Finding the Right Voice: How CEO Communication on the Russia-Ukraine War Drives Public Engagement and Digital Activism

Kedma Hamelberg (k.hamelberg@uva.nl), Ko de Ruyter (ko.de_ruyter@kcl.ac.uk), Willemijn van Dolen (w.m.vandolen@uva.nl) and Umut Konuş (u.konus@uva.nl)

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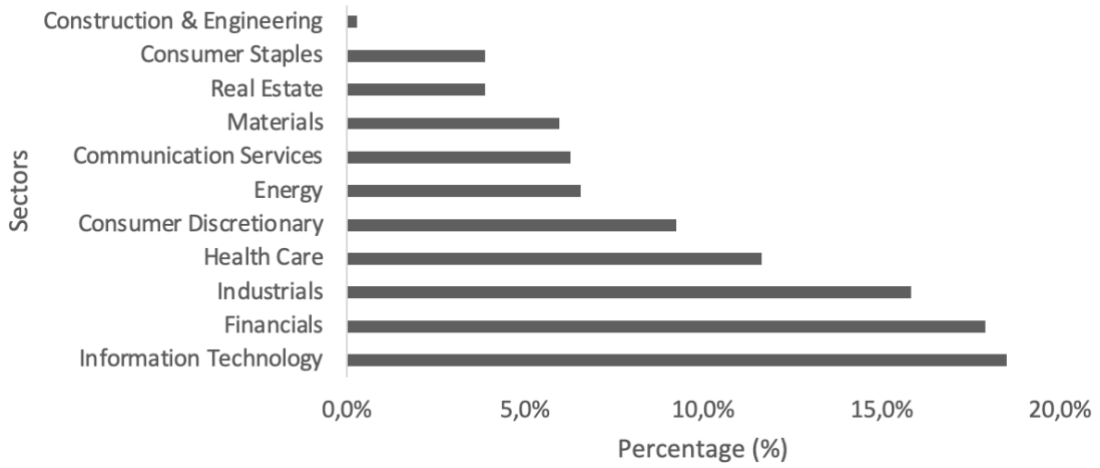
These materials have been supplied by the authors to aid in the understanding of their paper.

The AMA is sharing these materials at the request of the authors.

Web Appendix A: Glossary of Key Conceptual Terms

Term	Definition
Message / Communication (study 1)	It refers to each tweet or retweet submitted by CEOs or brands in Twitter during the first 6 months of the Russia-Ukraine war.
Message / Communication (study 2)	It refers to the CEO or brand communication of a public policy proposal to alleviate the consequences of the Russia-Ukraine war.
Public Engagement	Public engagement refers to the level of involvement, interaction, and participation of individuals or groups with a particular message, issue, or event. In the context of social media, public engagement can be measured by likes, retweets, and replies on posts related to a specific topic or event.
Digital Activism	In this research, it refers to the act of leveraging digital technologies to support a proposed public policy, either by sending a virtual postcard or writing local representatives to pressure them on the proposed changes.
Message sender	It refers to the individual or group who initiates and creates a message to be conveyed to a receiver or audience. The sender is responsible for encoding the message, which involves selecting the appropriate words, symbols, and nonverbal cues to effectively communicate their intended meaning. In this study the message senders are CEO and brands.
Message framing	It is the way that information is presented to influence people's attitudes and behaviors. It refers to how a message is constructed, highlighting either the benefits or the risks of a particular action, to encourage a specific response. In this study, we aim to investigate the engaging power of CEO messages related to the Russia-Ukraine war using other-self framing. This means examining how CEO messages that highlight the potential consequences to specific populations (i.e., "other") as well as the broader community or society (i.e., "self") can be effective in engaging stakeholders.
Message appeal	It refers to the way that a message is designed to appeal to an audience's emotions, values, or interests. The present study uses both informational and emotional appeal in CEO messages regarding the Russia-Ukraine war. Informational appeal focuses on providing facts, data, and statistics to support the message, while emotional appeal aims to evoke feelings such as fear, sadness, or empathy.

Web Appendix B: Sectors' Distribution in the Combined CEO and Brand Dataset



Web Appendix C: Descriptive Statistics of Study 1 (N=1580)

	Minimum	Maximum	Sum	M	SD
Public engagement (numbers)					
Likes	0	547.585	5041.883	3191.070	30447.849
Retweets	0	100.809	908.678	575.110	5268.490
Replies	0	27.934	206.042	130.41	1256.524
Message sender (dummy)					
CEO	0	1	287	.180	.386
Brand (reference)	0	1	1293	.818	.386
Framing (dummy)					
Other	0	1	745	.470	.499
Self	0	1	835	.529	.499
Appeal (dummy)					
Informational	0	1	1.202	.761	.427
Emotional	0	1	378	.240	.427
Time of the day (dummy)					
Morning (reference)	0	1	151	.096	.294
Afternoon	0	1	733	.464	.499
Evening	0	1	696	.441	.497
Day of the week (dummy)					
Weekday	0	1	1.446	.915	.279
Weekend (reference)	0	1	134	.085	.279
Hashtags (numbers)	0	13	802	.508	1.047
Mentions @ (numbers)	0	10	938	.594	.939
Presence links (dummy)	0	1	1.214	.768	.422
Message length (log)	0	4.043	5377.608	3.404	.398
Followers (log)	3.611	18.514	16788.151	10.625	2.060

Web Appendix D: Variables Classification and Description

Variables	Description	Operationalization
Dependent variables		
Likes	In Twitter, likes are an indicator of engagement, representing the count of users who have appreciated or agreed with a particular post.	Count: Total number of likes each tweet received
Retweets	Retweets are a prominent indicator of engagement, denoting the number of times a post has been shared or re-broadcasted by users.	Count: Total number of retweets each tweet received
Replies	Replies are a significant indicator of engagement, signifying the number of user responses or discussions a tweet has elicited.	Count: Total number of replies each tweet received
Digital activism	In this research, the online mobilization for public policy advocacy through methods like sending virtual postcards or digitally reaching out to representatives.	=1 if the participant agrees to send virtual postcards or digitally reach out to representatives. 0 otherwise
Independent variables		
Message sender	It is defined as the entity initiating and formulating a message for an audience	= 1 if the message is from CEO, and 0 if from brand
Message framing	In this study, framing refers to what the message sender says using other-self framing. We assess the impact of messages emphasizing the war consequences for specific groups (i.e., other) or the broader society (i.e., self).	= 1 if the message is framed on the war consequences for "other", and 0 if framed on the war consequences for "self". To address some hypotheses the inverse was also tested.
Message appeal	In this study, appeal refers to how the message sender communicates a message. We use informational appeal (relying on facts and data) and emotional appeal (intending to stir emotions like fear or empathy).	= 1 if the message has informational appeal, and 0 if it has emotional appeal. To address some hypotheses the inverse was also tested.
Controls		
Time of the day	Time of the tweet	= 1 if the message is sent in the afternoon, 0 otherwise = 1 if the message is sent in the evening, 0 otherwise
Workday	Day of tweeting: workday or weekend	= 1 if the message is sent on a workday (Monday-Friday), 0 otherwise
Number of hashtags (#)	Number of hashtags within a tweet; hashtags act as key terms, enhancing the tweet's visibility and searchability on the platform.	Count: Total number of hashtags (#) each message has
Number of mentions (@)	In tweets, the "@" symbol represents mentions, used to link or reference other Twitter's accounts within a post message.	Count: Total number of mentions (@) each message has
Links presence	It refers to the inclusion of URLs or web addresses directing users to external content or websites	= 1 if the message has at least 1 link, 0 otherwise
Message length	Number of words within a tweet; the more words in the tweet, the more effort required to process the message, but it may contain more information	The natural log of number of words in each message
Followers	It indicates the total count of users who have subscribed to see an account's tweets in their timeline.	The natural log of CEO number of followers

Web Appendix E: Model Free Evidence for Public Engagement Between CEO vs. Brand Communication About the War

Before presenting the major results, we present a two-sample t-test. It aims to determine if there is any significant difference in public engagement (measured as the number of likes, retweets, and replies) between CEO (N = 287) and brand (N = 1293) communication about the war. On average, CEO communication about the war receives higher public engagement regarding likes, retweets, and replies than brand communication. The difference between the two groups is statistically and practically significant in each type of engagement ($p < 0.001$). More specifically, a significant difference exists between CEOs' and brands' communication in terms of likes ($t_{286.149} = 3.912$, $p < 0.001$), retweets ($t_{286.346} = 3.958$, $p < 0.001$), and replies ($t_{287.826} = 3.550$, $p < 0.001$). The model-free evidence suggests that public engagement with CEOs' communication about the war is significantly larger than brands' communication about the war (see Table E1).

Table E1: T-Test for Public Engagement Between CEO vs. Brand Communication About the War

	CEO= 1		Brand = 0		t-test	95% Confidence interval	
Public Engagement	**M**	**SD**	**M**	**SD**	**t-value**	**Lower**	**Upper**
Likes	16392.45	69847.827	260.83	2395.322	3.912***	8015.329	24247.906
Retweets	2877.98	12039.909	63.96	628.296	3.958***	1414.757	4213.294
Comments	613.62	2813.691	23.15	337.193	3.550***	263.051	917.890
Note: *** p < 0.001							

Web Appendix F: The Effects of CEO Communication on Likes (Study 1)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Independent variables								
CEO communication	**16603.508*** **	**16786.560*** **	**16603.508*** **	**16783.447*** **	**16603.508*** **	**16789.968*** **	**16603.508*** **	**16786.892*** **
	(3714.269)	(3702.666)	(3714.269)	(3702.659)	(3714.269)	(3702.740)	(3714.269)	(3702.733)
Other-framing	782.919	296.409	782.919	296.859				
	(1498.944)	(1501.162)	(1498.944)	(1501.155)				
Self-framing					-782.919	-296.727	-782.919	-297.177
					(1498.944)	(1501.206)	(1498.944)	(1501.199)
Emotional appeal	2659.117	2436.860			2659.117	2438.892		
	(1720.668)	(1716.392)			(1720.668)	(1716.400)		
Informational appeal			-2659.117	-2437.463			-2659.117	-2439.493
			(1720.668)	(1716.389)			(1720.668)	(1716.397)
Interactions								
CEO X other-framing X emotional appeal		**27190.083*** **						
		(8129.161)						
CEO X other-framing X informational appeal				**-27176.037*** **				
				(8126.959)				
CEO X self-framing X emotional appeal						**-27131.606*** **		
						(8129.39)		
CEO X self-framing X informational appeal								**27117.556*** **
								(8127.151)
Control variables								
Time of the day - afternoon	-3289.405	-3352.180	-3289.405	-3351.117	-3289.405	-3349.822	-3289.405	-3348.762
	(2605.487)	(2597.132)	(2605.487)	(2597.134)	(2605.487)	(2597.167)	(2605.487)	(2597.170)
Time of the day - evening	-2650.645	-3107.804	-2650.645	-3107.121	-2650.645	-3104.713	-2650.645	-3104.032
	(2609.838)	(2604.989)	(2609.838)	(2604.985)	(2609.838)	(2604.996)	(2609.838)	(2604.992)
Workdays	**-14787.678*** **	**-15284.328*** **	**-14787.678*** **	**-15283.755*** **	**-14787.678*** **	**-15283.214*** **	**-14787.678*** **	**-15282.642*** **
	(2657.473)	(2653.041)	(2657.473)	(2653.038)	(2657.473)	(2604.996)	(2657.473)	(2653.078)
# hashtags	66.878	19.560	66.878	19.686	66.878	19.908	66.878	20.034
	(715.114)	(712.943)	(715.114)	(712.944)	(715.114)	(712.953)	(715.114)	(712.953)
# mentions @	-679.330	-743.585	-679.330	-743.874	-679.330	-743.923	-679.330	-744.212
	(785.193)	(782.890)	(785.193)	(782.894)	(785.193)	(782.906)	(785.193)	(782.909)
Presence links	1599.912	992.640	1599.912	991.598	1599.912	994.912	1599.912	993.872
	(3386.643)	(3380.574)	(3386.643)	(3380.599)	(3386.643)	(3380.610)	(3386.643)	(3380.635)
# words (log)	**-5954.416** **	**-6163.930*** **	**-5954.416** **	**-6163.356*** **	**-5954.416** **	**-6162.389*** **	**-5954.416** **	**-6161.816*** **
	(1867.962)	(1862.976)	(1867.962)	(1862.974)	(1867.962)	(1862.994)	(1867.962)	(1862.992)
# followers (log)	**3142.473*** **	**3121.914*** **	**3142.473*** **	**3121.454*** **	**3142.473*** **	**3121.832*** **	**3142.473*** **	**3121.373*** **
	(364.996)	(363.868)	(364.996)	(363.871)	(364.996)	(363.874)	(364.996)	(363.877)
(Constant)	1413.105	3931.215	4072.222	**6370.996*** **	2196.024	4217.530	4855.141	6659.779
	(9743.596)	(9741.233)	(9894.216)	(9886.177)	(9721.734)	(9709.366)	(9882.173)	(9865.231)
N	1580	1580	1580	1580	1580	1580	1580	1580

Notes. Significant coefficients *p < .05, **p < .01, ***p < .001. Standard errors are in parentheses.

Web Appendix G: The Effects of CEO Communication on Retweets (Study 1)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Independent variables								
CEO communication	2863.533***	2909.077***	2863.533***	2908.316***	2863.533***	29.09.911***	2863.533***	29.09.159***
	(650.946)	(646.556)	(650.946)	(646.553)	(650.946)	(646.582)	(650.946)	(646.579)
Other-framing	311.880	190.833	311.880	190.910				
	(262.698)	(262.131)	(262.698)	(262.130)				
Self-framing					-311.880	-190.949	-311.880	-191.026
					(262.698)	(262.144)	(262.698)	(262.143)
Emotional appeal	711.489*	656.190*			711.489*	656.712*		
	(301.556)	(299.715)			(301.556)	(299.722)		
Informational appeal			-711.489*	-656.324*			-711.489*	-656.846*
			(301.556)	(299.713)			(301.556)	(299.721)
Interactions								
CEO X other-framing X emotional appeal		**6765.073*** **						
		(1419.506)						
CEO X other-framing X informational appeal				-6763.530***				
				(1419.118)				
CEO X self-framing X emotional appeal						-6748.481***		
						(1419.569)		
CEO X self-framing X informational appeal								6746.939***
								(1419.180)
Control variables								
Time of the day - afternoon	-1016.279*	-1031.898*	-1016.279*	-1031.637*	-1016.279*	-1031.306*	-1016.279*	-1031.047*
	(456.626)	(453.509)	(456.626)	(453.508)	(456.626)	(453.524)	(456.626)	(453.523)
Time of the day - evening	-853.750	-967.494*	-853.750	-967.357*	-853.750	-966.691*	-853.750	-966.554*
	(457.388)	(454.880)	(457.388)	(454.879)	(457.388)	(454.891)	(457.388)	(454.889)
Workdays	-2194.418***	-2317.988***	-2194.418***	-2317.881***	-2194.418***	-2317.673***	-2194.418***	-2317.567***
	(465.737)	(463.271)	(465.737)	(463.270)	(465.737)	(463.288)	(465.737)	(463.286)
# hashtags	-13.482	-25.255	-13.482	-25.227	-13.482	-25.165	-13.482	-25.137
	(125.328)	(124.493)	(125.328)	(124.493)	(125.328)	(124.498)	(125.328)	(124.497)
# @	-122.734	-138.721	-122.734	-138.797	-122.734	-138.800	-122.734	-138.877
	(137.609)	(136.707)	(137.609)	(136.708)	(137.609)	(136.713)	(137.609)	(136.713)
Presence links	334.790	183.696	334.790	183.393	334.790	184.307	334.790	184.005
	(593.528)	(590.312)	(593.528)	(590.315)	(593.528)	(590.331)	(593.528)	(590.334)
# words (log)	-842.627*	-894.756**	-842.627*	-894.628**	-842.627*	-894.357**	-842.627*	-894.229**
	(327.370)	(325.311)	(327.370)	(325.310)	(327.370)	(325.321)	(327.370)	(325.320)
# followers (log)	420.531***	415.416***	420.531***	415.300***	420.531***	415.397***	420.531***	415.282***
	(63.967)	(63.538)	(63.967)	(63.539)	(63.967)	(63.541)	(63.967)	(63.541)
(Constant)	815.633	1442.156	1527.122	2099.237	1127.513	1630.325	1839.002	2288.002
	(1707.618)	(1701.004)	(1734.015)	(1726.310)	(1703.787)	(1695.474)	(1731.904)	(1722.687)
N	1580	1580	1580	1580	1580	1580	1580	1580

Notes. Significant coefficients *p < .05, **p < .01, ***p < .001. Standard errors are in parentheses.

Web Appendix H: The Effects of CEO Communication on Replies (Study 1)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Independent variables								
CEO communication	510.025**	514.546***	510.025**	514.471***	510.025**	514.625***	510.025**	514.550***
	(155.237)	(155.111)	(155.237)	(155.111)	(155.237)	(155.113)	(155.237)	(155.113)
	p=.001	p<.001	p=.001	p<.001	p=.001	p<.001	p=.001	p<.001
Other-framing	28.420	16.402	28.420	16.410				
	(62.648)	(62.886)	(62.648)	(62.886)				
Self-framing					-28.420	-16.425	-28.420	-16.433
					(62.648)	(62.888)	(62.648)	(62.887)
Emotional appeal	80.207	74.716			80.207	74.773		
	(71.915)	(71.903)			(71.915)	(71.903)		
Informational appeal			-80.207	-74.730			-80.207	-74.787
			(71.915)	(71.902)			(71.915)	(71.902)
Interactions								
CEO X other-framing X emotional appeal		671.630* (340.545)						
CEO X other-framing X informational appeal				-671.479* (340.452)				
CEO X self-framing X emotional appeal						-669.356 (340.551)		
CEO X self-framing X informational appeal								669.205 (340.458)
Control variables								
Time of the day - afternoon	-95.203	-96.753	-95.203	-96.727	-95.203	-96.693	-95.203	-96.667
	(108.896)	(108.799)	(108.896)	(108.798)	(108.896)	(108.799)	(108.896)	(108.799)
Time of the day - evening	-38.383	-49.676	-38.383	-49.662	-38.383	-49.585	-38.383	-49.572
	(109.078)	(109.128)	(109.078)	(109.127)	(109.078)	(109.127)	(109.078)	(109.127)
Workdays	-438.640***	-450.908***	-438.640***	-450.898***	-438.640***	-450.866***	-438.640***	-450.855***
	(111.069)	(111.141)	(111.069)	(111.140)	(111.069)	(111.142)	(111.069)	(111.141)
# hashtags	2.768	1.600	2.768	1.612	2.768	1.610	2.768	1.612
	(29.888)	(29.866)	(29.888)	(29.866)	(29.888)	(29.867)	(29.888)	(29.867)
# @	-29.630	-31.218	-29.630	-31.225	-29.630	-31.224	-29.630	-31.231
	(32.817)	(32.797)	(32.817)	(32.797)	(32.817)	(32.797)	(32.817)	(32.797)
Presence links	-70.474	-85.475	-70.474	-85.505	-70.474	-85.400	-70.474	-85.430
	(141.544)	(141.618)	(141.544)	(141.619)	(141.544)	(141.619)	(141.544)	(141.620)
# words (log)	-172.256*	-177.431*	-172.256*	-177.419*	-172.256*	-177.387*	-172.256*	-177.374*
	(78.071)	(78.043)	(78.071)	(78.043)	(78.071)	(78.044)	(78.071)	(78.043)
# followers (log)	130.674***	130.166***	130.674***	130.154***	130.674***	130.164***	130.674***	130.153***
	(15.255)	(15.243)	(15.255)	(15.243)	(15.255)	(15.243)	(15.255)	(15.243)
(Constant)	-264.156	-201.956	-183.950	-127.151***	-235.737	-185.865	-155.530	-110.995
	(407.232)	(408.078)	(413.527)	(414.149)	(406.318)	(406.740)	(413.024)	(413.269)
N	1580	1580	1580	1580	1580	1580	1580	1580

Notes. Significant coefficients at *p < .05, **p < .01, ***p < .001. Standard errors are in parentheses.

Web Appendix I: Pretests 1 and 2 (Study 2)

Selection of CEO/Brand Pairs and Stimuli Development

Given that research has not yet developed a process for selecting CEO/brand pairs, following past literature on brand and CEO separately, we relied on common measures from both message senders to select the pairs. Before pretesting the stimuli, we selected CEO/brand pairs based on familiarity and attitude toward the CEO (brand). To this end, we used the dataset of Study 1 as a departure point. The dataset had a total of 338 CEOs and brands (not necessarily in pairs). From that total, we identified a total of 34 CEO/brand pairs across different sectors. We pretested all the 34 CEO/brand pairs regarding familiarity and attitude.

The familiarity measure involves the question "*How familiar are you with CEO X (brand Y)?"* measured on a 7-point scale ranging from 1 = not at all familiar to 7 = very familiar (MacInnis and Park 1991). For the attitude towards the CEO (brand), we applied a three-item, seven-point semantic differential scale with subjects' evaluations of the CEO (brand) ranging from very bad to very good, unfavorable to favorable, and not at all likable to very likable (e.g., "*How likable do you find the CEO X (brand Y))".* The three items were adapted from Jin and Lee (2019), Kim and Sung (2021), MacInnis and Park (1991), and Muehling (1987).

We randomly assigned 40 participants (50% female, 50% male, Mage = 35.8 years) to all 34 CEOs and 34 brands in Prolific. Next, participants evaluated each CEO and brand separately regarding familiarity and attitude using a 7-point Likert scale. From that total, we selected 5 CEO-brand pairs from 5 different industries to guarantee the generalization of results (Dhaoui and Webster 2021). In sum, the selected pairs had the lowest familiarity mean score, and the participants had the most neutral mean score on attitude toward each of them (see Table I1).

Table I1: The 5 CEO/Brand Pairs Selected for Study 2 via Pretest 1

	CEO	Brand	Industry	Familiarity (Mean)	Attitude towards the CEO/brand (Mean)
Pair 1	Douglas Godshall	Shockwave Medical	Healthcare	1,50	4,05
Pair 2	Nick Deluliis	CNX	Energy	1,53	3,94
Pair 3	Yogesh Gupta	Progress	Information Technology	1,61	4,10
Pair 4	Rich Handler	Jefferies	Financial	1,81	4,04
Pair 5	Jonas Prising	Manpower	Employment agency	2,00	4,08

Pretest 2

We recruited 22 participants in Prolific (55% male, 45% female, Mage= 41.23) to test whether our message sender and framing manipulations are indeed understood. As a first step, the participants were asked to measure who the message sender is on a seven-point Likert scale. We manipulated the message sender by randomly allocating respondents to a vignette with either the CEO or a brand. The scores were analyzed on a one-way analysis of variance (ANOVA) to check whether our manipulation had the intended effect. Respondents who were presented with CEO vignettes (namely, Douglas Godshall, Nick Deluliis, Yogesh Gupta, Rich Handler, and Jonas Prising) scored higher on the CEO scale compared to those who were allocated to brand vignettes (namely, Shockwave Medical, CNX, Progress, Jefferies and Manpower) and scored lower on the same scale. (M_{CEO} = 5.92, SD = 0.29; M_{brand} = 2.70, SD = 1.77; F (1, 20) = 38.9, p < 0,001). Our results suggest that our message sender manipulation was successful.

Likewise, the framing test was successful. Respondents who were presented with other-framing vignettes (i.e., in support of Ukrainian civilians) scored higher on the Ukrainian civilian's scale compared to those who were allocated to self-framing vignettes (i.e., in support of American citizens) and scored lower on the same scale. (M_{other} = 6.46, SD = 0.69; M_{self} = 2.80, SD = 1.44, F (1, 20) = 61.27, p < 0,001).

Web Appendix J: Methodological Integration of BERTopic and ChatGPT in Vignette Crafting (Study 2)

To enhance the authenticity and realism of our campaign and manipulations, we integrated advanced topic modeling (i.e., BERT) and language generation techniques (i.e., ChatGPT). BERTopic is a contemporary topic modeling approach that leverages BERT embeddings to uncover and categorize distinct topics in a collection of textual data. Given the data input from real tweets by CEOs and brands centered around the Russia-Ukraine war from our Study 1, BERTopic identified "energy crisis" and "help Ukrainians" as the most salient topics. Within these topics, specific words were associated with varying weights indicating their significance and centrality to the topic.

Leveraging the words and their respective weights provided by BERTopic, we utilized ChatGPT to craft nuanced vignettes. This integration ensures that the narratives generated are not only coherent and contextually relevant but also reflective of the prevalent discourse surrounding the Russia-Ukraine war in real tweets. Specifically, the vignettes varied based on the sender of the call (CEO vs. brand) and the framing of the public policy campaign (self-framing vs. other-framing), ensuring they resonate with the real-world ramifications of the Russia-Ukraine war.

The self-framing vignette encapsulated a tweet and policy proposal by the CEO or brand directed at mitigating the adversities from the energy crisis faced by American citizens, a direct consequence of the Russia-Ukraine war. Conversely, the other-framing vignette highlighted the CEO or brand's policy initiative concentrated on aiding Ukrainian civilians affected by the war. To the best of our knowledge, this study is pioneering on leveraging a synergistic approach of BERTopic and ChatGPT for such experimental designs. In the following pages, we share the methodological integration in more detail.

BERT and BERTopics:

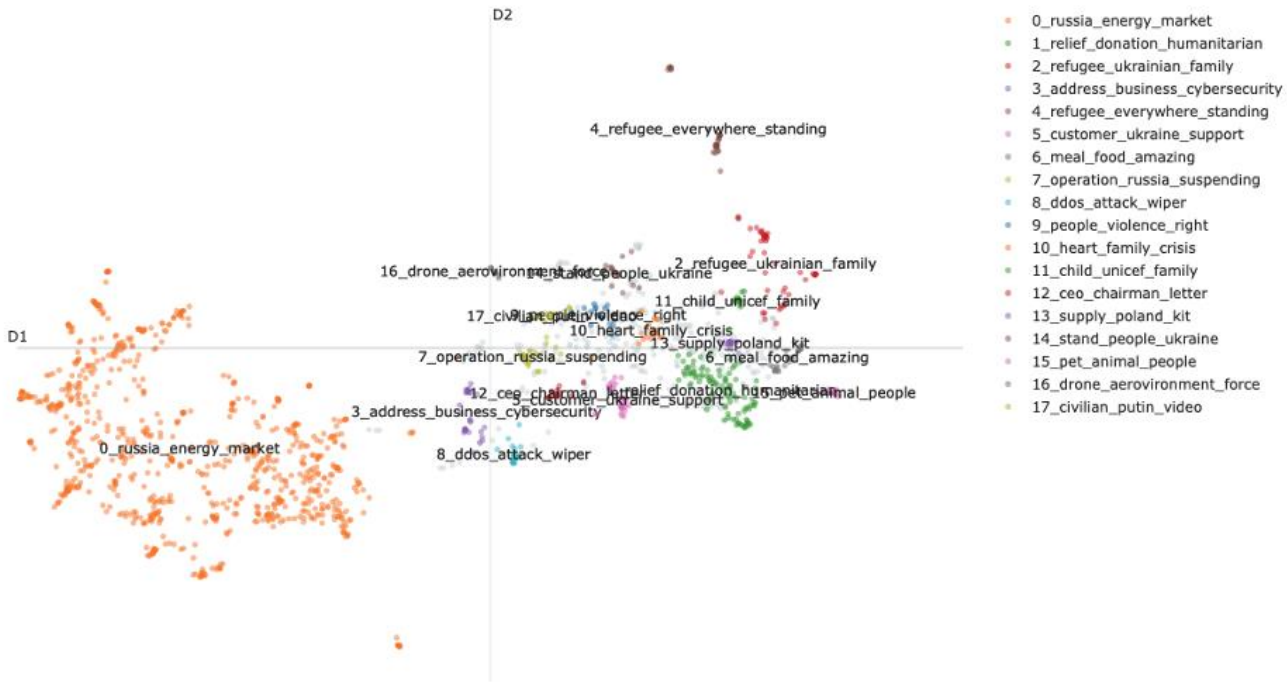
BERT (Bidirectional Encoder Representations from Transformers) is a state-of-the-art natural language processing (NLP) model introduced by Google in 2018. It uses Transformer architecture to understand the context of words in a sentence by reading the entire sequence of words at once rather than one by one (Devlin et al. 2018). This makes BERT especially potent at handling nuances in language.

BERTopics is a technique that utilizes BERT embeddings for topic modeling. Unlike traditional topic modeling techniques like LDA (Latent Dirichlet Allocation), BERTopics leverage the context-sensitive embeddings of BERT to capture the semantic meanings of words better and thereby generate more coherent and meaningful topics (Xu 2022).

Topic Word Scores from BERTopics:

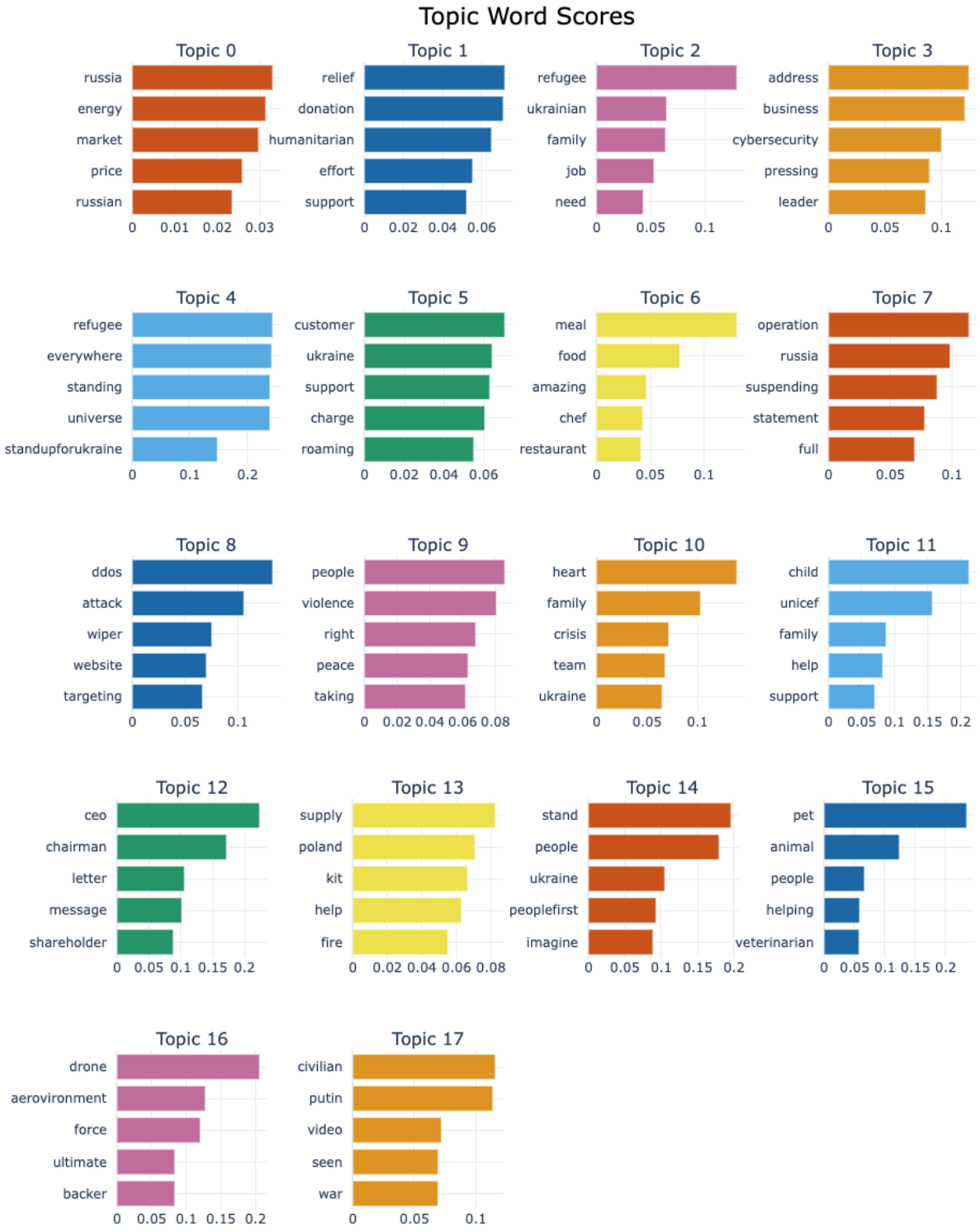
BERTopics operates unsupervised, meaning it automatically discovers the underlying topics without predefined labels or categories (Figure J1). Therefore, the 18 topics obtained from BERTopics are directly derived from the dataset containing CEO and brand tweets about the Russia-Ukraine war, representing the dominant themes within this dataset.

Figure J1: Dimensional Overview of the Key Topics from Dataset of Study 1 Applying BERTopics



In BERTopics, each topic consists of a set of words that define the topic's theme. The "Topic Word Scores" indicate the relevance or weight of each word within its respective topic (Grootendorst 2022). A higher score suggests that the word is more central or important to the topic's meaning, while a lower score indicates lesser relevance (Figure J2).

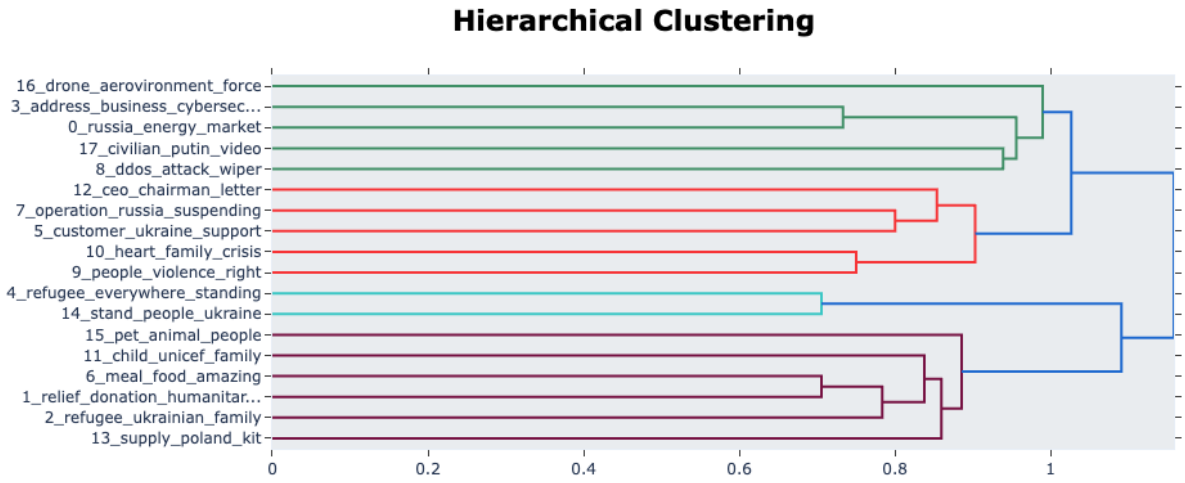
Figure J2: Key Topics From Dataset of Study 1 Applying BERTopics



Hierarchical Clustering from BERTopics:

Hierarchical clustering is a method of grouping similar objects into a hierarchy or tree-like structure called a dendrogram. Within the context of BERTopics, hierarchical clustering is applied to the topics themselves to identify broader themes or clusters of related topics (Grootendorst 2022). In the accompanying figure, it can be observed that there are two main groups of topics: those related to the "energy crisis" and those concerning "Ukrainian civilians.". These two main clusters corroborate the findings from Study 1, thereby validating the emergent topics from the tweets (Figure J3).

Figure J3: Hierarchical Clustering Using BERTopics



Using BERTopics for Vignette Confection in Chatgpt:

ChatGPT refers to versions of the OpenAI GPT (Generative Pre-trained Transformer) models that are fine-tuned specifically for conversational tasks (Zhou et al. 2023). For Study 2, the frequency of words per topic derived from BERTopics was used as input for ChatGPT. This input served as a foundation or guide for ChatGPT to generate vignettes for the experiment. Essentially, ChatGPT used the dominant words and their respective frequencies

to craft contextually relevant and meaningful vignettes that encapsulate the essence of each topic. Here we list some advantages of such a pioneer approach:

- **Data-Driven Insights:** By using BERTopics on real-world data (CEO and brand tweets), the generated topics are grounded in real discourse, ensuring relevance and authenticity.
- **Contextual Understanding:** BERT's capability to capture context provides a more nuanced and in-depth understanding of the topics than traditional topic modeling techniques (Grootendorst 2022).
- **Validation and Consistency:** The hierarchical clustering in BERTopics not only provides an organized view of topics but also acts as a validation mechanism, as evidenced by its alignment with Study 1 findings.
- **Integration with ChatGPT:** Utilizing the output of BERTopics as input for ChatGPT ensures that the vignettes are closely aligned with the dominant themes from the dataset, making the vignettes more accurate and representative.
- **Efficiency:** This approach streamlines the process of vignette generation, saving time and ensuring systematic consistency.

Incorporating the insights from BERTopics into experimental designs, like in Study 2, offers a novel and powerful method to craft contextually rich and data-driven vignettes, enhancing the validity and depth of experimental findings.

Web Appendix K: Example of Vignette (Study 2)

The vignette consists of two parts. In Part 1 (see Figure K1), participants receive a tweet from either a CEO or a brand, depending on the condition. In Part 2 (see Figure K2), participants also receive a link to the full policy proposal if they want more information. In both cases, we used BERT and ChatGPT to develop the vignettes.

Figure K1: CEO Tweet as Part of the Fictional Public Policy Campaign

Figure K2: CEO Full Fictional Public Policy Proposal

Policy Proposal to Assist Ukrainian Civilians Amidst the War

Background:

The ongoing war in Ukraine, intensified by geopolitical tensions, underscores the dire need for comprehensive support strategies for Ukrainian civilians. Their plight requires not just empathy but tangible interventions that promise safety, stability, and future recovery.

As Nick Deluliis, CEO of CNX Resources Corporation, understanding the interconnected nature of our global community, I call upon the U.S. government to take robust steps to ensure the safety and well-being of Ukrainian civilians. Thus, I present a comprehensive policy proposal that addresses both the immediate hardships of Ukrainian civilians and the long-term necessity of support for Ukraine.

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1. Immediate Humanitarian Assistance (2023-2024):

a. Comprehensive Aid Package

- **Objective:** To address the urgent humanitarian needs resulting from the war.
- **Proposal:** Allocate $10 billion to support international relief efforts in Ukraine. These funds should be channeled through reputable organizations, such as the Red Cross, which have been instrumental in providing emergency aid in war zones[1].
- **Impact:** This aid will cater to immediate necessities like emergency supplies, medical assistance, and secure transport facilities for displaced Ukrainians.

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2. Expansion of Refugee Resettlement Program (2023-2025):

a. Resettlement and Integration

- **Objective:** To offer a safe haven for those fleeing the war and to aid their seamless transition into American society.

- **Proposal:** Extend the refugee resettlement quota by 100,000 specifically for Ukrainian refugees over the forthcoming two years. Simultaneously, enhance funding for integration programs, focusing on language acquisition, job placement, and cultural assimilation, ensuring these new Americans find both refuge and a home.

- **Impact:** This strategy ensures that apart from the immediate escape from war, refugees have the tools and resources for long-term stability in the U.S., aligning with the *Migration Policy Institute's guidelines on integration*[2].

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3. Long-term Support for Ukraine (2023-2033):

a. Rebuilding and Stabilization

- **Objective:** To ensure the post-war rehabilitation and robustness of Ukraine as a nation.

- **Proposal:** Commit to a 10-year, $50 billion aid package, concentrating on rebuilding critical infrastructure, reinforcing democratic institutions, and stimulating economic recovery.

- **Impact:** Long-term investments in infrastructure and institutions provide a foundation for sustainable growth, resilience, and prosperity. The *World Bank's reconstruction strategies*[3] emphasize these areas as key to post-war recovery.

In conclusion, the Ukrainian war is not just a regional concern, but a humanitarian challenge that calls for collective responsibility. The proposed interventions seek to ensure that our actions, as an interconnected global community, pave the way for recovery, resilience, and prosperity for Ukraine.

Respectfully,

Nick Deluliis
CEO, CNX Resources Corporation

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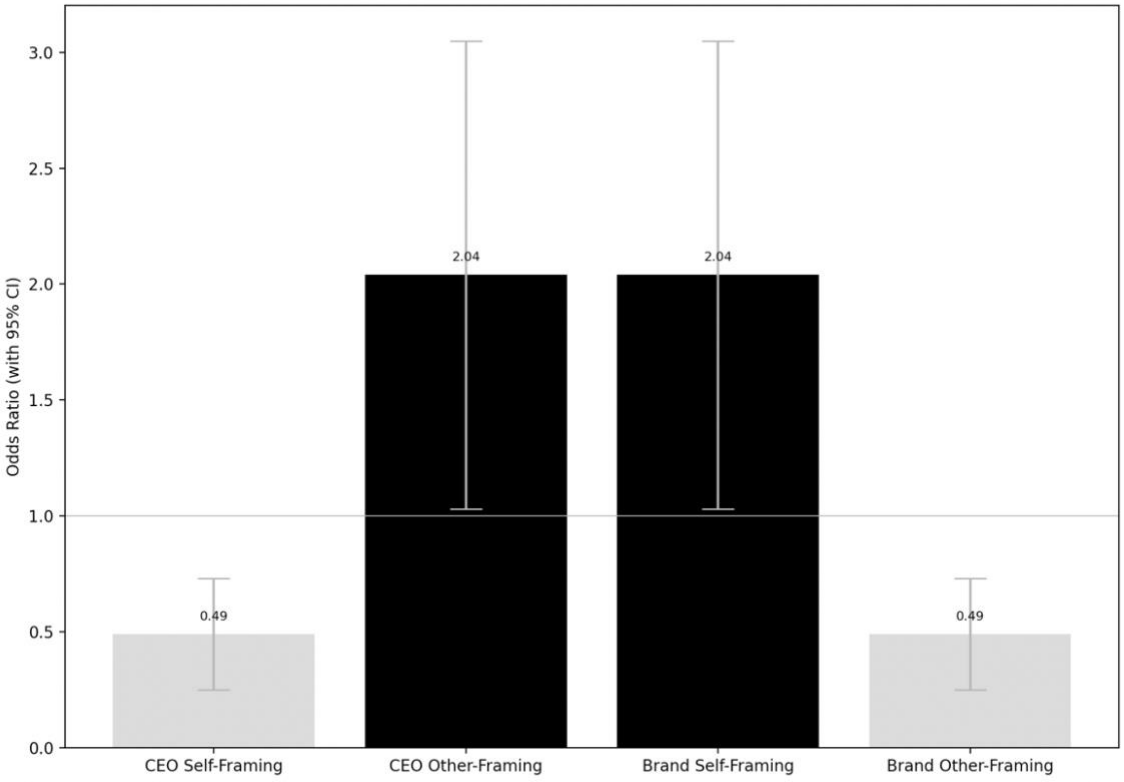
3. The World Bank. (2023). *Updated Ukraine Recovery and Reconstruction Needs Assessment*. https://www.worldbank.org/en/news/press-release/2023/03/23/updated-ukraine-recovery-and-reconstruction-needs-assessment ↩

Web Appendix L: The Effects of CEO Communication on Digital Activism (Study 2)

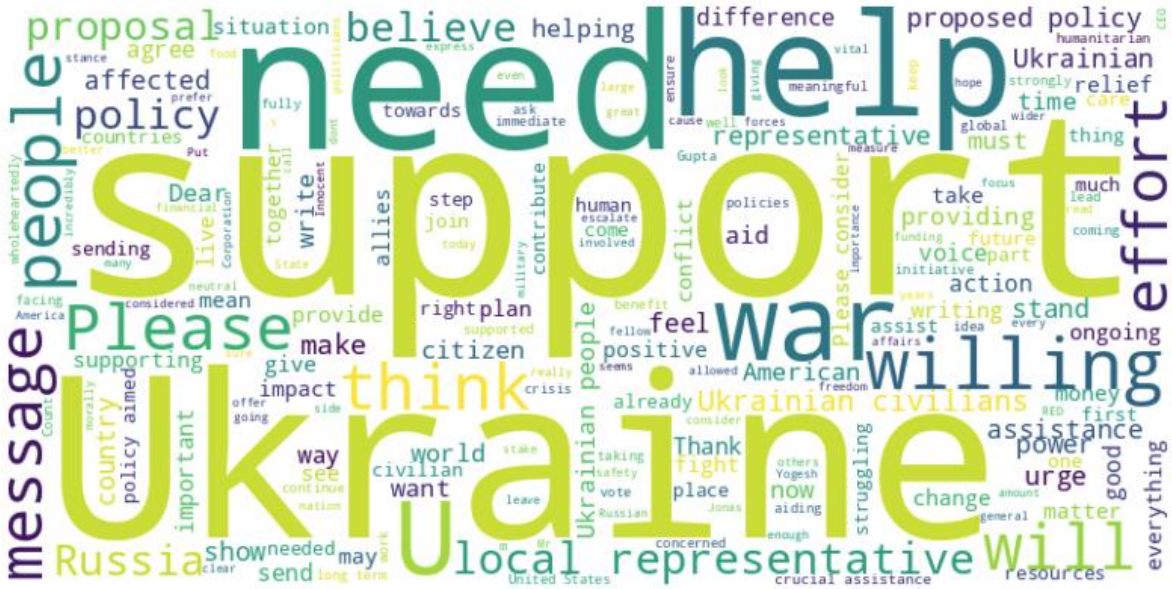
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Coefficient	OR	Coefficient	OR	Coefficient	OR	Coefficient	OR
Independent variables								
CEO communication	.437* (.174)	1.548	.045 (.259)	1.046	.437* (.174)	1.548	.758** (.236)	2.135
Other-framing	-.941*** (.174)	.390	-1.277*** (.243)	.279				
Self-framing					.941*** (.174)	2.563	1.277*** (.243)	3.585
Interactions								
CEO X other-framing			.713* (.349)	2.041				
CEO X self-framing							-.713* (.349)	.490
Control variables								
Gender[1]	.070 (.175)	1.072	.063 (.175)	1.065	.070 (.175)	1.072	.063 (.175)	1.065
Politics-republican[2]	-.690** (.245)	.502	-.704** (.246)	.494	-.690** (.245)	.502	-.704** (.246)	.494
Politics-independent[2]	-.470 * (.201)	.625	-.446* (.203)	.640	-.470* (.201)	.625	-.446* (.203)	.640
Politics- no political affiliation[2]	-.850 (.435)	.427	-.825 (.433)	.438	-.850 (.435)	.427	-.825 (.433)	.438
Diagnostics								
(Constant)	.942*** (.204)	2.565	1.127*** (.227)	3.086	.001 (.188)	1.001	-.150 (.203)	.861
X^2	49.308***	(df=6)	53.486***	(df=7)	49.308***	(df=6)	53.486***	(df=7)
N	608	608	608	608	608	608	608	608

Notes. Dependent variable: Public activism. Significant coefficients *p < .05, **p < .01, ***p < .001. Standard errors are in parentheses. [1] Reference group: Female. [2] Reference group: Democrats

Web Appendix M: The Effects of CEO Vs. Brand and Self vs. Other-Framing on Public Activism



Web Appendix N: Word Cloud with Frequent Terms Written by the Participants in the CEO X Other-Framing Condition (Study 2)



Web Appendix O: Word Cloud with Frequent Terms Written by the Participants in the Brand X Self-Framing Condition (Study 2)

Web Appendix P: Samples of Activist's Messages Crafted by the Participants (Study 2)

	CEO	Brand
Other-framing	"I want to express my support for Ukraine in the ongoing war against Russia. I hope that your support for Ukraine will unwavering in the coming years as well. Yogesh Gupta, CEO of Progress Software Corporation, has come up with a proposal for supporting and funding Ukraine in their time of crisis. I urge you to read the proposal and voice your support. "	
	"Dear (Local Representative), If we can we should. And that means everything when it comes to human rights. Supporting legislation that benefits Ukraine is not only showing you are on the side of human rights, but that you are a good person in general and care about helping those who are affected by things out of their control."	
	"Dear representatives, Ukrainian civilians need our support, so please read Mr. Jonas Prising's proposal (see attachment)."	
Self-framing		"Dear Local Representatives, I very much would like to support Shockwave Medical Inc. and the proposed policy for energy resilience and affordability, which aims to alleviate the challenges caused by the energy crisis and rising energy prices due to the ongoing Russia-Ukraine war. I would love to give my full support to these people and their plans to help America's energy sector. Sincerely, DD"
		"Dear local representatives. At the very basis of it, I'm on board with this plan as I want my money going toward better things. I'm tired of my money going toward this Russia Ukraine stuff which has no impact on our everyday affairs domestically."
		"The energy prices are raising. Please support and consider these policies for energy resilience and affordability. "

Web Appendix Q: Robustness' Check Linear Probability Model (LPM) of CEO Communication

	Model 1	Model 2	Model 3	Model 4
Independent variables				
CEO communication	.098*	.009	.098*	.184***
	(.039)	(.055)	(.039)	(.054)
Other-framing	-.215***	-.299***		
	(.038)	(.053)		
Self-framing			.215***	.299***
			(.038)	(.053)
Interactions				
CEO X other-framing		.175*		
		(.077)		
CEO X self-framing				-.175*
				(.077)
Control variables				
Gender[1]	.016	.014	.016	.014
	(.039)	(.039)	(.039)	(.039)
Politics-republican[2]	-.156**	-.158**	-.156**	-.158**
	(.055)	(.055)	(.055)	(.055)
Politics-independent[2]	-.105*	-.098*	-.105*	-.098*
	(.045)	(.045)	(.045)	(.045)
Politics-no political affiliation[2]	-.193	-.188	-.193	-.188
	(.099)	(.098)	(.099)	(.098)
(Constant)	.715***	.758***	.500***	.459***
	(0.45)	(.048)	(.043)	(.046)
N	608	608	608	608

Notes. Dependent variable: Public activism. Significant coefficients *p < .05, **p < .01, ***p < .001. Standard errors are in parentheses. [1] Reference group: Female. [2] Reference group: Democrats

Web Appendix R: Robustness' Check Subsample Logistic Regression of CEO Communication (N=323)

	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Coefficient	OR	Coefficient	OR	Coefficient	OR	Coefficient	OR
Independent variables								
CEO communication	-.451 (.250)	.637	.119 (.371)	1.126	.451 (.250)	1.571	.933 (.344)	2.542
Other-framing	-1.040*** (.251)	.354	-1.558*** (.362)	.211				
Self-framing					1.040*** (.251)	2.829	1.558*** (.362)	4.750
Interactions								
CEO X other-framing			1.052* (.506)	2.863				
CEO X self-framing							-1.052* (.506)	.349
Control variables								
Gender[1]	.335 (.249)	1.398	.348 (.251)	1.416	.335 (.249)	1.398	.348 (.251)	1.416
Politics-republican[2]	-.744* (.364)	.475	-.831* (.370)	.435	-.744* (.364)	.475	-.831* (.370)	.435
Politics-independent[2]	-.635* (.286)	.530	-.593* (.289)	.553	-.635* (.286)	.530	-.593* (.289)	.553
Politics-no political affiliation[2]	-1.235* (.593)	.291	-1.205* (.591)	.300	-1.235* (.593)	.291	-1.205* (.591)	.300
Diagnostics								
(Constant)	1.592*** (.288)	4.912	1.301*** (.309)	3.672	.100 (.271)	1.106	-.139 (.296)	.870
X^2	32.461***	(df=6)	36.823***	(df=7)	32.461***	(df=6)	36.823***	(df=7)
N	323	323	323	323	323	323	323	323

Notes. Dependent variable: Public activism. Significant coefficients *p < .05, **p < .01, ***p < .001. Standard errors are in parentheses. [1] Reference group: Female. [2] Reference group: Democrats

Web Appendix S: Robustness' Check Multicollinearity (VIF) of CEO Communication

	Model 1	Model 2	Model 3	Model 4
Independent variables				
CEO communication	1.017	2.050	1.017	2.001
Other-framing	1.004	1.944		
Self-framing			1.004	1.944
Interactions				
CEO communication X other-framing		2.907		
CEO communication X self-framing				3.003
Control variables				
Gender[1]	1.009	1.009	1.009	1.009
Politics-republican[2]	1.112	1.112	1.112	1.112
Politics-independent[2]	1.116	1.121	1.116	1.121
Politics-no political affiliation[2]	1.043	1.044	1.043	1.044
N	608	608	608	608

Note. Dependent variable: Public activism. [1] Reference group: Female. [2] Reference group: Democrats

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