632	0.227	0.011	0.011	-0.022
Attitude2	0.707	0.591	0.226	0.699	0.570	0.244	0.008	0.022	-0.018
Attitude3	0.919	0.746	0.063	0.922	0.746	0.058	-0.003	0.000	0.005
Attitude4	0.725	0.598	0.243	0.706	0.569	0.281	0.018	0.029	-0.037
Boycott intention (RMSE = 0.873, MAE = 0.710, Q² pred = 0.254)									
Intention3	0.720	0.581	0.232	0.714	0.569	0.247	0.007	0.012	-0.014
Intention4	0.743	0.604	0.227	0.735	0.589	0.243	0.008	0.015	-0.016
Purchasing behavior (RMSE = 0.961, MAE = 0.715, Q² pred = 0.103)									
Behaviour	2.270	1.697	0.101	2.313	1.697	0.067	-0.043	0.000	0.034

Note. The values in parentheses represent the LV (Latent Variable) prediction summary for each endogenous construct. RMSE: root mean squared error. MAE: mean absolute error. Q^2 pred: Q^2 predict. Source: Personal research data, 2025.

3.7. Multi-Group Analysis (MGA)

Multi-group analysis (MGA) revealed meaningful differences across gender (male vs. female) and boycott status (boycott vs. non-boycott; Table S6, Figure 4). Gender-based comparisons yielded limited statistically significant differences, though several paths approached significance. The FUB→CA path showed a non-significant yet notable difference (B = 0.154, p = 0.202), tentatively suggesting that males may be more reactive in forming counterarguments toward perceived corporate misconduct. The FUB→PB path likewise revealed only marginal variation between male and female responses (B = -0.113, p = 0.261).

In contrast, the comparison based on boycott status demonstrates more pronounced and statistically significant differences. The relationship between animosity towards Israel (ATI) and FUB is significantly stronger in the boycott group (B = -0.268, p = 0.025), indicating that individuals engaged in boycott behavior are more sensitive to perceived corporate misconduct. A similar pattern is observed in the relationship between FUB and boycott attitude (BA), where the boycott group exhibits a stronger negative effect (B = -0.262, p = 0.030), suggesting a greater tendency to develop boycott attitudes in response to unacceptable corporate practices.

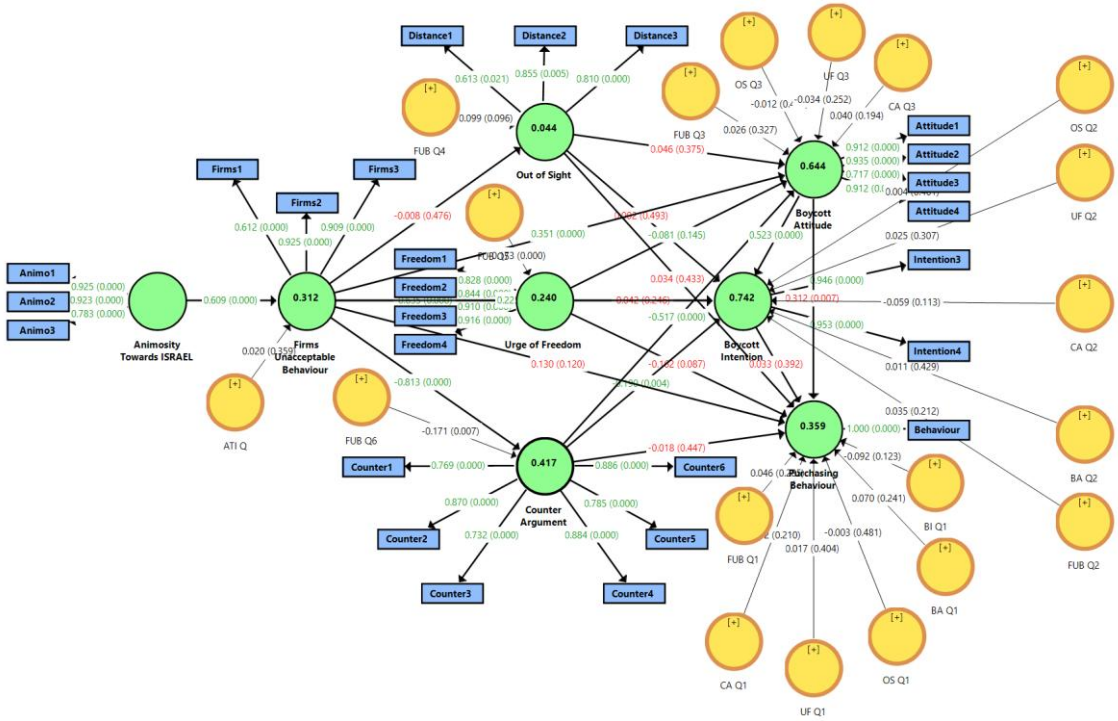


Figure 3. Assessment of nonlinearity effects in the structural model (Source: Authors' elaboration using SmartPLS)

Table 7. Results of FIMIX-PLS calculation

Parameters	Original sample		FIMIX PLS group 1		FIMIX PLS group 2	
N	212		105		107	
Relative seg. size (%)	100		49.528		50.471	
Measurement model						
Cronbach's Alpha	-		-		-	
Composite Reliability	+		+		+	
AVE	+		+		+	
HTMT	+		+		+	
Structural model						
Path	*B*	*p*	*B*	*p*	*B*	*p*
ATI ➔ FUB	0.557	< 0.001	0.548	< 0.001	0.587	< 0.001
FUB ➔ OS	-0.140	0.149	-0.308	0.007	0.052	0.312
FUB ➔ UF	-0.406	< 0.001	-0.336	0.001	-0.501	< 0.001
FUB ➔ CA	-0.586	< 0.001	-0.573	< 0.001	-0.613	< 0.001
FUB ➔ BA	0.297	< 0.001	0.254	0.016	0.337	< 0.001

Parameters	Original sample		FIMIX PLS group 1		FIMIX PLS group 2	
OS ➔ BA	0.015	0.364	-0.065	0.201	0.092	0.017
UF ➔ BA	-0.117	0.033	-0.127	0.064	-0.160	0.057
CA ➔ BA	-0.506	< 0.001	-0.515	< 0.001	-0.429	< 0.001
FUB ➔ BI	0.173	0.007	0.237	0.022	0.093	0.150
OS ➔ BI	0.024	0.237	-0.007	0.454	0.047	0.119
UF ➔ BI	-0.032	0.261	-0.014	0.411	-0.092	0.105
CA ➔ BI	-0.244	< 0.001	-0.352	< 0.001	-0.099	0.148
BA ➔ BI	0.512	< 0.001	0.377	0.001	0.652	< 0.001
FUB ➔ PB	0.059	0.243	0.111	0.235	-0.013	0.444
OS ➔ PB	0.040	0.319	0.051	0.373	-0.016	0.407
UF ➔ PB	-0.166	0.067	-0.285	0.031	0.078	0.244
CA ➔ PB	-0.072	0.304	-0.014	0.474	-0.182	0.121
BA ➔ PB	0.219	0.062	0.020	0.461	0.613	< 0.001
BI ➔ PB	0.164	0.092	0.209	0.116	0.041	0.410
Coefficient determination (R^2)						
FUB	0.310		0.300		0.344	
OS	0.020		0.095		0.003	
UF	0.164		0.113		0.251	
CA	0.343		0.328		0.376	
BA	0.640		0.619		0.690	
BI	0.737		0.741		0.769	
PB	0.343		0.269		0.536	

Note. *p < 0.05. **p < 0.01. ***p < 0.001. ATI: animosity towards Israel. FUB: firms' unacceptable behavior. OS: out of sight. UF: urge of freedom. CA: counterargument. BA: boycott attitude. BI: boycott intention. PB: purchasing behavior. *AVE*: average variance extracted. HTMT: heterotrait–monotrait ratio of correlations. R^2: R–square. +: All indicators meet the criteria; –: Not all indicators meet the criteria. Source: Personal research data, 2025.

Furthermore, the relationship between BA and PB differs significantly across boycott status groups (B = -0.601, p = 0.022), indicating that boycott attitudes translate more strongly into actual purchasing behavior among boycott participants. These findings underscore behavioral consistency within the boycott group, where attitudes more directly drive consumption decisions.

Additional insights emerge from the media–

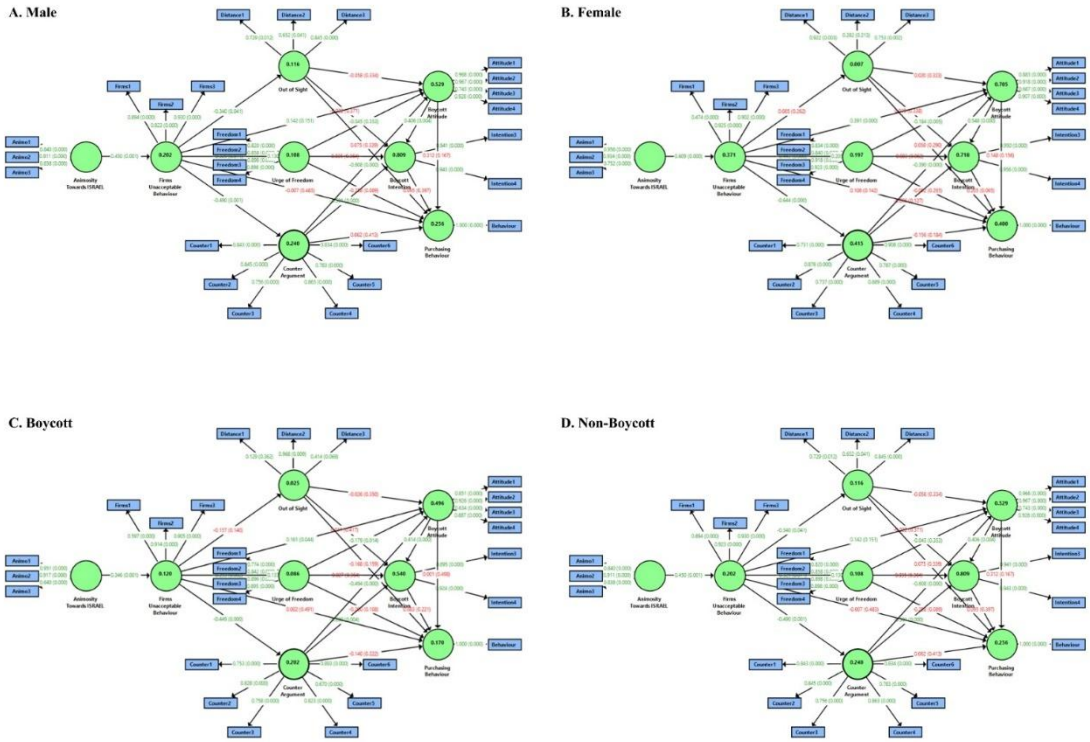


Figure 4. Multi-group structural model across gender and boycott status (Source: Authors' elaboration using SmartPLS)

tion analysis. The indirect effect of FUB on boycott intention (BI) through CA is significant in the male group ($B = 0.184$, $p = 0.038$) but not in the non-boycott group, suggesting that counter-arguments play a more prominent mediating role among male participants.

Overall, the MGA results indicate that boycott status represents a more substantial source of heterogeneity than gender. Individuals in the boycott group exhibit stronger and more consistent responses to corporate misconduct, particularly in shaping attitudes, intentions, and purchasing behavior (see Figure 4).

3.8. Neural Network Regression (NNR)

Performance of the artificial neural network–neural network regression (ANN–NNR) models was evaluated on training and testing datasets across 24 architectures (Table 8). Model comparison relied on root mean squared error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2), with primary emphasis on testing performance to ensure out-of-sample validity. Training–testing differentials (ΔRMSE, ΔR^2, ΔMAE) were further examined to assess stability and potential overfitting.

Predictive performance varied substantially across configurations. Model ANN–NNR 1 (7–3–1 architecture) emerged as the best performer, yielding the lowest RMSE (0.805) and MAE (0.614) and the highest R^2 (0.248) on the testing set. It also exhibited the smallest training–testing discrepancy (ΔRMSE = 0.149; $\Delta R^2 = -0.009$; ΔMAE = 0.096), indicating superior accuracy, stronger generalization, and minimal overfitting relative to more complex architectures.

Table 8. Comparison model ANN–NNR

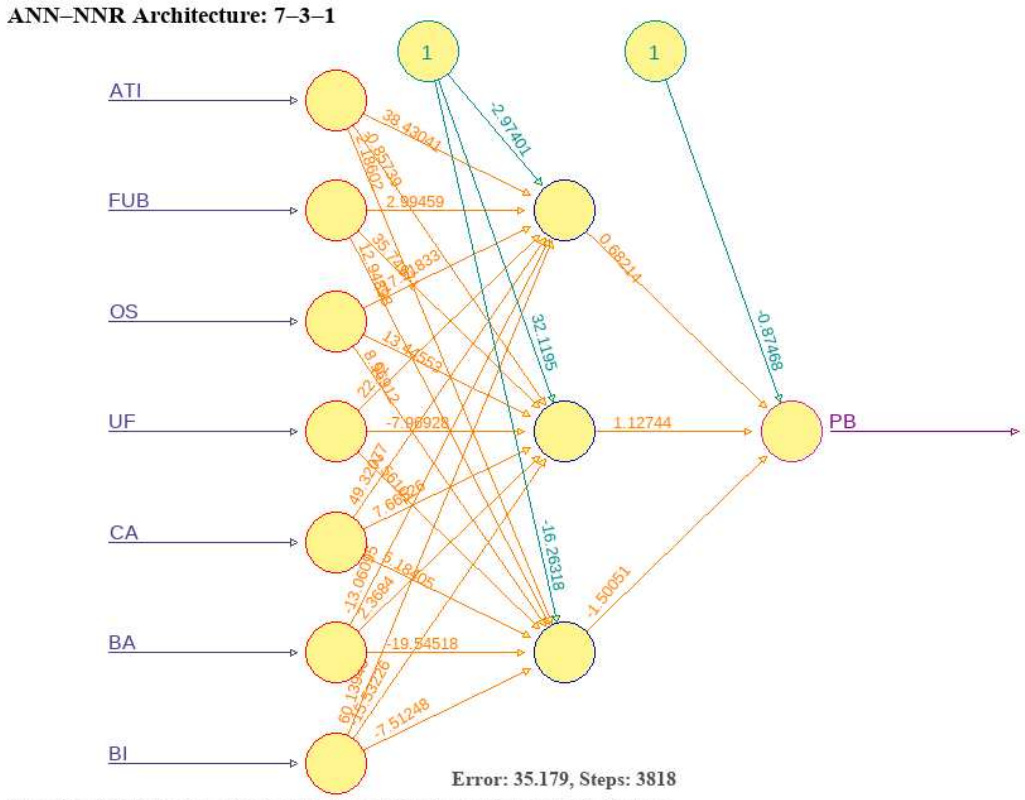
Model	ANN–NNR Architecture	Training Data Set (70%)			Testing Data Set (30%)			Different (Training – Testing)		
		RMSE	R^2	MAE	RMSE	R^2	MAE	ΔRMSE	ΔR^2	ΔMAE
Single hidden layer models										
Model ANN–NNR 1	7–3–1	0.955	0.239	0.710	0.805	0.248	0.614	0.149	-0.009	0.096
Model ANN–NNR 2	7–5–1	1.020	0.200	0.667	2.973	0.097	1.088	-1.953	0.103	-0.421
Model ANN–NNR 3	7–8–1	1.088	0.167	0.764	1.222	0.060	0.901	-0.134	0.107	-0.137
Model ANN–NNR 4	7–10–1	1.105	0.167	0.726	1.221	0.074	0.908	-0.116	0.092	-0.181
Model ANN–NNR 5	7–15–1	1.126	0.156	0.766	1.637	0.014	1.154	-0.512	0.141	-0.388
Model ANN–NNR 6	7–20–1	1.127	0.156	0.770	1.355	0.090	1.008	-0.229	0.066	-0.238
Two hidden layers models										
Model ANN–NNR 7	7–5–3–1	1.087	0.167	0.700	3.757	0.016	1.511	-2.669	0.150	-0.811
Model ANN–NNR 8	7–8–5–1	1.120	0.159	0.759	1.621	0.005	1.035	-0.501	0.153	-0.277
Model ANN–NNR 9	7–10–5–1	1.102	0.161	0.693	1.426	0.009	0.891	-0.324	0.152	-0.198
Model ANN–NNR 10	7–10–10–1	1.129	0.155	0.775	1.818	0.008	1.303	-0.689	0.147	-0.528
Model ANN–NNR 11	7–15–10–1	1.129	0.155	0.776	1.483	0.058	1.048	-0.354	0.097	-0.272
Model ANN–NNR 12	7–20–20–1	1.129	0.155	0.776	1.426	0.026	1.058	-0.296	0.129	-0.282
Three hidden layer models										
Model ANN–NNR 13	7–5–3–2–1	1.030	0.209	0.685	1.394	0.043	0.809	-0.364	0.166	-0.124
Model ANN–NNR 14	7–8–5–3–1	1.107	0.167	0.736	1.383	0.146	0.814	-0.276	0.021	-0.078
Model ANN–NNR 15	7–10–8–5–1	1.117	0.160	0.737	2.182	0.003	1.253	-1.066	0.156	-0.516
Model ANN–NNR 16	7–12–8–5–1	1.121	0.159	0.761	1.445	0.057	1.052	-0.324	0.102	-0.291
Model ANN–NNR 17	7–15–10–5–1	1.123	0.157	0.759	1.519	0.017	0.977	-0.397	0.140	-0.219
Model ANN–NNR 18	7–20–15–10–1	1.127	0.156	0.771	1.480	0.093	1.087	-0.353	0.063	-0.316
Four hidden layer models										
Model ANN–NNR 19	7–5–4–3–2–1	1.089	0.168	0.705	1.211	0.018	0.769	-0.122	0.151	-0.064
Model ANN–NNR 20	7–8–6–4–3–1	1.110	0.161	0.718	1.531	0.017	1.008	-0.421	0.144	-0.290
Model ANN–NNR 21	7–10–8–6–4–1	1.122	0.157	0.755	1.230	0.046	0.888	-0.108	0.111	-0.133
Model ANN–NNR 22	7–12–10–8–5–1	1.125	0.156	0.762	1.334	0.085	0.941	-0.209	0.071	-0.179
Model ANN–NNR 23	7–15–12–10–8–1	1.127	0.156	0.768	1.542	0.025	1.098	-0.415	0.130	-0.330
Model ANN–NNR 24	7–20–15–10–5–1	1.127	0.156	0.774	1.453	0.005	1.124	-0.326	0.150	-0.351

Note. ANN–NNR: artificial neural network-neural network regression. RMSE: root mean squared error. MAE: mean absolute error. R^2: R–square (coefficient of determination). The ANN–NNR architecture refers to the network topology used in the prediction model. Source: Personal research data, 2025.

Importantly, model performance did not improve with increasing network complexity. Models with deeper architectures (two, three, and four hidden layers) generally exhibited larger train–test discrepancies, higher prediction errors, and lower explanatory power on the testing dataset. Several complex models, such as Model ANN–NNR 7 (7–5–3–1), showed substantial performance deterioration between training and testing datasets (ΔRMSE = -2.669), suggesting pronounced overfitting. These findings indicate that more complex

ANN–NNR structures tend to memorize training patterns without improving generalization performance. In contrast, simpler architectures demonstrated more stable and reliable predictive behavior (see Figure 5).

To further interpret the contribution of each predictor variable within the best-performing ANN–NNR model (7–3–1 architecture), variable importance analysis was conducted using the variable importance function implemented in the H2o deep learning framework, which estimates the relative contribution of each predictor to the model's predictive performance.



Note. The ANN–NNR model employed a 7–3–1 architecture to predict purchasing behavior.
Abbreviation. ANN–NNR: Artificial Neural Network-Neural Network Regression; ATI: Animosity Towards Israel; FUB: Firms' Unacceptable-Behavior; OS: Out of Sight; UF: Urge of Freedom; CA: Counterargument; BA: Boycott Attitude; BI: Boycott Intention; PB: Purchasing Behavior.

Figure 5. Neural network structure (Source: Authors' elaboration using R and Positron)

The variable importance analysis (Table 9) shows that out of sight is the most influential predictor, accounting for 22.400% of overall model importance—suggesting that perceived proximity or visibility of boycott-related targets substantially shapes purchase behavior. Boycott attitude (22.000%) and urge of freedom (19.300%) follow closely, underscoring the role of cognitive and intentional processes in consumer decision-making. Boycott intention, firms' unacceptable behavior, and animosity toward Israel contributed moderately to predictive performance.

In contrast, counterargument exhibited the lowest contribution (7.400%), reflecting a comparatively smaller role within the ANN–NNR framework. Overall, variables related to behavioral proximity and boycott attitudes contributed more strongly to predictive performance than other motivational variables. These findings align with the superior performance of the parsimonious 7–3–1 architecture reported in Table 8, reinforcing the importance of model simplicity for better generalization. Figure 6 illustrates the validation performance and variable importance of the best-performing ANN–NNR model (7–3–1 architecture). Panels A, B, and C show the progression of RMSE, MAE, and deviance across training epochs for both training and validation datasets. Prediction errors decreased substantially during early training and gradually stabilized as epochs increased. Training curves consistently yielded lower error values than validation curves,

indicating that the model captured meaningful data patterns while maintaining stable generalization. RMSE and MAE declined sharply during the initial epochs before reaching a plateau, signaling convergence of the optimization process. Although a gap persisted between training and validation performance, the discrepancy remained moderate relative to more complex architectures in Table 8, supporting the conclusion that the 7–3–1 architecture achieved better predictive stability with reduced overfitting. The deviance curve likewise showed a continuous downward trend, further indicating improved model fit throughout training.

Table 9. Variable importance of ANN–NNR model in predicting purchase behavior

Importance Rank	Variables	Relative Importance	Scaled Importance	Percentage (%)
1	Out of sight (OS)	1.000	1.000	0.224 (22.400%)
2	Boycott attitude (BA)	0.985	0.985	0.220 (22.000%)
3	Urge of freedom (UF)	0.862	0.862	0.193 (19.300%)
4	Boycott intention (BI)	0.531	0.531	0.119 (11.900%)
5	Firms' unacceptable behavior (FUB)	0.389	0.389	0.087 (8.700%)
6	Animosity towards Israel (ATI)	0.372	0.372	0.083 (8.300%)
7	Counterargument (CA)	0.330	0.330	0.074 (7.400%)

Note. ANN–NNR: artificial neural network–neural network regression. Variable importance was computed using the H2o deep learning variable importance procedure based on the trained ANN–NNR model (architecture 7–3–1), which was identified as the best-performing model in Table 8. Relative importance reflects the model-derived contribution of each predictor, whereas scaled importance represents normalized relative contributions. Percentage values indicate each variable's proportional contribution to the model's predictive performance in purchase behavior. Source: Personal research data, 2025.

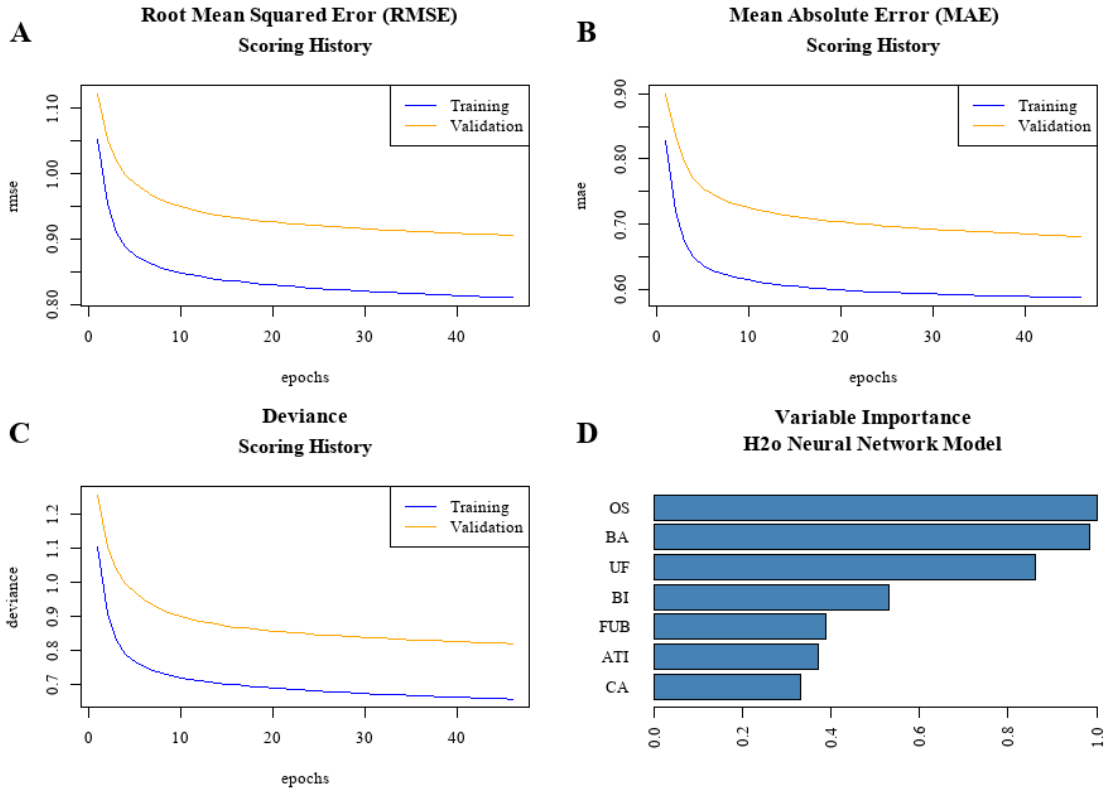


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Figure 6. Model validation and variable importance of the ANN–NNR model architecture 7–3–1 (Source: Authors' elaboration using R and Positron)

The ANN–NNR model was estimated using the Tanh activation function with 1000 epochs and one hidden layer consisting of three neurons. The model additionally employed *l1* regularization (0.0001), *l2* regularization (0.001), adaptive learning rate optimization, and 3-fold cross-validation. Variable importance analysis (Panel D) revealed that out of sight (OS), boycott attitude (BA), and urge of freedom (UF) contributed most strongly to the prediction of purchase behavior, whereas counterargument (CA) demonstrated the smallest contribution to the model.

4. DISCUSSION

The findings of this study extend prior work on collective-action inaction by integrating emotional, cognitive, and perceptual mechanisms within a single structural framework. Consistent with Yuksel (2013), the results demonstrate that multiple psychological factors simultaneously shape individuals' reluctance or willingness to engage in boycott behavior.

First, animosity toward Israel significantly predicted perceptions of firms' unacceptable behavior. This finding aligns with the classical spillover logic articulated by Friedman (1991), wherein consumers redirect anger toward associated entities when direct punishment of the primary target is infeasible. Klein et al. (1998) likewise argue that firms function as symbolic representatives of the target country, particularly when prior affiliations are salient. The Indonesian context reinforces this mechanism: geopolitical conflict translates into marketplace responses. Recent studies on consumer animosity and boycott behavior further confirm that such responses are contextually situated and shaped by the prevailing political-moral environment (Babu et al., 2025; Bröckerhoff & Qassoum, 2021; Davlembayeva et al., 2024; Hino, 2022; Kristiningsih et al., 2025), underscoring that boycott behavior is embedded in lived socio-political conflict rather than reducible to individual preference.

Second, firms' unacceptable behavior exerted both direct and indirect effects on boycott attitude and intention. The direct positive effects corroborate prior findings (e.g., Abdul-Talib et al., 2016) showing that perceived corporate wrongdoing intensifies collective-action tendencies. The present study extends this work by demonstrating that the relationship is contingent on mediating mechanisms—a pattern consistent with research on the ambiguous effectiveness of political brand communication, where corporate stances can be interpreted inconsistently depending on consumers' ideological alignment and contextual cues (e.g., Flight & Allaway, 2024; Guèvremont, 2025; Jungblut & Johnen, 2022; Ketron et al., 2022; S. Kim & He, 2025)

The role of counterargument aligns with bystander theory and collective-inaction frameworks (Klein et al., 2004), which suggest that individuals weigh potential costs and consequences before engaging in collective action. When boycott actions are perceived as ineffective—or even harmful (e.g., economic consequences for local workers)—individuals generate counterarguments that diminish participation willingness. This dovetails with recent behavioral decision-making research showing that perceived inefficacy and personal cost reduce engagement in prosocial or political consumption (e.g., Lee, 2026; Starke & Kelm, 2025).

Recent literature on digital activism further suggests that individuals increasingly experience activism fatigue and cognitive overload in online political environments, strengthening counterargument formation and behavioral disengagement (Lane et al., 2025; Simiti, 2024; Valli & Nai, 2023). The well-documented slacktivism–real-action gap likewise helps explain why online moral agreement does not always translate into offline boycott behavior (C. Kim, Kim, et al., 2022; S. Kim & He, 2025). Work on system-justifying tendencies in political consumption further suggests that individuals may rationalize non-participation by minimizing personal responsibility or the perceived efficacy of collective action (Nakagoshi & Inamasu, 2024).

By contrast, the urge of freedom can be interpreted through Psychological Reactance Theory (Brehm & Brehm, 1981). When individuals perceive social pressure to participate in boycotts, they may experience reactance and resist compliance in order to restore autonomy. As Yuksel (2013) observes, boycott calls can paradoxically trigger resistance when framed as social obligation rather than autonomous choice.

Recent empirical research extends reactance theory into digital environments, showing that persuasion resistance emerges on social media when users perceive moral pressure within online activism campaigns (Carpenter et al., 2026; Yang & Kruschke, 2025). Hashtag-activism backlash has likewise been documented when individuals reject symbolic participation demands perceived as socially coercive (Hong & Kim, 2021; Wang & Zhou, 2021). The construct of 'forced-activism perception' further highlights how normative pressure online can reduce behavioral compliance and amplify psychological resistance (Lu & Liang, 2024; Yang & Kruschke, 2025).

Interestingly, out of sight did not significantly mediate the relationship between firms' unacceptable behavior and boycott outcomes, suggesting that perceived distance from boycott consequences is not decisive in the present context. One plausible explanation lies in shared social identity: according to Social Identity Theory (Tajfel & Turner, 2004), individuals may act on the basis of group affiliation rather than personal proximity to consequences.

Recent extensions of identity theory emphasize moral identity in activism, with individuals engaging in collective action through internalized moral self-concepts rather than situational proximity (Leal et al., 2025; Shultziner, 2025). Research on collective identity in digital movements further shows that online communities strengthen perceived group belonging, sustaining engagement even when personal costs are diffuse or unclear (Brown et al., 2024; Greijdanus et al., 2020).

In addition, the concept of global solidarity consumption—particularly in politically sensitive contexts such as Palestine-related activism—suggests that individuals engage in boycott behavior as a form of transnational moral alignment rather than direct experiential proximity (Zejjari & Benhayoun, 2025). This finding adds nuance to prior work emphasizing psychological distance (Ram et al., 2024; Trope & Liberman, 2010), indicating possible boundary conditions in digitally mediated contexts of moral solidarity.

Furthermore, none of the variables significantly predicted purchasing behavior. This pattern supports the well-established attitude–behavior gap articulated by the Theory of Reasoned Action (Ajzen & Fishbein, 1980), which posits that attitudes and intentions do not always translate into actual behavior. Within this framework, attitudes are determined by beliefs about the consequences of behavior—particularly whether those consequences are positive or negative—such that individuals display more favorable attitudes when they expect positive outcomes (Mubin & Setyaningsih, 2020).

Recent work in ethical consumption further highlights that the intention–behavior gap persists in digital-era activism, where moral intentions expressed online are often unmirrored in real purchasing decisions(Azzopardi & Sluis, 2024; Casais & Faria, 2022). In addition, research on boycott inconsistency shows that individuals frequently experience cognitive dissonance between ideological support and habitual consumption patterns (J. Kim et al., 2025; Roth et al., 2025). Taken together, these findings suggest that structural constraints, habit formation, and competing preferences remain key barriers to translating boycott intentions into actual behavior.

Finally, the multi-group analysis revealed meaningful differences across gender and boycott status. These findings align with prior research indicating that demographic factors shape collective-action tendencies (e.g., Besta et al., 2024; Nelson et al., 2008). More recent work further shows that gendered patterns of political consumption shape moral decision-making in boycott contexts, with women tending to display higher ethical sensitivity and a stronger orientation toward collective responsibility (Jansesberger & Lefkofridi, 2025; Vasquez et al., 2025).

More importantly, differences between boycott and non-boycott groups suggest that prior commitment shapes how individuals interpret corporate behavior and translate it into action. This finding underscores the importance of segmentation for understanding consumer activism, particularly in politically charged consumption environments (Ateş, 2025; Garg & Saluja, 2022).

Overall, this study contributes to the literature by demonstrating that collective action in the context of boycotts is not solely driven by moral outrage but is simultaneously shaped by cognitive evaluation, perceived autonomy, and social identity processes. The

integration of these mechanisms yields a more comprehensive explanation of why individuals choose to engage or disengage from collective action. These findings suggest that boycott inaction should be understood not as a mere lack of motivation but as an active psychological process shaped by competing cognitive justifications, perceived autonomy threats, and digitally mediated social identities within contemporary political-consumerism contexts.

5. CONCLUSION

This study examined why individuals remain inactive in boycott movements despite holding negative attitudes toward companies associated with Israel, with particular attention to the role of animosity in shaping non-participation. The findings indicate that animosity toward targeted companies is indirectly linked to boycott attitudes and intentions through distinct psychological mechanisms. Of the three motivational factors proposed by Yuksel (2013), only urge for freedom and counterargument significantly mediated the relationship between perceived firm misconduct and both boycott attitude and intention, whereas out of sight showed no significant effect. These results suggest that boycott inaction is not a passive response, but an active process shaped by cognitive and motivational dynamics, particularly those tied to perceived autonomy and argumentative resistance. The divergence from prior findings highlights the contextual specificity of inaction in politically sensitive boycott settings. Future research should examine how animosity-related cognition interacts with motivational mechanisms across diverse sociopolitical contexts to better understand when negative attitudes translate into active boycott behavior.

6. REFERENCES

Abdul-Talib, A.-N., Abd-Latif, S.-A., & Abd-Razak, I.-S. (2016). A study on the boycott motivations of Malaysian non-Muslims. *Journal of Islamic Marketing*, *7*(3), 264–287. https://doi.org/10.1108/JIMA-11-2014-0071

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.

Amalia, H. K., Masruroh, A., & Prasetyo, A. (2025). Psychological determinants and mediating mechanisms of muslim consumers' intention to boycott Israeli products. *Jurnal Ekonomi Syariah Teori Dan Terapan*, *12*(4), 422–438. https://doi.org/10.20473/vol12iss20254pp422-438

Anwar, Moh. K., Rusanti, E., & Napitupulu, R. M. (2025). The power of social pressure in steering society toward intentional boycotts of Israeli-related products. *Journal of Islamic Marketing*, *17*(5), 1792–1813. https://doi.org/10.1108/JIMA-03-2024-0112

Appelbaum, M., Cooper, H., Kline, R. B., Mayo-Wilson, E., Nezu, A. M., & Rao, S. M. (2018). Journal article reporting standards for quantitative research in psychology: The APA Publications and Communications Board task force report. *American Psychologist*, *73*(1), 3–25. https://doi.org/10.1037/amp0000191

Atari, M., Kroupin, I., Morhayim, L., Blasi, D. E., Schulz, J., & Henrich, J. (2025). WEIRD questions: Diversifying conceptual sampling. *PsyArXiv*. https://doi.org/10.31234/osf.io/vxcrj_v1

Ateş, S. (2025). Expanding boycott repertoire: politically motivated consumer boycotts as a reaction to brands' political alignment. *Journal of Consumer Marketing*, *42*(7), 1089–1101. https://doi.org/10.1108/JCM-11-2024-7392

Azzopardi, L., & Sluis, F. van der. (2024). Seeking socially responsible consumers: Exploring the intention-search-behaviour gap. *Proceedings of the 2024 ACM SIGIR Conference on Human Information Interaction and Retrieval (CHIIR '24)*, 1–12. https://doi.org/10.1145/3627508.3638324

Baban, M., & Baban, C.-F. (2024). Addressing antecedents' importance of open innovation between industry and universities: A neural network-based importance-performance analysis with a fuzzy approach. *Alexandria Engineering*

Journal, *104*, 515–528. https://doi.org/10.1016/j.aej.2024.08.022

Babu, M. A., Alam, M. T. U., Jaman, S. M. S., & Islam, M. R. (2025). Understanding the psychology behind the boycott of Israeli-affiliated brands: A TPB-based study in Bangladesh. *Acta Psychologica*, *260*(105572), 1–15. https://doi.org/10.1016/j.actpsy.2025.105572

Banjaransari, H. (2025). The influence of consumer animosity, boycott participation, boycott motivation, and product judgment on purchase readiness or aversion in pizza hut in Indonesia. *Syntax Literate: Jurnal Ilmiah Indonesia*, *10*(2), 2154–2169. https://doi.org/10.36418/syntax-literate.v10i2.55817

Brehm, S. S., & Brehm, J. W. (1981). *Psychological reactance: A theory of freedom and control*. Academic Press.

Bröckerhoff, A., & Qassoum, M. (2021). Consumer boycott amid conflict: The situated agency of political consumers in the occupied Palestinian territory. *Journal of Consumer Culture*, *21*(4), 892–912. https://doi.org/10.1177/1469540519882483

Brown, O., Smith, L. G. E., Davidson, B. I., Racek, D., & Joinson, A. (2024). Online Signals of Extremist Mobilization. *Personality and Social Psychology Bulletin*. https://doi.org/10.1177/01461672241266866

Carpenter, C. J., Richards, A., & Zhuang, J. (2026). Psychological reactance theory and politeness theory: A test of competing explanations for the role of threat to freedom in conveying persuasive resistance. *Communication Monographs*, 1–24. https://doi.org/10.1080/03637751.2026.2615230

Casais, B., & Faria, J. (2022). The intention-behavior gap in ethical consumption: mediators, moderators and consumer profiles based on ethical priorities. *Journal of Macromarketing*, *42*(1), 100–113. https://doi.org/10.1177/02761467211054836

Chen, Z., Oh, P., & Chen, A. (2021). The role of online media in mobilizing large-scale collective action. *Social Media + Society*, *7*(3), 1–13. https://doi.org/10.1177/20563051211033808

Chin, W. W., Thatcher, J. B., & Wright, R. T. (2012). Assessing common method bias: Problems with the ULMC technique. *Management Information Systems Quarterly*, *36*(3), 1003–1019. https://doi.org/10.2307/41703491

Comrey, A. L. (1978). Common methodological problems in factor analytic studies. *Journal of Consulting and Clinical Psychology*, *46*(4), 648.

Copeland, L., & Boulianne, S. (2022). Political consumerism. *International Political Science Review*, *43*(1), 3–18. https://doi.org/10.1177/0192512120905048

Dancey, C. P., & Reidy, J. (2020). *Statistics without maths for psychology* (8th ed.). Pearson.

Davlembayeva, D., Marikyan, D., & Slade, E. (2024). Identifying current themes and important future research directions in the field of consumer animosity. In *Bringing the Soul Back to Marketing. AMSWMC 2023. Developments in Marketing Science: Proceedings of the Academy of Marketing Science* (pp. 42–55). https://doi.org/10.1007/978-3-031-53286-3_5

Diesburg, D. A., & Wessel, J. R. (2021). The pause-then-cancel model of human action-stopping: Theoretical considerations and empirical evidence. *Neuroscience & Biobehavioral Reviews*, *129*, 17–34. https://doi.org/10.1016/j.neubiorev.2021.07.019

Dillard, J. P., & Shen, L. (2005). On the nature of reactance and its role in persuasive health communication. *Communication Monographs*, *72*(2), 144–168.

Elliot, A. J., Higgins, E. T., & Nakkawita, E. (2024). The (absence of the) presence-absence distinction in motivation science. *Psychological Review*, *132*(1), 154–172. https://doi.org/10.1037/rev0000508

Evelyn, & Sekarasih, L. (2025). Social identity and consumer boycott participation in Indonesia: An extension of theory of planned behavior. *Psikostudia: Jurnal Psikologi*, *14*(4), 547. https://doi.org/10.30872/psikostudia.v14i3

Faizi, F., Putri, I. F., & Shuib, M. S. B. (2025). Social media, economic constraints, and humanitarian values: drivers of boycott behavior among young muslim consumers in Indonesia. *Al-Intaj*, *11*(2), 408. https://doi.org/10.29300/aij.v11i2.8236

Field, A. (2024). *Discovering statistics using IBM SPSS statistics* (6th ed.). Sage Publications Limited.

Fillon, A. A., Strauch, L., & Feldman, G. (2023). Evaluations of action and inaction decision-makers in risky decisions resulting in negative outcomes: Inaction agents are preferred to and perceived as more competent and normative than action agents. *Collabra: Psychology*, *9*(1), 1–16. https://doi.org/10.1525/collabra.74817

Flight, R. L., & Allaway, A. W. (2024). Brand activism induced consumer alienation. *Marketing Management Journal*, *34*(2), 16–33. https://doi.org/10.63963/001c.151166

Friedman, M. (1991). Consumer Boycotts: A Conceptual Framework and Research Agenda. *Journal of Social Issues*, *47*(1), 149–168. https://doi.org/10.1111/j.1540-4560.1991.tb01817.x

Garg, N., & Saluja, G. (2022). A tale of two "ideologies": Differences in consumer response to brand activism. *Journal of the Association for Consumer Research*, *7*(3), 325–339. https://doi.org/10.1086/719584

Ghosh, C. (2022). *Data analysis with machine learning for psychologists*. Springer.

Greijdanus, H., Roos, C. A., Postmes, T., de Matos Fernandes, C. A., Turner-Zwinkels, F., Rosenbusch, H., & Honari, A. (2020). The psychology of online activism and social movements: relations between online and offline collective action. *Current Opinion in Psychology*, *35*, 49–54. https://doi.org/10.1016/j.copsyc.2020.03.003

Guèvremont, A. (2025). Opportunistic or relevant brand? How context independence and past coherence shape the effectiveness of brand activism and its positive effect. *Journal of Brand Strategy*, *14*(1), 92. https://doi.org/10.69554/qufw3951

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis*. Cengage. https://books.google.co.id/books?id=0R9ZswEACAAJ

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*.

Hair, J. F., Hult, G. T. M., Ringle, C., Sarstedt, M., Danks, N., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A workbook*.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Number 1, pp. 2–24). Emerald Group Publishing Ltd. https://doi.org/10.1108/EBR-11-2018-0203

Heidary, S., Abdollahi, A., Jarrahi, E., & Ahmed, A. A. A. (2022). Psychometric Assessment of the Persian Version of Compassion Scale for Adolescents. *Evaluation & the Health Professions*, *45*(3), 297–302. https://doi.org/10.1177/01632787211053855

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). Beyond WEIRD: Towards a broad-based behavioral science.

Behavioral and Brain Sciences, *33*(2–3), 111–135. https://doi.org/10.1017/S0140525X10000725

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Hino, H. (2022). More than just empathy: The influence of moral emotions on boycott participation regarding products sourced from politically contentious regions. *International Business Review*, *32*(102034), 1–10. https://doi.org/10.1016/j.ibusrev.2022.102034

Hoffmann, S. (2013). Are boycott motives rationalizations? *Journal of Consumer Behaviour*, *12*(3), 214–222. https://doi.org/10.1002/cb.1418

Hong, H., & Kim, Y. (2021). What makes people engage in civic activism on social media? *Online Information Review*, *45*(3), 562–576. https://doi.org/10.1108/OIR-03-2020-0105

Husaeni, U. A., & Ayoob, M. A. (2025). Determinants of Muslim's intention to boycott Israel-affiliated products: Evidence from Indonesia. *Jurnal Ekonomi & Keuangan Islam*, *11*(1), 14–28. https://doi.org/10.20885/JEKI.vol11.iss1.art2

Jacobucci, R., Grimm, K. J., & Zhang, Z. (2023). *Machine learning for social and behavioral research*. The Guilford Press.

Jansesberger, V., & Lefkofridi, Z. (2025). Gender, politics, and the market: evidence from Finland. *European Journal of Politics and Gender*, *8*(2), 283–307. https://doi.org/10.1332/25151088Y2024D000000069

Jungblut, M., & Johnen, M. (2022). When Brands (Don't) Take My Stance: The Ambiguous Effectiveness of Political Brand Communication. *Communication Research*, *49*(8), 1092–1117. https://doi.org/10.1177/00936502211001622

Ketron, S., Kwaramba, S. C., & Williams, M. E. (2022). The "company politics" of social stances: How conservative vs. liberal consumers respond to corporate political stance-taking. *Journal of Business Research*, *146*, 354–362. https://doi.org/10.1016/j.jbusres.2022.03.086

Kim, C., Kim, W., & Nakami, S. (2022). Do online sales channels save brands of global companies from consumer boycotts? A geographical analysis. *Journal of Retailing and Consumer Services*, *68*(103069), 1–10. https://doi.org/10.1016/j.jretconser.2022.103069

Kim, C., Yan, X., Kim, J., Terasaki, S., & Furukawa, H. (2022). Effect of consumer animosity on boycott campaigns in a cross-cultural context: Does consumer affinity matter? *Journal of Retailing and Consumer Services*, *69*(103123), 1–11. https://doi.org/10.1016/j.jretconser.2022.103123

Kim, J., Yang, K., & Min, J. (2025). Exploitation of third world labor and consumer moral response: Investigating the attitude-behavior gap through cognitive dissonance and moral disengagement. *Journal of Consumer Behaviour*, *24*(6), 2931–2947. https://doi.org/10.1002/cb.70041

Kim, S., & He, H. (2025). The impact of brand activism on consumer behaviors: Examining the contrasting roles of admiration and anger. *Journal of Business Research*, *201*(115704), 1–28. https://doi.org/10.1016/j.jbusres.2025.115704

Klandermans, B. (1988). The formation and mobilization of consensus. In B. Klandermans, H. Kriesi, & S. Tarrow (Eds.), *International Social Movement Research* (Vol. 1, pp. 173–179). JAI-Press.

Klein, J. G., Ettenson, R., & Morris, M. D. (1998). The Animosity Model of Foreign

Product Purchase: An Empirical Test in the People's Republic of China. *Journal of Marketing*, *62*(1), 89. https://doi.org/10.2307/1251805

Klesel, M., Schuberth, F., Henseler, J., & Niehaves, B. (2019). A test for multigroup comparison using partial least squares path modeling. *Internet Research*, *29*(3), 464–477. https://doi.org/10.1108/IntR-11-2017-0418

Kovač, N., Ratković, K., Farahani, H., & Watson, P. (2024). A practical applications guide to machine learning regression models in psychology with Python. *Methods in Psychology*, *11*(100156), 1–13. https://doi.org/10.1016/j.metip.2024.100156

Kristiningsih, Soebandhi, S., Trimarjono, A., & Imron, M. A. (2025). Consumer motivations in politically charged boycotts: analysis of brand attitude dynamics and impact on boycott intentions. *Lex Localis-Journal of Local Self-Government*, *23*(S6), 526–537. https://doi.org/10.52152/801803

Kryś, K., Almeida, I. de, Wasiel, A., & Vignoles, V. L. (2025). WEIRD-Confucian comparisons: Ongoing cultural biases in psychology's evidence base and some recommendations for improving global representation. *American Psychologist*, *80*(2), 247–263. https://doi.org/10.1037/amp0001298

Lane, D. S., Molina-Rogers, N., & Gagrčin, E. (2025). Worn out & tuned out: Does politics fatigue on social media foster participatory inequality among Americans? *Mass Communication and Society*, *28*(3), 387–412. https://doi.org/10.1080/15205436.2023.2289650

Leal, A. L., Zomeren, M. van, González, R., Gordijn, E., Carozzi, P., Reifen-Tagar, M., Álvarez, B., Frigolett, C., & Halperin, E. (2025). Attitude moralization in the context of collective action: How participation in collective action may foster moralization over time. *Journal of Personality and Social Psychology*, *129*(6), 1130–1150. https://doi.org/10.1037/pspi0000486

Lee, F. L. F. (2026). The impact of perceived consumer effectiveness and consumer cynicism on political consumerism. *International Journal of Consumer Studies*, *50*(1), e70160. https://doi.org/10.1111/ijcs.70160

Li, M. (2025). Mediating forgetting as memory activism: The Hedao community's independent documentary and online activism in contemporary China. *Memory Studies*, *18*(2), 456–474. https://doi.org/10.1177/17506980251320916

Louis, W., Thomas, E., McGarty, C., Lizzio-Wilson, M., Amiot, C., & Moghaddam, F. (2020). The Volatility of Collective Action: Theoretical Analysis and Empirical Data. *Political Psychology*, *41*(S1), 35–74. https://doi.org/10.1111/pops.12671

Lu, S., & Liang, H. (2024). Reactance to uncivil disagreement? The integral effects of disagreement, incivility, and social endorsement. *Journal of Media Psychology: Theories, Methods, and Applications*, *36*(1), 15–26. https://doi.org/10.1027/1864-1105/a000378

Matthews, L. M., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: Part II-A case study. *European Business Review*, *28*(2), 208–224. https://doi.org/10.1108/EBR-09-2015-0095

Maydeu-Olivares, A., Shi, D., & Rosseel, Y. (2017). Assessing fit in structural equation models: A Monte-Carlo evaluation of RMSEA versus SRMR confidence intervals and tests of close fit. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(3), 389–402. https://doi.org/10.1080/10705511.2017.1389611

Mongo, C. N. (2025). Rethinking Tarde's model in the social media era and digital news: The moderating role of proximity.

European Journal of Communication, *40*(5), 491–506. https://doi.org/10.1177/02673231251349309

Mubin, N., & Setyaningsih, S. (2020). Pengaruh konten radikal terhadap sikap radikalisme (Analisis berdasarkan Theory of Planned Behavior dari Ajzen dan Fishbein). *Personifikasi: Jurnal Ilmu Psikologi*, *11*(2), 125–223. https://doi.org/10.21107/personifikasi.v11i2.9104

Nakagoshi, M., & Inamasu, K. (2024). The role of system justification in voting behavior. *The Annals of the Japanese Political Science Association*, *75*(2), 2_286-2_305. https://doi.org/10.7218/nenpouseijigaku.75.2_286

Narayanan, S., & Singh, G. A. (2025). From stimulus to response: Understanding the causes and outcomes of consumer activism. *Journal of Consumer Behaviour*, *24*(2), 820–845. https://doi.org/10.1002/cb.2438

Orrù, G., Monaro, M., Conversano, C., Gemignani, A., & Sartori, G. (2020). Machine learning in psychometrics and psychological research. *Frontiers in Psychology*, *10*(2970), 1–10. https://doi.org/10.3389/fpsyg.2019.02970

Pargent, F., Schoedel, R., & Stachl, C. (2023). Best practices in supervised machine learning: A tutorial for psychologists. *Advances in Methods and Practices in Psychological Science*, *6*(3), 1–35. https://doi.org/10.1177/25152459231162559

Posit Software, P. B. C. (2025). *Positron*. https://positron.posit.co/

Ram, H., Liberman, N., & Unkelbach, C. (2024). Psychological distance increases conceptual generalization. *Social Psychological and Personality Science*, *15*(2), 204–214. https://doi.org/10.1177/19485506231164701

Roth, P. L., Bobko, P., Suh, H., Walker, H. J., Pu, W., & Thatcher, J. (2025). Politically related boycotts diminish organizational liking and may have unintended consequences. *Academy of Management Annual Meeting Proceedings*, *2025*(1), 1–10. https://doi.org/10.5465/AMPROC.2025.394bp

Shultziner, D. (2025). Identity, collective action and inaction: The role of self-esteem and psychological benefits. *Journal for the Theory of Social Behaviour*, *55*(1), e12440. https://doi.org/10.1111/jtsb.12440

Simiti, M. (2024). Disengaging from political activism: A critical review of the literature. *The Greek Review of Social Research*, *162*, 3–28. https://doi.org/10.12681/grsr.36638

Starke, C., & Kelm, O. (2025). Political consumerism. In *Elgar Encyclopedia of Political Communication* (pp. 212–215). https://doi.org/10.4337/9781035301447.vol3.00055

Stekelenburg, J., & Klandermans, B. (2017). *Individuals in Movements: A Social Psychology of Contention* (pp. 103–139). https://doi.org/10.1007/978-3-319-57648-0_5

Tajfel, H., & Turner, J. C. (2004). The Social Identity Theory of Intergroup Behavior. In *Political Psychology* (pp. 276–293). Psychology Press. https://doi.org/10.4324/9780203505984-16

Team, R. C. (2025). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.r-project.org/

Thomas, E. F., McGarty, C., & Mavor, K. I. (2009). Aligning identities, emotions, and beliefs to create commitment to sustainable social and political action. *Personality and Social Psychology Review*, *13*(3), 194–218. https://doi.org/10.1177/1088868309341563

Trope, Y., & Liberman, N. (2010). Construal-level theory of psychological distance. *Psychological Review*, *117*(2), 440–463. https://doi.org/10.1037/a0018963

Ulfah, M., Sabrina, N., & Putri, A. L. (2025). Psychological drivers of consumer boycott: Understanding emotional and social identity influences in Batam. *Journal of Applied Business Administration*, *9*(1), 36–51. https://doi.org/10.30871/jaba.v9i1.9152

Üskül, A. K., Thalmayer, A. G., Bernardo, A. B. I., González, R., Kende, A., Laher, S., Lášticová, B., Saab, R., Salas, G., Singh, P., Zeinoun, P., Norenzayan, A., Chao, M. M., Shoda, Y., & Cooper, M. L. (2024). Challenges and opportunities for psychological research in the majority world. *Collabra: Psychology*, *10*(1), 1–19. https://doi.org/10.1525/collabra.123703

Valli, C., & Nai, A. (2023). Let me think about it: Cognitive elaboration and strategies of resistance to political persuasion. *Media Psychology*, *26*(2), 89–112. https://doi.org/10.1080/15213269.2022.2098774

van Zomeren, M., Kutlaca, M., & Turner-Zwinkels, F. (2018). Integrating who "we" are with what "we" (Will not) stand for: A further extension of the social identity model of collective action. *European Review of Social Psychology*, *29*(1), 122–160. https://doi.org/10.1080/10463283.2018.1479347

Vasquez, A., Becchetti, L., & Pelligra, V. (2025). The power of the purse: gender, cooperation, and socially responsible consumption. *Frontiers in Behavioral Economics*, *4*(1612211), 1–10. https://doi.org/10.3389/frbhe.2025.1612211

Vélez, J. I. (2021). Machine learning based psychology: Advocating for a data-driven approach. *International Journal of Psychological Research*, *14*(1), 6–11. https://doi.org/10.21500/20112084.5365

Verba, S., Schlozman, K. L., & Brady, H. E. (1995). *Voice and equality: Civic voluntarism in American politics*. Harvard University Press.

Wang, R., & Zhou, A. (2021). Hashtag activism and connective action: A case study of #HongKongPoliceBrutality. *Telematics and Informatics*, *61*(101600), 1–10. https://doi.org/10.1016/j.tele.2021.101600

Wetzels, M., & Odekerken, G. (2009). Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration. *Management Information Systems Quarterly - MISQ*, *33*. https://doi.org/10.2307/20650284

Wright, S. C., Taylor, D. M., & Moghaddam, F. M. (1990). Responding to Membership in a Disadvantaged Group: From Acceptance to Collective Protest. In *journal of Personality and Social Psychology* (Vol. 58, Number 6).

Yang, S., & Kruschke, J. K. (2025). Reactance to persuasive messages depends on felt obligation. *Communication Research*, *52*(5), 649–682. https://doi.org/10.1177/00936502241253302

Yuksel, U. (2013). Non-participation in Anti-consumption. *Journal of Macromarketing*, *33*(3), 204–216. https://doi.org/10.1177/0276146713484153

Zejjari, I., & Benhayoun, I. (2025). Predicting the determinants of consumer's intention to boycott surrogate Israeli products - evidence. *Academy of Management Annual Meeting Proceedings*, *2025*(1), 1–10. https://doi.org/10.5465/AMPROC.2025.15664abstract