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Public Segmentation and the Impact of AI Use in E-Rulemaking

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Abstract

Digitization has profoundly changed how government interacts with its publics. The expanding use of AI promises even more advancement. However, the rollout of AI is not without risk. This work explores the use of AI in federal rulemaking, the process by which regulations are introduced and revised. The US federal government has created digital platforms that dramatically expand access for the public commenting on pending regulations. However, these platforms also attract volumes of opinion spam that attempt to influence regulatory decision-making. Using AI to identify opinion spam may offer a potential remedy, but removing or limiting comments with the help of AI may threaten rulemaking legitimacy. This research uses the situational theory of problem-solving as a framework, segmenting publics based on their problem recognition, constraints, and involvement with a specific issue, then predicting how each public behaves. We examined how employing AI in the processing of rulemaking comments affects public segments' intention to comment, their perceptions of legitimacy of the resulting rules, trust in agencies, and control mutuality between the public and the agency. This work describes two controlled, randomized experiments ($N = 149$; $N = 250$) that capture public segments' reactions to AI use in analyzing comments in the presence or absence of opinion spam. We show that public segmentation is a key aspect in shaping attitudes and behaviors regarding the use of AI for e-rulemaking purposes. These findings suggest that communicating effectively with publics is essential for agencies, and that the use of AI does not make the publics' attitudes differ.

Keywords

AI; commenting behavior; comment filtering; content moderation; electronic rulemaking; notice-and-comment; opinion spam

1. Introduction

Electronic rulemaking, or e-rulemaking, is a participatory process that encompasses the use of information technology to facilitate citizens' input on proposed regulations (Department of Defense Open Government, n.d.). Established in the US in 2002 (Regulations.gov, n.d.), e-rulemaking expands the possibilities of citizen participation, providing access to more users and encouraging more people to engage. However, increased accessibility also resulted in adverse consequences such as mass commenting (Shulman, 2009), when a large number of identical or nearly identical comments are posted on regulation sites (Balla et al., 2021).

Activist groups or corporate interests often organize these mass commenting campaigns, aiming to generate support for their causes. However, these initiatives often make it difficult for federal agencies to identify substantive contributions (Farina et al., 2012). Campaigns from activist groups are likely to include comments, expressing support or opposition without offering substantive contributions on the issue at hand; comments submitted by such campaigns are known as opinion spamming (Liu, 2012). Beyond making American federal agencies overwhelmed by the number of comments (Farina et al., 2012), mass commenting and opinion spamming can obstruct efforts to achieve deliberative democracy by overwhelming the plurality of citizens' voices (J.-N. Kim et al., 2025; Shulman, 2009).

Since the digitalization of the rulemaking process, there have been efforts to implement more cutting-edge technologies (Park et al., 2015). The use of AI in the context of e-rulemaking can help group repetitive comments, highlight their distinct contributions, and categorize information within comments (Eidelman & Grom, 2019) without compromising the time and efforts of an agency's staff. In this context, AI has been used to classify comments, detect duplicates, and highlight keywords for the proposed regulation. AI is a possible response to the opinion spamming problem, offering a remedy to the comment overload and tediousness of dealing with these repetitive comments. While AI may directly solve the issue at hand, it can also bring several related problems (Li et al., 2020). First, the utilization of AI tools raises questions regarding ethics; second, it could impact public participation depending on citizens' response to the use of these advanced tools; and third, comment removal may threaten rulemaking legitimacy.

In light of the aforementioned concerns, this article has two objectives. The first is to explore the reactions of citizens when they observe opinion spamming in e-rulemaking. Previous work has focused on the impact opinion spamming has on American federal agencies' staff (Farina et al., 2012; J.-N. Kim et al., 2025) and the effects on the e-rulemaking process as a whole (Shulman, 2009), but citizens' behaviors as a result of opinion spamming are yet to be explored. Therefore, it is essential to know the effects of opinion spamming on publics: its influence on their willingness to participate in the e-rulemaking process as well as their perceptions of agencies and resulting regulations.

Although opinion spam detection and filtering technologies powered by AI may be a potential solution to opinion spamming, the implementation of AI is not free of risks (Li et al., 2020). Thus, the second objective of this research relates to understanding citizens' perceptions of and behaviors related to the application of AI to the e-rulemaking process. Before using AI to combat opinion spamming, assessing how publics perceive and respond to this technology is essential.

These ideas were tested in two experiments. The first study focused on citizens' reactions to the problem of opinion spamming depending on their segmentation type, a classification rooted in the situational theory of problem-solving (STOPS; J.-N. Kim & Grunig, 2011) that segments publics depending on their involvement in specific issues. The second study examined the perceptions of AI as a possible solution to the problem, testing not only publics' attitudes and behavioral intentions about opinion spamming but also their response to the agency using AI to filter comments.

The present research has implications for both theory-building and practice. This article contributes to the growing body of research on e-rulemaking, applying public relations theory to this specific context. This approach is necessary for exploring publics' attitudes and behaviors surrounding the use of AI and its impact on resulting regulations and federal agencies, thereby examining the social component of e-rulemaking and the acceptance of new technologies. In addition, this article provides guidance on what agencies should do and what their stance on technologies should be when managing the e-rulemaking process.

2. Literature Review

2.1. E-Rulemaking Evolution

While e-rulemaking was established in 2002 (Regulations.gov, n.d.), publics' participation in the rulemaking process has a long history. It was in 1946 when publics were first able to comment on proposed regulations, based on the Administrative Procedure Act (Moxley, 2016). The first round of changes to the commenting process took place during the 1990s, when agencies proactively started using online tools to collect citizens' comments (Benjamin, 2006). The next round of changes in the e-rulemaking process took place in 2002, with agencies posting proposed rules and enabling comments on a centralized website, Regulations.gov (Regulations.gov, n.d.). As technologies evolved, the system also transitioned into e-rulemaking. Agencies post regulatory materials online so that they are publicly available. In the same portal, Regulations.gov, publics can share their voices by commenting on proposed regulations as well as read other participants' comments.

Different administrations aimed to enable publics to freely comment and access the materials, including President Bush's Honest Leadership and Open Government Act of 2007, and President Obama's Memorandum on Transparency and Open Government in 2009 (Farina et al., 2011). Centralization was made mandatory for all agencies via Regulations.gov, which connects to a database that enables document management, maintains digital versions of rulemaking documents, and provides search mechanisms (Moxley, 2016). This switch to online procedures was motivated by the need for accessibility, publics' participation, openness, and transparency (Perez, 2020).

2.2. Opinion Spamming in E-Rulemaking

The use of online platforms for rulemaking purposes arose from the need for accessibility and an increase in public participation (Benjamin, 2006; Perez, 2020). Citizen participation increased because of the openness of the e-rulemaking process, yet unfortunately, agencies have struggled to find substantive feedback among the vast volume of comments they now receive (Farina et al., 2012). The abundance of comments creates challenges for agencies' staff, who, overwhelmed by volume, may struggle to synthesize all the content provided by citizens (Farina et al., 2012).

As noted, mass commenting refers to large quantities of nearly identical comments on regulations coordinated by corporate interests or activist organizations, who create the comment content and enable mass sharing among their followers (Balla et al., 2021). Within mass commenting, we refer to cases where the sources or underlying intentions of comments are obscured as opinion spamming (Liu, 2012).

Research has examined the detrimental effects of mass commenting and opinion spamming, including difficulties for agencies to manage their work regarding the rulemaking process (Farina et al., 2012; Perez, 2020), impacts on deliberative democracy (Shulman, 2009; Widyatama & Mahbob, 2024), and also the possibility of discouraging feedback from citizens (Benjamin, 2006; Grossman, 2004). Grossman (2004) explained how the presence of opinion spamming can be off-putting for other users, who criticized the abundance of spamming and can't escape or opt out of spamming; and Benjamin (2006) found that after observing opinion spamming, publics became less engaged in providing feedback. Taken together, these findings suggest that opinion spamming is a serious issue both for regulatory agencies and for deliberative democracy.

2.3. Public Segmentation in E-Rulemaking

In order to understand the extent to which public behaviors are a reaction to the issue of opinion spamming, it is worth considering the nature of these publics per se. Opinion spamming refers to a response orchestrated by an organization (Liu, 2012); in the case of e-rulemaking, the organization advocating for its interests behind the scenes may be an activist group (Balla et al., 2021) reacting to proposed regulations related to their mission. As commenting effectively requires a degree of regulatory savvy and issue-relevant knowledge, to boost support and encourage less engaged individuals to comment, activist groups provide their publics with form letters to make commenting easier, which require that publics only sign, send, and, optionally, make their own edits (Schlosberg et al., 2009). Thus, activist groups generate the statement, disseminate the information, and even enable automatic posting settings from their websites to make the mass posting of comments easier.

There are many publics associated with specific issues who communicate with each other. The discipline and theory of public relations focuses on the study of publics' nature, their attitudes, behaviors, relationships, and classification (Hallahan, 2018; J.-N. Kim et al., 2008; J.-N. Kim & Grunig, 2011). Specifically, STOPS helps identify different publics and predict the communication behaviors of each public segment (J.-N. Kim & Grunig, 2011). Grounded in publics and public opinion concepts, this theory explains how to segment publics depending on their perceived problem recognition, involvement recognition, and constraint recognition (J.-N. Kim & Grunig, 2011). Problem recognition refers to the state in which a problem is a product of experiences and expectations, arising from discrepancies between experiential and expectation states (J.-N. Kim & Grunig, 2011). Involvement recognition refers to the connection between oneself, the environment, and the problem (J.-N. Kim & Grunig, 2011). Constraint recognition assesses both the internal and external barriers that limit one's actions and efforts to do something about the problem (J.-N. Kim & Grunig, 2011).

The variables utilized for classifying publics respond to publics' perceptions of themselves and a pre-existing issue or problem, meaning this segmentation technique has been applied to different issues and problems. Empirical research supports the theory's propositions (Chon & Park, 2021; Chon et al., 2023; H. J. Kim & Hong, 2022; J.-N. Kim & Krishna, 2014).

Depending on motivations and self-perceptions associated with the problem (i.e., problem, involvement, and constraint recognitions), publics can be segmented into non-publics, latent, aware, active, and activist publics (J.-N. Kim & Grunig, 2011). Non-publics are those who are not connected to the issue (J.-N. Kim et al., 2008). Similarly, latent publics have low awareness about the issue and lack concern about it (J.-N. Kim et al., 2008). Because of their lack of engagement and involvement with the problem, researchers often refer to these two groups as passive publics, combining these two groups into one category (J. E. Grunig & Kim, 2017). Aware publics recognize the existence of the problem and feel more connected or impacted by the issue (J.-N. Kim et al., 2008). Active publics, like aware publics, recognize the problem, but they go one step beyond in their degree of organization, willingness to discuss the problem, and do something about it (J.-N. Kim et al., 2008).

Citizens who participate in the e-rulemaking process by commenting have greater displays of motivation, making them active and activist publics J.-N. (J.-N. Kim & Grunig, 2011). Active publics engage in collective solutions to the specific issue they are active about (J. E. Grunig & Kim, 2017; J.-N. Kim et al., 2010). Activists are motivated to produce change and know the repercussions that decisions have for them, so they organize themselves and generate issues out of the consequences of an organization's (institution or corporation) decisions, having the ability to address the problem (J. E. Grunig & Kim, 2017).

As commenters are members of highly motivated publics, it becomes vital to understand the impact that the presence of opinion spamming has on each segment of the public. One potential effect of opinion spam is its impact on citizen's behavioral intention to comment, as the presence of opinion spam tends to discourage participation (Grossman, 2004).

Publics are segmented depending on their issue perceptions. These are not static groups: Differences in perceived constraints can "deactivate" publics, making active publics become aware publics as the number of perceived constraints increases (J.-N. Kim et al., 2008). As mass commenting discourages participation (Benjamin, 2006; Grossman, 2004), citizens who are more likely to comment and participate will perceive opinion spamming as a barrier and may potentially disengage:

> H1: The more active publics are, the lower their intention to use Regulations.gov will be when exposed to opinion spamming.

As noted, the process of e-rulemaking is closely connected to democracy and the legitimacy of the process, agencies, and resulting regulations (Benjamin, 2006; Perez, 2020; Shapiro, 2019). Flaws in the rulemaking process affect citizens' perceptions of legitimacy, with opinion spamming being one of the most prevalent issues undermining rule legitimacy (Rinfret et al., 2022). Given that active publics may feel discouraged by opinion spam and deactivate, they are also more likely to see opinion spam as damaging to the legitimacy of resulting regulations. Based on this reasoning, we hypothesize:

> H2: The more active publics are, the lower regulation legitimacy they perceive when exposed to opinion spamming.

Publics, especially active publics, are the target of communication from various organizations, as publics' management is indispensable for organizations (e.g., corporations, institutions; L. A. Grunig et al., 2002). Organizational goals can only be achieved when the organization is engaged in relationship-building and communication with publics. In the e-rulemaking context, citizens involved with proposed regulations are publics, and the organizations citizens develop relationships with are the agencies. In public relations, relationships between publics and different organizations have been studied using the organization-public relationship assessment scale (J. E. Grunig & Huang, 2000; Huang, 2001), which include the notions of control mutuality and trust, described as key factors to successful communication between organizations and the publics (Hon & Grunig, 1999; Huang, 2001).

Control mutuality is the extent to which publics and an organization permit their influence on each other to determine goals and behavioral routines (Huang, 2001). Control mutuality is critical for interdependence and relational stability. As opinion spamming directly impacts publics, their levels of control mutuality with the agency posting and reviewing the regulations may differ if they perceive large amounts of duplicated comments, as opinion spamming can be considered a constraint with the power of reducing publics' levels of activity (J.-N. Kim et al., 2008). STOPS explains that communication behaviors vary depending on levels of activity (J.-N. Kim & Grunig, 2011), as their situational motivation in problem-solving varies in function to their perceptions and cognitive evaluation of the problem. Communication is, at the same time, the germ of control mutuality in relationships between publics and organizations (Huang, 2001). When examining relationships with the agency, control mutuality (thus, power bargaining and perceived right to influence) is a factor that assesses relationship quality (Hon & Grunig, 1999; Huang, 2001) and is directly influenced by communication actions:

> H3: The more active publics are, the lower control mutuality they experience when exposed to opinion spamming.

Trust is the level of confidence and willingness to open oneself to another party (Hon & Grunig, 1999). Trust is an indication of relationship quality between publics and agencies. Similar to control mutuality, trust in the agency is at risk when citizens observe the problem of mass commenting on a proposed regulation. In this case, publics will be less likely to perform communicative actions, and the lack of communication diminishes the trust publics feel towards organizations (Huang, 2001; here, federal agencies). Previous research about opinion spamming in online spheres has indicated that publics' trust diminishes with the presence of opinion spamming (Gupta & Bala, 2024). Bringing these findings into the e-rulemaking context results in the following prediction:

> H4: The more active publics are, the lower the trust they experience when exposed to opinion spamming.

2.4. AI in E-Rulemaking

In addition to understanding the nature of publics in relation to opinion spamming exposure, it is also necessary to explore how possible solutions to opinion spamming could affect publics' attitudes and behaviors about e-rulemaking.

AI and machine learning capabilities have piqued the interest of policymakers, who see model mapping and predictability as features to implement in their work (Strandburg, 2019). Some AI features in e-rulemaking could include categorizing and generating more objective answers to each policy or regulation (Eidelman &

Grom, 2019; Strandburg, 2019), as well as filtering repetitive comments and highlighting relevant portions within comments (Eidelman & Grom, 2019).

Opinion spamming produces high numbers of duplicated comments, with little differences from one another, which makes manual filtering and classification tedious and slow. AI capabilities offer a remedy to comment overload. However, specific AI tools, which may work in certain instances, may not fit the full array of contexts in which they can be applied in rulemaking (i.e., these could erase nuances regarding proposed regulation value balance, embed biases in the system producing discriminatory errors, and introduce incorrect interpretations of the regulation, challenging constitutional democracy; Rangone, 2023), evoking mixed responses from citizens.

In addition to examining publics' responses to mass commenting, we also assessed how people view the agencies' use of different comment-management techniques such as when (a) the agency's staff manually reviews comments, (b) AI is being used to manage comments, or (c) a hybrid option, with humans reviewing the comments in addition to the use of AI. Examining the responses to these three approaches designed to mitigate opinion spam will shed light on people's perception of how the use of these techniques affects behavioral intention to comment, legitimacy of the resulting rule, control mutuality with the agency, and trust in the agency.

Users' acceptance of AI determines how much they will be able to successfully adopt newer technologies utilizing AI (Kelly et al., 2023). Exposure to duplicated mass comments can affect perceptions of the usefulness of AI. In addition, because of their levels of activity and engagement, each public segment tends to react differently to issues and problems. Since their perceptions of the issue along with constraints and solutions may differ, the actions they plan on taking may also vary, producing differences in willingness to comment, perceptions of an agency's work, and the resulting regulation. For that reason, we explore the potential three-way interaction between opinion spamming presence, public segmentation, and the use of AI to filter comments:

> RQ: What is the relationship between opinion spamming, public segmentation, and comment-management techniques on (RQa) behavioral intention to use Regulations.gov, (RQb) legitimacy of the resulting regulation, (RQc) control mutuality with the agency, or (RQd) trust toward the agency?

3. Methods

3.1. Participants

This research included two experiments. In both studies, participants were US citizens recruited using Prolific. Prolific is an online data collection panel that has been shown to yield more complete and meaningful data relative to other online panels, as Prolific participants are more likely to pass attention checks, follow instructions, and are required to have unique IP addresses (Douglas et al., 2023). Those participants who took part in Study 1 were not allowed to participate in Study 2.

Sample sizes were determined based on Cohen's power calculation for medium effect sizes (Bhattacherjee, 2012). A commonly cited guideline suggests a minimum of 20 participants per cell (Bhattacherjee, 2012), these being a minimum of 120 participants in Study 1, and 240 participants for Study 2.

In Study 1 (N = 149), 37.6% (n = 56) of the participants were male, while 60.4% (n = 90) were female. There were 1.3% (n = 2) non-binary participants, and one participant who did not disclose their gender. Participants ranged from 18 to 77 years of age (M = 39.66, SD = 13.74). As for the racial distribution, 61.1% were White (n = 91), 18.1% were Black or African American (n = 27), 3.4% were Latinx (n = 5), 9.4% were Asian (n = 14), 1.3% were American Indian or Alaska Native (n = 2), 4.7% participants recorded their belonging in the "other" category (n = 7), and 2% (n = 3) preferred not to disclose their race.

In Study 2 (N = 250), 44% (n = 110) reported they were male, 54.8% (n = 137) were female, .8% (n = 2) were non-binary, and one participant did not disclose their gender. Age ranged from 18 to 95 years of age (M = 39.66, SD = 13.41). In regard to race, 65.2% (n = 163) were White, 16.4% (n = 41) were Black, 6.4% (n = 16) were Latinx, 9.2% (n = 23) were Asian, one participant was American Indian or Alaska Native, five self-identified as "other," and one participant did not report their ethnicity.

3.2. Design and Procedure

Study 1 followed a 3 (publics segmentation: passive publics, aware publics, active publics) × 2 (opinion spam: absent, present) factorial design. Study 2 expanded on the first experiment by including the approaches utilized by agencies to deal with opinion spam. The second experiment followed a 3 (publics segmentation: passive publics, aware publics, active publics) × 2 (opinion spam: absent, present) × 3 (comment-management technique: human, AI, mix of human and AI) between-subjects design. These studies aimed to reveal how these experimental conditions affected behavioral intention to comment, perceived legitimacy of the resulting rule, trust towards the agency, and control mutuality with the agency. Both experiments were housed in Qualtrics, with Prolific disseminating the link to the survey to their panel participants.

In both studies, after consent procedures, the first set of questions was designed to capture public segmentation regarding the rights of gun ownership. Gun ownership is a controversial issue that was selected as the topic. Given that public segmentation is done using self-reported views on an issue, a controversial topic is more likely to produce higher numbers of active publics, which are typically difficult to recruit, as it is complicated to find people who are truly involved. The segmentation set of questions utilized for both studies was a reduced version of problem recognition, constraint recognition, and involvement recognition, taken from STOPS (J.-N. Kim & Grunig, 2011). There were three items for each of the utilized STOPS variables for segmentation: problem recognition (Study 1: M = 4.21, SD = 1.08, α = .89; Study 2: M = 4.21, SD = 1.10, α = .95), constraint recognition (Study 1: M = 2.72, SD = 1.14, α = .86; Study 2: M = 2.67, SD = 1.12, α = .89), and involvement recognition (Study 1: M = 3.33, SD = 1, α = .70; Study 2: M = 3.28, SD = 1.10, α = .79). All items were measured with Likert scales ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

The segmentation method has been applied before in several studies that utilized STOPS, including J.-N. Kim et al. (2011), and is fully explained in Chon et al. (2023). Using midpoint splits, the data from the three situational variables was dichotomized, creating dummy variables, wherein 1 = *high* and 0 = *low*. These dummy variables were then summed, which resulted in four groups of public segmentation, wherein the score of 0 = non-publics, 1 = latent publics, 2 = aware publics, and 3 = active publics (Chon et al., 2023). As this research examines passive publics, those with a score of 0 (i.e., non-publics) or 1 (i.e., latent publics) were considered passive publics. In Study 1, as a result of segmentation, 49 participants were passive publics (a combination of non-publics and latent publics), 68 were aware publics, and 32 were active publics. In Study 2, 95 participants were passive publics, 104 were aware publics, and 51 were active publics. These groups were obtained from the segmentation method outlined above.

Next, participants were randomly assigned to one of the experimental scenarios. The randomization was performed by Qualtrics, the online platform that administered the survey. All participants initially read the same request for comments regarding the proposed gun control rule from the Bureau of Alcohol, Tobacco, Firearms, and Explosives (ATF). The scenario was a shortened version of an actual proposed regulation posted by the ATF on Regulations.gov. The proposed regulation suggested a modification of the definition of when a person is considered engaged in the business or trade of firearms as a dealer and the paperwork individuals need to complete to transfer firearms to other individuals. Participants were told that citizens could comment on the proposed regulation on Regulations.gov, expressing their thoughts, and that the ATF would review these comments and modify the proposed rule if necessary.

After reading this information, participants were randomly assigned to one of the opinion spam conditions, wherein they either read all unique comments (i.e., opinion-spam-absent condition; $n_{\text{Study 1}} = 62$; $n_{\text{Study 2}} = 124$) or comments that included opinion spam, with repetitive duplicated comments from both pro- and anti-gun control publics (i.e., opinion-spam-present condition; $n_{\text{Study 1}} = 87$; $n_{\text{Study 2}} = 126$). Comments in both opinion-spam conditions were shortened versions of actual comments shared by citizens on Regulations.gov. Afterwards, participants were asked to complete manipulation checks capturing whether they perceived the presence or absence of opinion spamming before continuing with the experiment. Manipulation checks contained one open-ended question and several multiple-choice questions. Participants were not allowed to continue if they failed the manipulation checks and had the chance to re-read the information and comments before completing the manipulation check for a second time. Failing the check implied answering the open-ended question with an answer that did not make sense and answering wrongly the multiple-choice question. In Study 1, three participants did not complete the manipulation check questions satisfactorily and were excluded from the study. The next set of questions measured the four dependent variables: trust in the ATF, control mutuality, behavioral intention to use Regulations.gov, and legitimacy of the proposed rule. The survey concluded with demographic questions.

In Study 2, the main change involved adding the third independent variable, comment-management techniques. Participants read that for reviewing and filtering comments, agencies used human reviewers ($n = 82$), AI ($n = 87$), or a combination of both ($n = 81$). AI was explained as a tool utilized to clean comments submitted on Regulations.gov. These manipulations all included one brief paragraph that explained how the agencies deal with comments, including those considered offensive, duplicated, or irrelevant. Extra manipulation checks were included for this variable, to make sure that participants understood the method of filtering comments. In Study 2, three participants did not complete the manipulation check questions satisfactorily and were removed from the final sample. After the manipulation checks, a set of questions was administered to measure the dependent variables and a set of demographic questions.

3.3. Measurement

All dependent variables were measured on a 1 to 5-point scale, wherein 1 = *strongly disagree* and 5 = *strongly agree*. Four items from Shroff and Keyes (2017) were used to measure behavioral intention to use Regulations.gov (Study 1: $M = 2.78$, $SD = 1.27$, $\alpha = .95$; Study 2: $M = 2.91$, $SD = 1.22$, $\alpha = .95$). Five items were used to capture perceptions of legitimacy (Study 1: $M = 3.38$, $SD = 1.15$, $\alpha = .93$; Study 2: $M = 3.48$, $SD = .99$, $\alpha = .92$). Both trust and control mutuality were taken from Hon and Grunig (1999) and Huang (2001). Trust includes six items (Study 1: $M = 2.93$, $SD = 1.01$, $\alpha = .92$; Study 2: $M = 3.13$, $SD = .98$, $\alpha = .92$). Control mutuality comprised four items (Study 1: $M = 2.95$, $SD = .85$, $\alpha = .71$; Study 2: $M = 3.09$, $SD = .80$, $\alpha = .81$).

Several covariates were measured in both experiments. These were the demographic questions—gender, race, age, education, income, and political ideology—and positions on gun control and referent criterion. Position on gun control was a single-item measure, capturing participants' preference for free gun ownership or limited gun ownership. Referent criterion is the previous experience in deciding or solving a similar problem (J.-N Kim & Grunig, 2011), and it is a variable associated with the STOPS framework, although not utilized for publics segmentation purposes. It was measured using three items (e.g., I know how to deal with issues related to gun control) taken from J.-N. Kim and Grunig (2011; Study 1: $M = 3.19$, $SD = .89$, $\alpha = .70$; Study 2: $M = 3.03$, $SD = .92$, $\alpha = .70$). In Study 2, an extra question regarding attitudes toward AI was also included ($M = 2.70$, $SD = 1.30$).

4. Results

4.1. Study 1

Study hypotheses were tested using MANCOVAs. Omnibus effects indicated statistically significant differences in public segmentation, Wilk's $\Lambda = .83$, $F(8, 264) = 3.14$, $p < .01$, $\eta_p^2 = .12$; but no significant differences for the presence of opinion spamming or the interaction between public segmentation and opinion spamming presence. Gender, race, age, education, income, position on gun control, political ideology, and referent criterion were entered as covariates. Among them, the following covariates were significant: position on gun control, Wilk's $\Lambda = .85$, $F(4, 132) = 3.14$, $p < .001$, $\eta_p^2 = .14$; political ideology, Wilk's $\Lambda = .88$, $F(4, 132) = 4.30$, $p < .01$, $\eta_p^2 = .11$; and referent criterion, Wilk's $\Lambda = .91$, $F(4, 132) = 2.93$, $p < .01$, $\eta_p^2 = .08$.

H1 predicted an interaction between opinion spamming presence and public segmentation, and its influence on behavioral intention to comment such that the more active publics are, the lower their intention to comment they would be when exposed to opinion spamming. While the interaction was not significant, there was a statistically significant main effect of segmentation on behavioral intention to use Regulations.gov, $F(2, 135) = 5.91$, $p < .01$, $\eta_p^2 = .11$. There was no effect of opinion spamming presence on the intention to use Regulations.gov. A Bonferroni test was performed to further explore the differences between groups. There were statistical differences between all three publics (see Table 2). Mean comparisons across the three public segmentation groups indicated that passive publics had a lower intention to comment ($M = 2.19$, $SD = 1.11$), than aware publics ($M = 2.76$, $SD = 1.26$), or active publics ($M = 3.71$, $SD = .94$). Thus, the more active publics were, the more willing they were to use Regulations.gov, regardless of presence or absence of opinion spam; meaning that opinion spamming does not produce public deactivation, with publics still engaging to use Regulations.gov. Thus, H1 was not supported.

H2 tested the interaction effect of public segmentation and the presence of opinion spamming on the legitimacy of the resulting regulation, predicting that the more active publics are, the lower perceived regulation legitimacy they perceive when exposed to opinion spamming. H2 was not supported. However, there was a marginally significant main effect of public segmentation on legitimacy, $F(2, 135) = 2.76$, $p = .06$, $\eta_p^2 = .03$. Significant differences were found between passive publics and aware ($\bar{d} = .70$, $p < .01$) as well as passive publics and active publics ($\bar{d} = .96$, $p < .001$), yet there were no significant differences between aware and active publics, hence perceptions of the legitimacy of the resulting rule were significantly lower for passive publics (see Tables 1 and 3). Active ($M = 3.82$, $SD = .87$) and aware publics ($M = 3.56$, $SD = 1.12$) felt a stronger legitimacy of the resulting rule than passive publics ($M = 2.85$, $SD = 1.16$).

H3 examined an interaction between public segmentation and opinion spamming presence on control mutuality with the agency, predicting that the more active publics are, the lower control mutuality they experience when exposed to opinion spamming. Public segmentation had a significant main effect on control mutuality $F(2, 135) = 6.72$, $p < .01$, $\eta_p^2 = .13$. The main effect was superseded by a significant interaction between public segmentation and opinion spamming on control mutuality $F(2, 135) = 3.29$, $p < .05$, $\eta_p^2 = .05$. However, the shape of the interaction effect was contrary to what was hypothesized in H3. When comparing group differences, active publics were significantly different from two other groups, aware ($\bar{d} = .70$, $p < .001$) and passive ($\bar{d} = .88$, $p < .001$), and no statistical differences were found when comparing passive and aware publics (see Tables 1 and 2). There was a significantly higher control mutuality with the agency than the other two groups (active: $M = 3.56$, $SD = .78$; aware: $M = 2.86$, $SD = .89$; passive: $M = 2.67$, $SD = .64$). Thus, H3 was not supported.

H4 proposed an interaction between public segmentation and opinion spamming on citizens' trust in the agency, predicting that the more active publics are, the lower the trust they experience when exposed to opinion spamming. The significant main effect of public segmentation on trust toward the agency,

Table 1. Public segmentation group differences in Study 1.

Dependent variable	Group comparison	Mean difference	*p*	CI
Behavioral intention to comment	Active and passive	1.52	<.001	.9045, 2.1453
	Active and aware	.95	<.001	.3689, 1.5392
	Aware and passive	.57	.02	.0593, 1.0823
Legitimacy	Active and passive	.96	<.001	.3701, 1.5656
	Active and aware	−.26	.79	−.3035, .8241
	Aware and passive	.70	.002	.2148, 1.2004
Control mutuality	Active and passive	.88	<.001	.4569, 1.3109
	Active and aware	.70	<.001	.2995, 1.1050
	Aware and passive	−.70	.64	−1.1050, −.2995
Trust	Active and passive	1.18	<.001	.6846, 1.6808
	Active and aware	.82	<.001	.3559, 1.2955
	Aware and passive	.35	.11	−.0536, .7677

Table 2. Public segments' mean scores for the dependent variables in Study 1.

Dependent variable	Public Segment	*M*	*SD*
Behavioral intention to comment	Passive	2.19	1.11
	Aware	2.76	1.26
	Active	3.71	.94
Legitimacy of the resulting regulation	Passive	2.85	1.16
	Aware	3.56	1.12
	Active	3.82	.87
Control mutuality	Passive	2.67	.64
	Aware	2.86	.89
	Active	3.56	.78
Trust	Passive	2.52	.75
	Aware	2.87	1.07
	Active	3.70	.79

$F(2, 135) = 8.94$, $p < .001$, $\eta_p^2 = .13$, was superseded by a marginally significant interaction between public segmentation and opinions spam on trust, $F(2, 135) = 2.91$, $p = .058$, $\eta_p^2 = .04$. Despite the significant interaction, the same pattern found for control mutuality emerged when analyzing trust, with significant differences between active publics compared to both aware ($\bar{d} = .82$, $p < .001$) and passive publics ($\bar{d} = 1.18$, $p < .001$). Active publics trusted more the agency ($M = 3.70$, $SD = .79$) than aware ($M = 2.87$, $SD = 1.07$) and passive publics ($M = 2.52$, $SD = .75$; see Tables 1 and 2). Thus, H4 was not supported.

4.2. Study 2

In addition to the effects of public segmentation and opinion spam, Study 2 also examined the effect of comment-management techniques (i.e., human comment filtering only, AI filtering only, and a combination of both human and AI filtering of comments). The data revealed a significant omnibus effect of public segmentation, Wilk's $\Lambda = .84$, $F(8, 438) = 4.75$, $p < .001$, $\eta_p^2 = .10$, and a significant omnibus three-way interaction between public segmentation, opinion spam, and comment-management techniques, Wilk's $\Lambda = .88$, $F(16, 669.94) = 1.72$, $p < .05$, $\eta_p^2 = .03$. Significant covariates in the model were: race—Wilk's $\Lambda = .94$, $F(4, 219) = 3.1$, $p < .05$, $\eta_p^2 = .05$; position on gun control—Wilk's $\Lambda = .86$, $F(4, 219) = 8.67$, $p < .001$, $\eta_p^2 = .13$; political ideology—Wilk's $\Lambda = .90$, $F(4, 219) = 5.81$, $p < .001$, $\eta_p^2 = .09$; reference criterion—Wilk's $\Lambda = .87$, $F(4, 219) = 7.57$, $p < .001$, $\eta_p^2 = .12$; and attitudes toward AI—Wilk's $\Lambda = .95$, $F(4, 219) = 2.78$, $p < .05$, $\eta_p^2 = .04$. The effects of all other main effects or interactions as well as gender, age, education, income, and use of AI were not significant.

RQa asked about a three-way interaction between opinion spamming, public segmentation, and comment-management techniques on behavioral intention to comment. The three-way interaction was not significant, but similar to Study 1, public segmentation had a significant main effect on behavioral intention to use Regulations.gov: $F(2, 222) = 10.67$, $p < .001$, $\eta_p^2 = .13$. All three publics differed in their behavioral intentions (see Table 3): Active publics had a stronger intention to use Regulations.gov ($M = 4.03$, $SD = .94$) than aware ($M = 2.88$, $SD = 1.10$) and passive publics ($M = 2.33$, $SD = 1.06$). Neither opinion spamming, comment-management techniques, or their interactions had effects on the intention to use Regulations.gov. These results replicated the same we obtained in Study 1, with no interaction between the presence of opinion spamming and public segmentation, finding the significant differences among public segments, with active publics being more likely to use Regulations.gov.

RQb focused on the aforementioned three-way interaction on the legitimacy of the resulting regulation. Neither opinion spamming nor comment-management techniques had significant effects on the intention to comment. However, public segmentation produced significant differences on legitimacy of the resulting regulation: $F(2, 222) = 3.29$, $p < .05$, $\eta_p^2 = .02$. Identical to the results obtained in Study 1, there were differences between the passive group with the other two public segments, active ($\bar{d} = .80$, $p < .001$) and aware publics ($\bar{d} = 50$, $p < .001$), and there were no differences between the perceived legitimacy of aware and active publics. Passive publics perceived less legitimacy toward the resulting regulation than the other two groups (active: $M = 3.90$, $SD = .71$; aware: $M = 3.61$, $SD = .93$; passive: $M = 3.10$, $SD = 1.07$; see Tables 3 and 4 for more details).

RQc explored a three-way interaction between the presence of opinion spamming, public segmentation, and comment-management techniques to control mutuality with the agency. There was a significant main effect of public segmentation on control mutuality, $F(2, 222) = 10.16$, $p < .001$, $\eta_p^2 = .10$, and a significant two-way interaction between the effects of public segmentation and opinion spam on control mutuality, $F(2, 222) = 3.18$, $p < .05$, $\eta_p^2 = .008$. The same pattern found for Study 1 repeated in Study 2, as group comparison tests with a Bonferroni correction showed that there were differences in control mutuality of active groups as compared to other public types (aware: $\bar{d} = .77$, $p < .001$; passive: $\bar{d} = 1.01$, $p < .001$), and no significant differences between passive and aware publics. Active publics showed a stronger control mutuality than the other two groups (active: $M = 3.56$, $SD = .78$; aware: $M = 2.86$, $SD = .89$; passive: $M = 2.67$, $SD = .64$; see Tables 3 and 4 for more details).

RQd asked about the same three-way interaction on trust towards the agency. There was a significant main effect of segmentation on trust toward the agency: $F(2, 222) = 12.57$, $p < .001$, $\eta_p^2 = .10$. The same pattern

Table 3. Public segmentation group differences in Study 2.

Dependent variable	Group comparison	Mean difference	p	CI
Behavioral intention to comment	Active and passive	1.70	<.001	1.2602, 2.1552
	Active and aware	1.15	<.001	.7116, 1.5928
	Aware and passive	.55	<.001	.1896, .9212
Legitimacy	Active and passive	.80	<.001	.4003, 1.2088
	Active and aware	.29	.22	−.1017, .6944
	Aware and passive	.50	<.001	.1777, .8387
Control mutuality	Active and passive	1.01	<.001	.7103, 1.3141
	Active and aware	.77	<.001	.4729, 1.0674
	Aware and passive	.24	.06	−.0048, .4888
Trust	Active and passive	1.10	<.001	.7263, 1.4747
	Active and aware	.88	<.001	.5146, 1.2516
	Aware and passive	.21	.26	−.5233, .0885

Table 4. Public segments' mean scores for the dependent variables in Study 2.

Dependent variable	Public segment	*M*	*SD*
Behavioral intention to comment	Passive	2.33	1.06
	Aware	2.88	1.10
	Active	4.03	.94
Legitimacy of the resulting regulation	Passive	3.10	1.07
	Aware	3.61	.93
	Active	3.90	.71
Control mutuality	Passive	2.78	.69
	Aware	3.02	.72
	Active	3.79	.81
Trust	Passive	2.82	.94
	Aware	3.03	.90
	Active	3.92	.77

found for Study 1 was replicated in Study 2, as there were significant differences in control mutuality between active group and other public types (aware: $\bar{d} = .88$, $p < .001$; passive: $\bar{d} = 1.10$, $p < .001$), and no significant differences between passive and aware publics. Active publics showed a control mutuality with the agency than the other two groups (active: $M = 3.92$, $SD = .77$; aware: $M = 3.03$, $SD = .90$; passive: $M = 2.82$, $SD = .94$; see Tables 3 and 4 for more details).

5. Discussion

5.1. Advocacy for Public Segmentation in E-Rulemaking Contexts

The present work, consisting of two studies, highlights the importance of publics in the context of e-rulemaking. The key finding is that, consistent with STOPS, those publics who perceive the problem as more relevant are the most involved and find fewer barriers to engaging in communicative actions (J.-N. Kim & Grunig, 2011), as opinion spamming is not perceived as a constraint for publics, who in consequence are not deactivated. In the e-rulemaking context, commenting is a communicative action, as citizens share their opinions and concerns on public websites designated for that purpose. For that reason, active publics are more likely to use Regulations.gov than aware publics, and aware publics are more likely than passive publics, who are just not interested enough in the issue—here, gun control—to participate in the process.

Consistently, public segmentation made a difference in the perceived legitimacy of proposed regulations. Those who are passive were not interested enough in the process, sought less information about the process, and did not feel the proposed regulation was as legitimate compared to active and aware publics, who are more informed about the process and more involved in the issue.

Public segmentation also led to differences in the relationship with the agency proposing the regulation, in this case, the ATF. These differences were observed in both control mutuality and trust toward the agency. We found that active differed significantly on these relationship measures as compared to the less-active groups. The nature of active publics makes them more prone to communicate and build relationships, seeking to know more about the organization and craving to be heard by the organization (J.-N. Kim & Grunig, 2011). There were, however, no differences between aware and passive publics.

5.2. Lack of Differences in Opinion Spamming and Comment-Management Techniques

Conversely, this research also highlights the lack of effects that opinion spamming has on publics. While opinion spamming presents a serious issue for the agency, whose members struggle to classify the information, and for democracy, as some voices may be silenced, no differences were found between participants exposed to opinion spamming and those who were not. Publics do not seem to react negatively to the presence of opinion spamming, though its potential consequences should not be overlooked.

The abundance of information and opinions is not a problem exclusive to e-rulemaking, as the internet has become a widespread tool for real-time information dissemination (Meel & Vishwakarma, 2020). The so-called "information pollution" brings in risks of misinformation, disinformation, and fake news spread, which can further hinder democracy (Bessarabova & Banas, 2023; Gil de Zúñiga & Kim, 2022; Jamalzadeh et al., 2024; Meel & Vishwakarma, 2020). In the context of e-rulemaking, these risks become more pronounced, as misinformation and disinformation could potentially influence government actions, thereby exacerbating the risk for democracy.

5.3. The Use of AI in Federal Agencies

As research on e-rulemaking suggests, the application of AI can be of help in mitigating opinion spamming without compromising an agency's staff outcomes (Eidelman & Grom, 2019; Strandburg, 2019). To that end, this research sought to examine how various opinion-spam-identification approaches affect different segments of citizens. No significant differences were found in whether the agency staff conducted comment filtering, AI was employed, or a combination of humans and AI were tasked with comment filtering. It appears that the type of approach used to deal with opinion spam does not matter for publics as in our study they did not seem to be influenced by an agency's methods.

A practical implication from our research is that agencies should engage in communication to reach publics, attempting to decrease the constraints and barriers that prevent publics from participating. The use of AI, as long as its capability is to classify duplicated comments and filter offensive or irrelevant comments (i.e., when people comment under the wrong regulation proposal) does not appear to impact publics' attitudes toward agencies and regulations as well as people's commenting behavior. Taken together, our data suggest that as long as AI capabilities are described to publics, they should find AI deployment for comment processing as acceptable as manual or human-AI combination techniques

5.4. Moving Forward

More attention should be paid to active publics during e-rulemaking processes, as their involvement is key in shaping participation, attitudes toward, and behaviors surrounding proposed regulations. The most optimal participation and best outcomes occur when publics are active. Therefore, it is essential to foster active publics. Agencies should work to lower barriers and constraints to encourage broader participation.

In e-rulemaking, activist groups play an important role in disseminating information to both in-group and out-group members. They are also often behind the organization of opinion spamming campaigns, which most directly affects regulatory agencies. As a result, agencies should communicate and build relationships with activist groups to better understand their needs, integrate their ideas, achieve agreements, and ultimately reduce opinion spamming, while ensuring that activist groups' voices are heard. One solution might be to seek more deliberative comments from activist groups that could help avoid heavily circulated form comments, as these groups can debate and share their concerns, feeling heard and abandoning opinion spamming (Schlosberg et al., 2009).

One important implication of this research is that agencies should invest their resources in generating participation, directly scouting active publics, and enabling channels to reach their voices. It is worth noting that based on our data the use of AI was not inherently harmful for public participation. However, the agencies should remain vigilant regarding potential risks that may obscure the democratic process, silence voices, and raise privacy issues concerning the e-rulemaking process.

Organizations already utilize mechanisms to recognize active publics, and they should communicate symmetrically with these groups, as building strong relationships with activist groups generates greater rates of success in working with these groups (L. A. Grunig et al., 2002; J. E. Grunig, 2008).

5.5. Limitations

This study's main limitation is the lack of information about participants' actual knowledge about AI. While the experiment considered previous uses of this kind of technology, it does not imply that users will have accurate knowledge about AI and its different uses.

Future research should account for greater nuances in participants' understanding of how AI works and include more detailed explanations of how agencies utilize AI in e-rulemaking. In this study, AI was introduced as a filtering software. However, if AI is used by agencies for other purposes—for example, summarizing comments or crafting messages rather than filtering and classifying information—publics' response might have been more critical of AI. Given that all conclusions about AI use in e-rulemaking are limited to AI being used as a filtering software, future research should examine the effects of differences in affordances of AI to make broader generalizations about AI acceptance.

In addition, the study inductions consisted of hypothetical scenarios related to only one proposed regulation on the topic of gun control. That regulation was chosen because gun control generates strong reactions among American citizens, making it easier to detect relevant active publics. Future research should replicate the study results with other regulations, focusing on both controversial and non-controversial issues, to examine differences in publics' attitudes and behavioral intentions.

6. Conclusion

This work advances public relations theory by applying publics segmentation to the e-rulemaking context. Furthermore, this work offers important practical implications, highlighting the benefits of relationship-building and proactive strategies designed to reduce constraints and make publics more active.

Active publics are vital in achieving positive consequences, such as a higher intention to use e-rulemaking official sites to make comments, better perceptions of the resulting regulations, and more trust and control mutuality with the agency proposing the regulation.

While opinion spamming is an important concern for government agencies, who are forced to deal with thousands of identical non-substantive comments, the spamming campaigns do not appear to produce changes in the ways citizens interact with Regulations.gov or the agencies. Furthermore, the introduction of AI to filter the comments did not produce significant differences in publics' attitudes and behaviors regarding e-rulemaking, suggesting that, as long as the AI technology is limited to filtering comments, people should not be reluctant to participate in the process of e-rulemaking.

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Conflict of Interests

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References

Balla, S. J., Dooling, B. C. E., Bull, R., Hammond, E., Herz, M., Livermore, M., & Noveck, B. S. (2021, May 28). *Mass, computer-generated, and fraudulent comments* [Paper presentation]. Administrative Conference of the United States, Washington, DC, United States.

Benjamin, S. M. (2006). Evaluating e-rulemaking: Public participation and political institutions. *Duke Law Journal*, *55*(5), 893–941.

Bessarabova, E., & Banas, J. A. (2023). Emotions and the QAnon conspiracy theory. In M. Miller (Ed.), *The social science of QAnon: Understanding a new social and political phenomenon* (pp. 87–103). Cambridge University Press.

Bhattacherjee, A. (2012). *Social science research: Principles, methods, and practices*. Global Text Project. http://scholarcommons.usf.edu/oa_textbooks/3

Chon, M.-G., & Park, H. (2021). Predicting public support for government actions in a public health crisis: Testing fear, organization-public relationship, and behavioral intention in the framework of the situational theory of problem solving. *Health Communication*, *36*(4), 476–486. https://doi.org/10.1080/10410236.2019.1700439

Chon, M.-G., Tam, L., Lee, H., & Kim, J.-N. (2023). Situational theory of problem solving (STOPS): A foundational theory of publics and its behavioral nature in problem solving. In C. Botan & E. Sommerfeldt (Eds.), *Public relations theory III* (pp. 58–76). Routledge.

Department of Defense Open Government. (n.d.). *Electronic rulemaking*. https://open.defense.gov/Transparency/Electronic-Rulemaking

Douglas, B. D., Ewell, P. J., & Brauer, M. (2023). Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA. *PLoS ONE*, *18*(3), Article e0279720. https://doi.org/10.1371/journal.pone.0279720

Eidelman, V., & Grom, B. (2019). Argument identification in public comments from eRulemaking. In K. Benyekhlef (Ed.), *ICAIL '19: Proceedings of the Seventeenth International Conference on Artificial Intelligence and Law* (pp. 199–203). ACM. https://doi.org/10.1145/3322640.3326714

Farina, C. R., Newhart, M. J., Cardie, C., & Cosley, D. (2011). Rulemaking 2.0. *Cornell Law Faculty Publications*, Article 179. https://scholarship.law.cornell.edu/facpub/179

Farina, C. R., Newhart, M.J., & Heidt, J. (2012). Rulemaking vs. democracy: Judging and nudging public participation that counts. *Michigan Journal of Environmental and Administrative Law*, *2*(1), 123–171. http://ssrn.com/abstract=2054750

Gil de Zúñiga, H., & Kim, J.-N. (2022). Intervening troubled marketplace of ideas: How to redeem trust in media and social institutions from pseudo-information. *American Behavioral Scientist*, *69*(2), 103–112. https://doi.org/10.1177/00027642221118279

Grossman, S. (2004). Keeping unwanted donkeys and elephants out of your inbox: The case for regulating political spam. *Berkeley Technology Law Journal*, *19*, 1533. https://heinonline.org/HOL/LandingPage?handle=hein.journals/berktech19&div=63&id=&page=

Grunig, J. E. (2008). *Excellence in public relations and communication management*. Routledge.

Grunig, J. E., & Huang, Y.-H. (2000). From organizational effectiveness to relationship indicators: Antecedents of relationships, public relations strategies and relationship outcomes. In J. A. Ledingham & S. D. Bruning (Eds.), *Public relations as relationship management: A relational approach to the study and practice of public relations* (pp. 23–53). Lawrence Erlbaum.

Grunig, J. E., & Kim, J.-N. (2017). Publics approaches to health and risk message design and processing. In M. Powers (Ed.), *Oxford encyclopedia of health and risk message design and processing*. https://doi.org/10.1093/acrefore/9780190228613.013.322

Grunig, L. A., Grunig, J. E., & Dozier, D. M. (2002). *Excellent public relations and effective organizations: A study of communication management in three countries*. Lawrence Erlbaum.

Gupta, P., & Bala, R. (2024). Exploring ethical dimensions of marketers' influence on electronic word-of-mouth and its effect on customer trust. In S. Saluja, V. Nayyar, K. Rojhe, & S. Sharma (Eds.), *Ethical marketing through data governance standards and effective technology* (1st ed, pp. 92–101). IGI Global. https://doi.org/10.4018/979-8-3693-2215-4.ch008

Hallahan, K. (2018). Public relations. In R. L. Heath & W. Johansen (Eds.), *The International Encyclopedia of Strategic Communication*.

Hon, L. C., & Grunig, J. E. (1999). *Guidelines for measuring relationships in public relations*. Institute for Public Relations. https://instituteforpr.org/wp-content/uploads/Guidelines_Measuring_Relationships.pdf

Huang, Y.-H. (2001). OPRA: A cross-cultural, multiple-item scale for measuring organization-public relationships. *Journal of Public Relations Research*, *13*(1), 61–90. https://doi.org/10.1207/S1532754XJPRR1301_4

Jamalzadeh, S., Mettenbrink, L., Barker, K., Gonzalez, A. D., Radhakrishnan, S., Johansson, J., & Bessarabova, E. (2024). Disinformation interdiction: Weaponized disinformation spread and its impact on multi-commodity critical infrastructure networks. *Reliability Engineering & Systems Safety*, *243*, Article 109819. https://doi.org/10.1016/j.ress.2023.109819

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, *77*, Article 101925. https://doi.org/10.1016/j.tele.2022.101925

Kim, H. J., & Hong, H. (2022). Predicting information behaviors in the COVID-19 pandemic: integrating the role of emotions and subjective norms into the situational theory of problem solving (STOPS) framework. *Health Communication*, *37*(13), 1640–1649. https://doi.org/10.1080/10410236.2021.1911399

Kim, J.-N., Andreu Perez, L., Lee, H., Hollenczer, J., Jensen, M. L., Bessarabova, E., Talbert, N., & Li, Y. (2025). Managing opinion spamming with AI in regulatory public engagement. *International Journal of Strategic Communication*, *19*(2), 261–283. https://doi.org/10.1080/1553118X.2025.2459611

Kim, J.-N., & Grunig, J. E. (2011). Problem solving and communicative action: A situational theory of problem solving. *Journal of Communication*, *61*(1), 120–149. https://doi.org/10.1111/j.1460-2466.2010.01529.x

Kim, J.-N., Grunig, J. E., & Ni, L. (2010). Reconceptualizing the Communicative Action of Publics: Acquisition, Selection, and Transmission of Information in Problematic Situations. *International Journal of Strategic Communication*, *4*(2), 126–154. http://doi.org/10.1080/15531181003701913

Kim, J.-N., & Krishna, A. (2014). Publics and lay informatics: A review of the situational theory of problem solving. In E. L. Cohen (Ed.), *Communication yearbook 38* (pp. 71–106). Routledge.

Kim, J.-N., Ni, L., & Sha, B.-L. (2008). Breaking down the stakeholder environment: A review of approaches to the segmentation of publics. *Journalism & Mass Communication Quarterly*, *85*(4), 751–768. https://doi.org/10.1177/107769900808500403

Kim, J.-N., Shen, H., & Morgan, S. E. (2011). Information behaviors and problem chain recognition effect: Applying situational theory of problem solving in organ donation issues. *Health Communication*, *26*(2), 171–184. https://doi.org/10.1080/10410236.2010.544282

Li, J., Wang, X., Yang, L., Zhang, P., & Yang, D. (2020). Identifying ground truth in opinion spam: an empirical survey based on review psychology. *Applied Intelligence*, *50*, 3554–3569.

Liu, B. (2012). Opinion spam detection. In B. Liu (Ed.), *Sentiment analysis and opinion mining* (pp. 113–125). Springer.

Meel, P., & Vishwakarma, D. K. (2020). Fake news, rumor, information pollution in social media and web: A contemporary survey of state-of-the-arts, challenges and opportunities. *Expert Systems with Applications*, *153*, Article 112986. https://doi.org/10.1016/j.eswa.2019.112986

Moxley, L. (2016). E-rulemaking and democracy. *Administrative Law Review*, *68*(4), 661–699. https://www.jstor.org/stable/44648602

Park, J., Blake, C., & Cardie, C. (2015). Toward machine-assisted participation in e-rulemaking: An argumentation model of evaluability. In T. Sichelman (Ed.), *ICAIL '15: Proceedings of the 15th International Conference on Artificial Intelligence and Law* (pp. 206–210). ACM. http://doi.org/10.1145/2746090.2746118

Perez, O. (2020). Collaborative e-rulemaking, democratic bots, and the future of digital democracy. *Digital Government: Research and Practice*, *1*(1), Article 8. https://doi.org/10.1145/3352463

Rangone, N. (2023). Artificial intelligence challenging core State functions: A focus on law-making and rule-making. *Revista de Derecho Público: Teoría y Método*, *8*, 95–126. https://doi.org/10.37417/RDP/vol_8_2023_1949

Regulations.gov. (n.d.). *About the e-rulemaking initiative*. https://www.regulations.gov/about

Rinfret, S., Duffy, R., Cook, J., & St. Onge, S. (2022). Bots, fake comments, and E-rulemaking: the impact on federal regulations. *International Journal of Public Administration*, *45*(11), 859–867. https://doi.org/10.1080/01900692.2021.1931314

Schlosberg, D., Zavestoski, S., & Shulman, S. (2009). Deliberation in e-rulemaking? The problem of mass participation. In T. Davies & S. P. Gangadharan (Eds.), *Online deliberation: Design, research, and practice* (pp. 133–148). CSLI Publications.

Shapiro, S. A. (2019). Law, expertise and rulemaking legitimacy. *Environmental Law*, *49*(3), 661–682.

Shroff, R. H., & Keyes, C. J. (2017). A proposed framework to understand the intrinsic motivation factors on university students' behavioral intention to use a mobile application for learning. *Journal of Information Technology Education Research*, *16*, 143–168.

Shulman, S. W. (2009). The case against mass e-mails: Perverse incentives and low quality public participation in US federal rulemaking. *Policy & Internet*, *1*(1), 23–53.

Strandburg, K. J. (2019). Rulemaking and inscrutable automated decision tools. *Columbia Law Review*, *119*(7), 1851–1886.

Widyatama, R., & Mahbob, M. H. (2024). The potential hazards of fake accounts and buzzer behaviour on deliberative democracy. *Jurnal Komunikasi: Malaysian Journal of Communication*, *40*(1), 324–341.

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