# Platform Governance with Algorithm-based Content Moderation: An Empirical Study on Reddit

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## Abstract

With increasing volumes of participation in social media and online communities, content moderation has become an integral component of platform governance. Volunteer (human) moderators have thus far been the essential workforce for content moderation. Because volunteer-based content moderation faces challenges in achieving scalable, desirable, and sustainable moderation, many online platforms have recently started to adopt algorithm-based content moderation tools (bots). When bots are introduced into platform governance, it is unclear how volunteer moderators react in terms of their community-policing and -nurturing efforts. To understand the impacts of these increasingly popular bot moderators, we conduct an empirical study with data collected from 156 communities (subreddits) on Reddit. Based on a series of econometric analyses, we find that bots augment volunteer moderators by stimulating them to moderate a larger quantity of posts, and such effects are pronounced in larger communities. Specifically, volunteer moderators perform 20.9% more community policing, particularly over *subjective* rules. Moreover, in communities with larger sizes, volunteers also exert increased efforts in offering more explanations and suggestions after their community adopted bots. Notably, increases in activities are primarily driven by the increased need for nurturing efforts to accompany growth in subjective policing. Moreover, introducing bots to content moderation also improves the retention of volunteer moderators. Overall, we show that introducing algorithm-based content moderation into platform governance is beneficial for sustaining digital communities.

**Keywords**: Content moderation, human-machine collaboration, bot, volunteer moderators, platform governance

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# 1. Introduction

As online platforms and communities grow, inappropriate content such as hate speech and trolling pose safety challenges and economic loss to platforms (Matias 2019a, Roberts 2014, Wu et al. 2021). Diverse and complex online environments increase the need for devising platform policies and, consequently, content moderation when content policies are violated. Typically, a small subset of community members has served an important role as volunteer (human) content moderators. Platforms, such as Reddit, Wikipedia, and Stack Overflow (Zheng et al. 2019), have largely relied on volunteers to moderate their content and platform environment (Matias 2019a, Jhaver et al. 2019b). With the increasing reach and influence of digital platforms, there is a growing emphasis on more platform accountability. Volunteer moderators play an important role in meeting the challenges of creating a safe environment for all users on digital platforms.

Based on the functionality of moderation tasks, volunteer moderators play community-policing and -nurturing roles. Volunteers and platforms broadly face several challenges in content moderation. First, content moderation is expected to scale in response to the fast-growing user base and the corresponding growth in the volume of online content. It is, however, unrealistic to expect volunteer moderation capacity to scale without effective automation support. Volunteer moderators' time is not scalable, and they frequently experience burnout in handling the large volume of online content and rule violations (Dosono and Semaan 2019, Grimmelmann 2015, Gillespie 2018, Matias 2019b). Second, besides preventing the community from being exposed to inappropriate content, volunteer moderators are also expected to nurture community discourse, which emphasizes curating discussions through user education on community norms and fostering improved dialogue with community members (Jiang 2020, Ruckenstein and Turunen 2020, Yu et al. 2018). Nurturing-oriented moderation requires more moderators' effort and attention to individuals' needs than policing-oriented moderation. Motivating desirable nurturing moderation has been a great challenge for online platforms. Last, as volunteer moderators engage in unpaid work, their retention has been the key to the sustainability of the volunteerbased platform governance model. Platforms are motivated to seek solutions that attract and sustain volunteers' engagement and contributions and minimize attrition.

The developments in algorithms and machine learning techniques open a new avenue for platforms to address the challenges to achieve scalable, desirable, and sustainable content moderation (Hammer 2016, Seering et al. 2019). For instance, Facebook has applied machine learning techniques to detect pornographic content (Robert 2014, Gillespie 2018). On Reddit, many communities have started to embed moderation tasks and processing logic into algorithms (often called bots) to screen and remove inappropriate content (Chandrasekharan et al. 2018). While platforms are moving towards the algorithmassisted mode of content moderation, findings from researchers and reactions from the public are mixed. On the one hand, the direct interaction between volunteer moderators and users is critical for communitybuilding (Ruckenstein and Turunen 2020). Thus, bots may substitute volunteers in moderating content, leading to reduced volunteers' moderation effort and engagement with community users. On the other hand, automating moderation tasks through bots may also result in an increased volunteer effort. The automation eases the workload on volunteer moderators by reducing the need to handle tedious tasks, e.g., detecting rule violations and removing inappropriate content (Jhaver et al. 2019a). The reduced workload and improved work environment (e.g., less tedious work) can, in turn, enhance commitment (Alfes et al. 2016, Smith 1994). Simultaneously, volunteer moderators are better able to expand their role as community rule compliance officers, allowing them to engage in moderation that requires more subjective judgment and even offering more support to their community to nurture its members (Karusala et al. 2017).

Relevant academic research on human-bot collaboration in content moderation is still in its infancy. First, IS researchers have long studied platform governance models (Sambamurthy and Zmud 1999, Tiwana et al. 2010) and content moderation (Kraut and Resnick 2012, Ren and Kraut 2014). However, despite calls for research into the hybrid mode of content moderation with both human and technological effort (Ren and Kraut 2014), few studies have empirically examined the influence of machine adoption on volunteers' moderation efforts in online platforms. Second, the machine substitution and augmentation literature has investigated various contexts focusing predominantly on compensated workers (Autor and Dorn 2013,

Acemoglu and Restrepo 2018). As an emerging context of great importance to modern society, content moderation has, however, received little attention, particularly regarding the role of automation in volunteer-based work. Third, an emerging literature on content moderation has started to provide qualitative and descriptive evidence on human and bot performance (Jhaver et al. 2019a, Ruckenstein and Turunen 2020). These studies have laid the foundation for our empirical investigation into the influences of bots on volunteers' moderation.

In this study, we seek to investigate the impact of algorithm-powered bot moderators on volunteer moderators' activities. Formally, with the focus on two critical roles of volunteer moderators and the challenges in content moderation (i.e.,  a growing need for more scalable and nurturing moderation), we approach our research objectives by investigating two research questions: (***RQ1)*** *How do bots affect volunteer moderators' community-**policing** efforts?* ***(RQ2)*** *How do bots affect volunteer moderators' community-**nurturing** efforts?*

To answer the research questions, we select Reddit as our research context. The Reddit platform has a plethora of communities named subreddits, with each having a small number of volunteer moderators. To address the

scale of the user base, Reddit has developed bots (e.g., 'AutoModerator') to facilitate routine content moderation. Volunteer moderators of subreddits can integrate the bots to assist in content moderation. Once integrated, when a bot detects a rule violation on Reddit, it will follow the subreddit community guidelines and pre-defined workflow to take actions such as flagging and removing content.

We collect bot and volunteer public moderation records from 156 subreddits on Reddit from 2013 to 2014. We identify the bot-automated moderation tasks from the public moderation records. To identify volunteer moderators' activities, we employ an advanced natural language processing technique, BERT (Bidirectional Encoder Representations from Transformers). A Difference-in-Differences (DiD) model is then applied to estimate the impact of moderation automation. Our results suggest that bots stimulate volunteer moderators to increase their policing activities by 20.9%. Meanwhile, bots encourage volunteers to exert more community-nurturing efforts. The number of explanations created by volunteers in a month increases by 15.2% after adopting bots. And such effects are more pronounced in larger communities with greater moderation needs. We find that bots augment rather than substitute volunteer moderators by stimulating more of their policing efforts to enforce subjective rules and expand their scope of work. Moreover, the increased community-nurturing efforts are primarily driven by the increasing need to accompany policing activities over subjective rules. Additionally, volunteer-based moderation becomes more sustainable with bots, as we observe increased retention of volunteer moderators after bot implementation. We perform a series of robustness checks and validate the findings.

This research contributes to three streams of literature. We first contribute to the platform governance literature (Sambamurthy and Zmud 1999, Tiwana et al. 2010, Ren and Kraut 2014) by investigating the hybrid mode of content moderation that integrates humans and algorithms and how the two types of moderators achieve augmentation. Our study suggests that algorithms can augment humans by stimulating more policing and nurturing moderation. Second, our work contributes to the machine substitution and augmentation literature by extending this stream of work into volunteer-based content moderation tasks (Autor and Dorn 2013, Acemoglu and Restrepo 2018, Dixon et al. 2021, Fügener et al. 2022). Our research suggests that machines complement voluntary labor by shifting their attention to tasks requiring specific responses and subjective judgment. Third, our study contributes to the growing content moderation literature (Zheng et al. 2019, Dosono and Semaan 2019, Matias 2019b) by providing novel empirical evidence on the role of bot moderators. We offer comprehensive analyses of how bots affect volunteers' activities and retention. Our research indicates that bots are an effective tool for improving the scale and quality of content moderation in online communities.

## 2. Related Literature & Hypotheses

### *2.1 Content Moderation and the Role of Volunteer Moderators*

Content moderation refers to the mechanism that regulates individuals' participation in a community to increase the quantity and quality of engagement (Grimmelmann 2015, Ren and Kraut 2014). Content moderation is an important aspect of platform governance, especially for platforms that rely on usergenerated content.

Central to content moderation on online platforms are volunteer moderators. Drawing on the role theory (Biddle 1986, Seering et al. 2018, Tarafdar et al. 2023, Zheng et al. 2019) and the extant literature on online communities (Kraunt and Resnick 2011, Ruckenstein and Turunen 2020, Yu et al. 2020, West 2018, Jiang 2020), we conceptualize volunteer moderators' functional roles based on the tasks and associated goals into two categories: *community-policing* and *community-nurturing*. Appendix A summarizes related literature and categorization. Community-policing focuses on coercing compliance, such as tools used to limit inappropriate content and user behavior, and it emphasizes the speed and efficiency of content removal. In contrast, community-nurturing focuses on curating discussion by educating users about community norms and improving dialogue with community members. Volunteer moderators are expected to perform community-policing activities to remove undesirable and harmful content because it can effectively reduce community noncompliance rates and further maintain community integrity and order (Srinivasan et al. 2019, Wu et al. 2021). In addition, they are expected to engage in community-nurturing endeavors to provide valuable support to the community (Yu et al. 2020). Such activities hold the promise of fostering more constructive interactions within the community, nurturing long-term community growth (West 2018, Ruckenstein and Turunen 2020, Karusala et al. 2017, Yu et al. 2018).

Community-policing and -nurturing are interdependent. On the one hand, more policing can elicit increasing needs for community-nurturing efforts, such as offering explanations and suggestions. On the other hand, nurturing moderation complements policing-oriented moderation in achieving more effective platform governance. For example, Jhaver et al. (2019c) found that while executing content removal, offering sufficient explanations would significantly reduce the possibility of future rule violations.

In practice, community-nurturing moderation widely suffers from inadequate effort (Jiang 2020, West 2018, Ruckenstein and Turunen 2020) compared to community-policing moderation because of the greater cognitive complexity involved in nurturing-oriented activities. Moreover, existing literature primarily focuses on policing-oriented moderation and its influence. Little attention has been paid to volunteer moderators' dual roles in content moderation and examining potential approaches to encourage greater and more desirable community-nurturing efforts from moderators. We herein focus on whether and how bot-assisted moderation may affect volunteer moderators' efforts in policing- and nurturingoriented moderation.

### *2.2 Bot Capability and Automation Impacts*

Online platforms increasingly rely on human and algorithmic agents (e.g., bots) in content moderation (Ren and Kraut 2014). Extant literature has studied the capability of human and bot moderators (Seering et al. 2018, Gillespie 2018, Jhaver et al. 2019a, Zheng et al. 2019). For example, Zheng et al. (2019) extract bot functions based on bot description and activity history from Wikipedia and then categorize bots' roles. They found that bots play both protector and advisor roles on Wikipedia. The protector role is analogous to the community-policing role, focusing on tasks such as identifying spam, vandals, and policy violations. The advisor role is analogous to the community-nurturing role, focusing on tasks such as providing suggestions for users and greeting newcomers. Notably, with a focus on bot usage in content moderation on Reddit, Jhaver et al. (2019a) found that bots prove effective in replacing human moderators to remove inappropriate content. Nonetheless, the study also revealed deficiencies in the bots' ability to navigate situations that demand an understanding of nuanced contextual details. As a result, human moderation remains indispensable for enforcing community guidelines that necessitate subjective interpretation.

A great deal of literature has also investigated machine substitution and augmentation in various contexts, such as productivity and employment (Autor and Dorn 2013, Acemoglu and Restrepo 2018, Dixon et al. 2021, Rai et al. 2019, Fügener et al. 2022). Researchers find that machines show great strength in performing routine, simple, and highly predictable tasks without requiring complex cognitive effort. Therefore, machine automation tends to substitute humans in performing such tasks. However, constrained by machine capability in cognitively complex tasks, automation may also increase the need for human efforts to perform tasks that complement automated ones. Plentiful empirical evidence indicates the substitutional and complementary impacts of machine automation on human productivity in various contexts. For example, Dixon et al. (2021) studied robot adoption in the manufacturing industry and found that robots decrease the employment of middle-skilled workers (such as technicians) who follow working protocols. In contrast, robots increase the employment of high-skilled labor who can work with robots and conduct more cognitively complex tasks.

Extant literature has thus established a great foundation for understanding machine capability and how automation affects labor demand and human productivity. However, prior literature mainly focuses on compensated labor; little attention has been paid to automation and its influences on content moderation that heavily relies on voluntary human effort. As granular moderation data is needed to dissect the effects of bot automation in content moderation, to this end, we collect data from a real-world setting and utilize measures of volunteers' moderation efforts to empirically investigate whether and how the adoption of algorithm-based moderation bots substitutes or complements volunteer moderators.

### *2.3 Bot Adoption and Community-policing Moderation*

Drawing on the machine substitution and augmentation literature, the impact of bot adoption on volunteers' community-policing moderation efforts is heavily contingent upon task-specific characteristics (Autor and Dorn 2013, Acemoglu and Restrepo 2018, Dixon et al. 2021). Volunteer moderators exercise their policing decisions by following respective community guidelines. These guidelines outline a series of community rules governing acceptable user-generated content, primarily focusing on content format and quality standards (Fiesler et al. 2018, Seering et al. 2019). Considering the inherent complexity of community rules, bots could exhibit varying capabilities in automating each rule, leading to a diverse range of impacts on the workload of volunteer moderators.

In the case of simple and objective rules, bots possess the potential to efficiently automate related policing tasks on a scalable basis, thereby reducing the reliance on human effort. For instance, research has demonstrated that employing bots for policing simple and objective tasks can yield comparable performance levels to those achieved by human moderators. Interviews with volunteer moderators on Reddit found that bots can effectively identify certain forms of personal attacks and other inappropriate content (Jhaver et al. 2019a). Follow-up research further reveals that when platform moderation maintains high transparency, users perceive no distinction between removals carried out by human or bot moderators (Jhaver et al. 2019c).

In contrast, when handling complex and subjective rules that involve more cognitive evaluation and contextual judgment, bots exhibit limitations in displacing humans to exercise policing decisions (Jhaver et al. 2019a, Seering et al. 2019). Complex community rules such as detecting satirical languages and hate speech still largely rely on human judgment; thus, bots show limited capability in automating policing-oriented moderation on subjective tasks. Moreover, as discussed earlier, when bots automate simple and objective rules, volunteer moderators will have more bandwidth to enforce subjective rules. Therefore, volunteer moderators' moderation activities will not necessarily decrease after bots are introduced to the community governance process.

To summarize, bots can exhibit both substitutional and complementary effects on moderators' community-policing efforts. On the one hand, bots can substitute volunteer effort by effectively detecting and automating policing on objective tasks. On the other hand, bots can complement volunteers' efforts by enabling them to tackle policing more subjective tasks. Thus, volunteers' effort in performing community-policing moderation is determined by the net influences of substitutional and complementary effects from bot adoption. Therefore, we propose a set of hypotheses as follows:

*H1a: Communities' bot adoption for content moderation will lead volunteer moderators to perform* ***more*** *(subjective) community-policing moderation.*

*H1b: Communities' bot adoption for content moderation will lead volunteer moderators to perform* ***less*** *(objective) community-policing moderation.*

### *2.4 Bot Adoption and Community-nurturing Moderation*

Given the volunteer moderators' dual roles as community compliance officers and nurturers, we theorize that communities' bot adoption for content moderation has the potential to impact volunteer moderators' efforts in community-nurturing moderation because of attention reallocation and increased need for complementary labor. Community-nurturing moderation involves volunteers' thoughtful decisions and active support for the community. When exercising nurturing-centered moderation, volunteer moderators normally need to handle various requests from community members and offer personalized and contextualized assistance. The task characteristics of community-nurturing moderation make it difficult to automate. A growing body of evidence shows that labor substitution through automation can induce demand and productivity for nonautomated tasks (Dixon et al. 2021, Acemoglu and Restrepo 2018, Brynjolfsson et al. 2018). For example, Gombolay et al. (2018) studied robots and patient care in hospitals, and they found that when hospitals adopt robots for the purpose of lifting patients from their beds, nurses are not only relieved from such physically demanding tasks but also able to perform more caring activities such as more interactions with patients. In the moderation automation context, prior to the adoption of automated solutions for content moderation, volunteer moderators need to allocate their limited time and effort to policing and nurturing work. However, when bots automate policing activities, volunteer moderators are able to pay more attention to nurturing moderation work.

Moreover, machine augmentation literature suggests that automation may increase the demand for existing tasks that complement automated ones. It is important, therefore, to recognize that policing and nurturing moderation are interdependent. The changes in community-policing moderation after bot adoption may *increase* the need for complementary nurturing activities. Effective policing typically requires accompanying nurturing actions, such as justifying policing decisions, addressing individual users' special requests, and providing personalized suggestions (Yu et al. 2020). Considering the potential increase in volunteers' engagement in policing subjective rules following the adoption of bots in content moderation, as discussed in Section 2.3, this increase will prompt a greater demand for communitynurturing activities centered around policing decisions. Direct and personalized involvement by volunteer moderators is, therefore, likely required to tackle confusion and elucidate their thought process behind the decision. For example, volunteer moderators may be expected to provide subtle nudges or point to alternative solutions to community members to assist their further participation on the platform. To summarize, due to the reallocated efforts and increased need for complementary nurturing activities, we propose the following hypothesis:

*H2: Communities' bot adoption for content moderation will lead volunteer moderators to perform* ***more*** *community-nurturing moderation.*

## 3. Empirical Setting

### *3.1 Research Context*

We collected and compiled a data set from Reddit, a large online discussion and community platform. Reddit comprises more than 130,000 active communities, termed subreddits, covering a wide range of subjects such as world news, sports, writing, and movies. Reddit users can engage with the subreddits by posting content, leaving comments, and voting on others' content on Reddit. Reddit has more than 52 million daily active users, and it has become the seventh most visited user-generated content platform in the world as of 2020.[4]

Reddit used to rely solely on volunteer moderators to manage all their communities. Most volunteer moderators are community users who have a deep understanding of the subreddit's community theme and rules. These volunteer moderators design community rules and monitor community activity regularly. When a rule violation happens, they are authorized to remove content and take disciplinary actions against users.

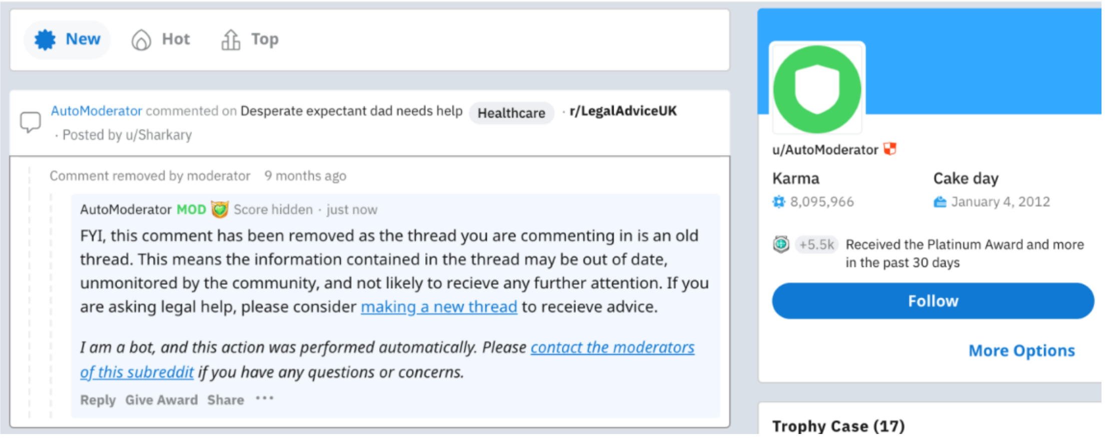
[4] https://www.redditinc.com/blog/reddits-2020-year-in-review/ Accessed August 10, 2023.

Since 2012, some subreddits have started to utilize algorithm-based moderation tools, known as bots, to assist their content moderation. Two characteristics make Reddit an ideal research context for our study: availability of moderation records and varied timings of bot adoption by different subreddits. First, due to security and intellectual property concerns, most platforms do not disclose details of the technical strategies used for their content moderation. We observe moderation records for neither human moderators nor bot moderators for those platforms. In contrast, Reddit makes task automation and moderation records available to the public. On Reddit, researchers can identify subreddits that use bots to assist with their community governance (Chandrasekharan et al. 2018, Chandrasekharan and Gilbert 2019, Fiesler et al. 2018). Typically, these bot moderators automatically inspect newly submitted content and conduct a series of actions accordingly, such as removing offensive content (Dosono and Semaan 2019). Each bot moderator has a profile page displaying its creation date and historical moderation records. Most importantly, moderation records are presented in the form of public comments, as shown in Figure 1. These comments include details such as moderation time, action, explanations, and suggestions to the content creator. Volunteer moderators perform their moderation in a similar manner. When they find a rule violation, they can perform moderation and inform the content creators through public comments, submission flairs, or private messages. Public comment is the dominant form of recording moderation on Reddit (Jhaver et al. 2009b); therefore, it is the primary data source for our study. Based on these records, we recover the moderation automation timeline and investigate its impacts on volunteer moderators' activities.

Second, the adoption timings of bot moderators in different subreddits are varied, which provides an opportunity to leverage a Difference-in-Differences (DiD) research design. The focal bot moderator in our study is called "AutoModerator."[5] AutoModerator was first introduced in 2012 and has been the most influential bot moderator on Reddit. More than 4,000 subreddits have adopted AutoModerator as of

[5] https://www.reddit.com/wiki/automoderator/ Accessed August 10, 2023.

December 2019. The bot generates thousands of moderation records every day. To utilize AutoModerator, volunteer moderators need to follow simple syntaxes to add bot-related codes to their subreddit meta page. Common rules automated by AutoModerator are listed in Table C1 in the appendix. For example, AutoModerator can restrict users below a certain reputation level threshold on the platform. They can also prevent users from posting content from blocklisted sources. Subreddits have the flexibility to adapt and integrate AutoModerator functions to meet the subreddit guidelines and moderation needs.



AutoModerator commented on Desperate expectant dad needs help Healthcare · r/LegalAdviceUK · Posted by u/Sharkary

Comment removed by moderator 9 months ago

AutoModerator MOD Score hidden · just now

FYI, this comment has been removed as the thread you are commenting in is an old thread. This means the information contained in the thread may be out of date, unmonitored by the community, and not likely to recieve any further attention. If you are asking legal help, please consider making a new thread to receieve advice.

*I am a bot, and this action was performed automatically. Please contact the moderators of this subreddit if you have any questions or concerns.*

u/AutoModerator

Karma 8,095,966

Cake day January 4, 2012

+5.5k Received the Platinum Award and more in the past 30 days

**Figure 1. AutoModerator's Profile Page and Moderation Records**

### *3.2 Data Collection and Measures*

Our data collection includes the following steps. First, we collected all moderation records by AutoModerator from 2013 to 2014 using PushShift API (Baumgartner et al. 2020).[6] We situated our study in this observation period because AutoModerator's function was relatively stable after being released for a year. Further, more subreddits started deploying bots for moderation after 2013. Thus, the selection of subreddits in that period would contain ample variations for empirical analyses. Second, we marked the time when the first AutoModerator's moderation was performed in a subreddit as the moment when that

[6] https://pushshift.io/ Accessed August 10, 2023.

specific subreddit adopted AutoModerator. With the complete moderation records collected in the first step, we observed that 156 subreddits adopted AutoModerator from 2013 to 2014. We report the complete list of subreddits in Appendix B. Next, we identified volunteer moderators for each studied subreddit. Reddit grants moderators a "mod" flair to signify their role as community managers, and this flair is shown along with moderators' comments. Taking advantage of this platform design feature, we obtained the list of users with the "mod" flair and further collected their comments during the observation window.

Lastly, using AutoModerator and volunteer moderators' comments, we performed natural language processing (NLP) to extract the automated rules and volunteers' moderation types.

To facilitate the analyses, we performed two data pre-processing steps. On the AutoModerator side, we extracted the automated moderation tasks and corresponding implementation time to recover the timeline of task automation. We utilized this timeline to construct the independent variable of interest $AutomatedTasks_{it}$ in our empirical analyses. Given that AutoModerator follows standardized formats for any moderation record, we employed a rule-based approach to extract automated tasks and their implementation time.

On the volunteer moderator side, our pre-processing task is to identify their moderation types. We first performed a theory-driven annotation (labeling) for a sample of volunteer moderators' comments. Following community-policing and -nurturing moderation categorization, we first included *policing* as one category in our annotation. Next, we measured community-nurturing moderation with two typical nurturing activities highlighted in extant literature: *explanation* and *suggestions* (Jhaver et al. 2019c, West 2018, Jiang 2020). Following real-world practices, a moderation-related comment can have both community-policing and nurturing components (Jhaver et al. 2019c, West 2018). Thus, our annotation allows policing- and nurturing-oriented moderation to coexist in a volunteer moderator's comment. Additionally, we included *casual talk* as the fourth activity category in our annotation, which includes remaining volunteer moderators' activities besides community-policing and -nurturing ones. Table 1 illustrates example comments for each category. Compared to the pre-processing of bot comments, this task is relatively challenging due to the diversity and complexity of human language. Our methods need to go beyond the vocabulary to grasp the semantic meaning and purpose of a comment.

We utilized BERT, a deep learning approach, to classify volunteer moderators' moderation types (Devlin et al. 2018). BERT was proposed in 2018; it has quickly become the state-of-the-art NLP technique and has achieved exceptional performance in tasks such as classification and commonsense reasoning. Compared to traditional NLP methods, BERT is a bidirectional language model trained on a large-scale corpus. It has a better sense of the language context and the relationship between all words regardless of their position. Therefore, BERT can capture the meaning of comments regardless of the vocabulary choice and sentence sequence. We used BERT-based classifiers to identify volunteers' moderation types.

**Table 1. Examples of Different Types of Moderator Comments**

| Category | Sub-category | Example |
|---|---|---|
| Communitypolicing moderation | Policing | "Removed/approved." |
| Community-nurturing moderation | Explanation | "… because you did not include the resolution in the title and because you did not include the location in the title." |
|  | Suggestion | "There are instructions in the FAQ as well as our other submission guidelines. Your submission would be more appropriate in r/villageporn. Feel free to resubmit with the resolution in the title. Thanks!" |
| Others | Casual talk | "Thank you, and it is even more beautiful in reality, especially the very special light of Iceland." |

Operationally, we used the pre-trained BERT model and then fine-tuned the parameters with the labeled dataset. Pre-trained BERT can capture the context-free meaning of the comments, whereas the labeled data provides more details about our context. We obtained the pre-trained model from Google Research, which is trained on large corpora collected from Wikipedia and book chapters.[7] Then, we randomly sampled 1,017 comments from our whole dataset and manually labeled these comments for each category. Two graduate students in the computer science master's program at a large public research university labeled these comments after a training session with the researchers on the annotation task. They achieved 85% consistency in their labeling. For the remaining 15% of comments, they further discussed their annotation discrepancies to reach an agreement. We fed the pre-trained model with the labeled data to fine-tune the parameters. We created a classifier for each comment category, thus forming a total of four binary classifiers. Lastly, we used the fine-tuned model to predict all collected volunteer comments.

**Table 2. Variables and Descriptive Statistics**

| Variable | Description | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|---|
| BotAfter$_{it}$ | Dummy variable. The value equals 1 if subreddit *i* had adopted AutoModerator in month *t*; 0, otherwise. | 0.616 | 0.487 | 0 | 1 |
| AutomatedTasks$_{it}$ | The number of moderation tasks automated by AutoModerator on subreddit *i* in month *t*. | 2.231 | 3.342 | 0 | 29 |
| Num_Policing$_{it}$ | The number of policing-type comments created by volunteer moderators on subreddit *i* in month *t*. | 63.882 | 247.128 | 0 | 4,452 |
| Policing_Scope$_{it}$ | The number of unique rules enforced by volunteer moderators on subreddit *i* in month *t*. | 2.426 | 4.322 | 0 | 40 |
| Num_Explanation$_{it}$ | The number of explanation-type comments created by volunteer moderators on subreddit *i* in month *t*. | 80.166 | 282.480 | 0 | 4,460 |
| Num_Suggestion$_{it}$ | The number of suggestion-type comments created by volunteer moderators on subreddit *i* in month *t*. | 84.352 | 256.130 | 0 | 4,634 |
| Num_Others$_{it}$ | The number of casual comments created by volunteer moderators on subreddit *i* in month *t*. | 215.862 | 446.524 | 0 | 3,711 |

|  |  |  |  |  |  |
|---|---|---|---|---|---|
| Num_Mods$_{it}$ | The number of active volunteer moderators on subreddit $i$ in month $t$. | 3.827 | 4.440 | 0 | 52 |
| Num_User_Cmts$_{it}$ | The number of comments created by users on subreddit $i$ in month $t$. | 89,351.66 | 358,182.9 | 0 | 5,192,588 |

Table C3 In the appendix shows the classification results of the four classifiers.

We achieved above 90% on the F1 scores in three out of four classification tasks.

Notably, the policing classifier reached 97.34% accuracy, 96.99% precision, 95.68% recall, and 96.33% F1 score. Compared to typical

NLP classification tasks, our BERT-based classifiers achieved excellent performance.

With all the collected data, we constructed a series of variables for the corresponding data analyses.

We aggregated our data at the subreddit-monthly level.

We used the number of comments created by volunteer moderators in each category to measure their various types of engagement. In addition to the data mentioned above, we collected the number of community users' comments from each subreddit and used it as the proxy for user engagement in that subreddit. Table 2 depicts detailed descriptions and summary statistics of variables used in this study. The correlation table is presented in Table C4 in Appendix C.

## 4. Empirical Analyses and Results

### *4.1 Identification Strategy and Main Model*

Considering the automation of moderation tasks is a shock to the subreddit and different subreddits adopted bots for moderation at different times, we apply the difference-in-differences (DiD) model as our identification strategy. Specifically, the treatment group comprises communities that adopted bot moderators during a given month in the observational window, whereas the control group includes communities that relied entirely on volunteer moderators in a given month. We note that the same approaches were applied in prior literature studying the impacts of ride-sharing entry (Greenwood and Wattal 2017, Babar and Burtch 2020) and technology adoption (Tan and Netessine 2020). By comparing volunteer moderators' activities in the treatment group with those in the control group, we can estimate how the introduction of bots into content moderation affects volunteers' moderation efforts.

Formally, our empirical model is presented in Equation (1). Note that $VolunteerModeration_{!"}$ denotes the dependent variable. It refers to several variables that measure different kinds of volunteer moderator activities, including their community-policing efforts (*Num_Policing*$_{it}$), community-nurturing efforts (*Num_Explanation*$_{it}$, *Num_Suggestion*$_{it}$), and other casual activities (*Num_Others*$_{it}$). $BotAfter_{!"}$ is the key independent variable. It is a time-variant, binary variable, and the value of 1 means the subreddit *i* had adopted AutoModerator in month *t*. Additionally, each volunteer moderator's activity may be subject to changes in the number of active volunteer moderators and the number of submissions their subreddit receives. Thus, we add two control variables—the number of active volunteer moderators (*Num_Mods*$_{it}$) and the number of user comments (*Num_User_Cmts*$_{it}$) in respective subreddits—to the analysis. Another source of empirical concern is the unobserved intrinsic difference among communities and temporary shocks on the platforms. We therefore add the subreddit fixed effects $\theta_{!}$ and month fixed effects $\delta_{"}$ to control the unvarying subreddit effects and common time trends. $\varepsilon_{!"}$ is the error term.

$$VolunteerModeration_{!"} = \alpha + \beta \times BotAfter_{!"} + \gamma \times Controls_{!"} + \delta_{"} + \theta_{!} + \varepsilon_{!"}$$

[redacted]

4.2 Results

Table 3 reports the main estimation results. Several interesting findings are found. First, from the estimates of $BotAfter_{!"}$ in the first column, we can see that volunteers' community-policing efforts significantly increased by 20.9% after their subreddit automated moderation tasks with AutoModerator. This result indicates that although bots automate some policing tasks, bot automation augments rather than substitutes volunteer efforts in achieving more policing moderation. Overall, we see volunteer moderators exhibit more policing efforts, which we break down into objective and subjective rule-related policing in a later analysis in Section 5.1.1.

Second, with regard to volunteers' community-nurturing efforts, from the second column, we observe that the number of explanations volunteer moderators made in a month increased by 15.2% after adopting bots to assist community moderation. Although we do not observe significant changes in the number of suggestions created by volunteer moderators following the bot adoption under the conventional significance level, the estimated sign aligns with the changes in volunteers' explanation activities. Note that using a seemingly unrelated regressions (SUR) approach and several other estimation approaches (in the Robustness Check sections with tables reported in Appendix G), we do observe significant effects on both explanations and suggestions. Overall, we observe evidence that supports H2.

Moreover, estimates associated with control variables align with our expectations. For example, volunteer moderators' activities increase when there are more user submissions and active volunteers in the moderation team. We also tested the incremental impact of moderation automation and performed analyses using the Poisson pseudo maximum likelihood estimator, as presented in Appendices D and E (Kummer et al. 2020, Burtch et al. 2018). Overall, the results remain consistent.

**Table 3. The Impact of AutoModerator on Volunteers' Moderation**

| Variables | Community_Policing | Community_Nurturing | | Others |
|---|---|---|---|---|
| | Num_Policing | Num_Explanation | Num_Suggestion | Num_Others |
| **BotAfter** | 0.209** (0.090) | 0.152*<br>(0.084) | 0.077<br>(0.071) | -0.044<br>(0.062) |
| Num_User_Cmts | 0.108*** (0.037) | 0.116*** (0.037) | 0.108*** (0.036) | 0.177***<br>(0.038) |
| Num_Mods | 1.447*** (0.090) | 1.596*** (0.083) | 1.729*** (0.073) | 1.916***<br>(0.075) |
| Constant | -1.051*** (0.309) | -0.970***<br>(0.319) | -0.783** (0.306) | -0.628*<br>(0.329) |
| Subreddit fixed effects | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes |

|  |  |  |  |  |
|---|---|---|---|---|
| No. Observations | 3,744 | 3,744 | 3,744 | 3,744 |
| R-squared | 0.805 | 0.835 | 0.858 | 0.904 |

Note: (1) Cluster-robust standard errors in parentheses, clustered at the subreddit level; *** p<0.01, ** p<0.05, * p<0.1; (2) For all dependent variables and control variables, we use natural log transformation (i.e., ln(x+1)) to accommodate skewed distribution and zeros.

Additionally, we performed heterogeneity analysis to examine how demand for moderation interacts with bot adoption (Demerouti et al. 2001; Bakker and Demerouti 2017; Tarafdar and Saunders 2022). Specifically, we consider the moderating role of community size (Butler et al. 2014, Ren and Kraut 2014). Compared to subreddits with fewer members, large communities usually have greater moderation demand to accommodate the scale of user-generated content and user requests. Volunteer moderators face a greater need for their time to moderate community content; thus, they are likelier to experience a shortage of moderation efforts in large communities. When algorithm-assisted moderation tools become available, adopting these tools is more likely to augment volunteers to accomplish more moderation, including policing- and nurturing-oriented ones.

To test the moderating role of community size, we proxy the community size using the number of commenters in a subreddit as of the month when AutoModerator was adopted. Next, we split all studied subreddits into two groups based on the median value of the community size and construct a binary variable *PopSubreddit*$_{it}$ to denote subreddits with relatively more members. We add an interaction term between *PopSubreddit*$_{it}$ *and BotAfter*$_{it}$ into Equation (1). Table 4 presents the estimation results. Overall, our results suggest that the impact of bot adoption on volunteer moderators is dependent on the community size. As expected, we note that automating moderation tasks does not change moderators' policing and nurturing efforts in small communities but positively affects voluntary moderation in larger

communities. Compared to small communities, volunteer moderators from larger communities achieve

53.5% more policing activities after adopting bots. Meanwhile, these volunteers contribute 53.6% and

44.1% more explanation- and suggestion-related comments to the community with the assistance of bots.

We also test another type of demand for moderation–volunteers' scope of work–and present the results in Appendix F. Overall, we find volunteers' scope of work positively moderates the impacts of bot adoption on volunteers' policing and nurturing activities.

**Table 4. The Moderating Effect of Community Size**

| Variables | Community_Policing | Community_Nurturing | | Others |
|---|---|---|---|---|
| | Num_Policing | Num_Explanation | Num_Suggestion | Num_Others |
| BotAfter | -0.061<br>(0.093) | -0.118<br>(0.095) | -0.146<br>(0.090) | -0.148*<br>(0.088) |
| **BotAfter × PopSubreddit** | **0.535*** (0.167)** | **0.536*** (0.152)** | **0.441*** (0.130)** | 0.206<br>(0.129) |
| Num_User_Cmts | 0.112*** (0.034) | 0.121*** (0.035) | 0.111*** (0.034) | 0.179***<br>(0.037) |
| Num_Mods | 1.432*** (0.091) | 1.582*** (0.085) | 1.718*** (0.074) | 1.910***<br>(0.075) |
| Constant | -1.063*** (0.290) | -0.982***<br>(0.300) | -0.793*** (0.284) | -0.633*<br>(0.321) |
| Subreddit fixed effects | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | Yes | Yes | Yes |
| No. Observations | 3,744 | 3,744 | 3,744 | 3,744 |
| R-squared | 0.808 | 0.838 | 0.860 | 0.904 |

Note: (1) Cluster-robust standard errors in parentheses, clustered at the subreddit level; *** p<0.01, ** p<0.05, * p<0.1; (2) For all dependent variables and control variables, we use natural log transformation (i.e., ln(x+1)) to accommodate skewed distribution and zeros.

## 5. Additional Analyses

### *5.1 Mechanism Exploration*

### *5.1.1 Effort Allocation Between Subjective and Objective Rule Enforcement*

To explore the underlying mechanisms of the changes in volunteer moderators' policing-oriented effort after adopting bots, we first focus on the subjectivity of volunteers' enforced rules and investigate how volunteer moderators allocate their attention to enforcing objective and subjective rules. The procedure is as follows. First, two annotators manually labeled the subjectivity of community rules in each subreddit independently. 90% of the labels from these two annotators were consistent. They discussed inconsistent annotations to reach a consensus. Table C2 in Appendix C presents examples of subjective and objective rules. Second, following the NLP procedure, we pre-processed the labeled rules and volunteers' moderation comments by removing the stop words and obtaining the stemmed words. Then, we calculated the cosine similarity between each

labeled community rule and each volunteer's moderation comments. A higher similarity score suggests that a community rule is highly associated with the task enforced in that comment. Based on similarity scores, we identified the associated rule in each moderation comment and then labeled the enforced rule's subjectivity.

With the labeled subjectivity of moderation comments, we next aggregated volunteers' policing as objective or subjective rules-related (i.e., $\mathit{Num\_Policing\_Obj}_{it}$ and $\mathit{Num\ \_Policing\_Sub}_{it}$) at the monthly level. We additionally calculated the number of unique rules volunteers enforced each month (i.e., $\mathit{Policing\_Scope}_{it}$) and used that to capture volunteer moderation scope. We used all newly constructed measures as the dependent variables in Equation (1). Given the innate substitutive relationship between objective and subjective policing, we used a seemingly unrelated regression model (SUR) to account for the correlations between the error terms of the two dependent variables. We ran two sets of SUR models for bot adoption and the number of automated tasks in the respective bot in each subreddit. As attested in Table 5, there is a clear increase in subjective policing-oriented moderation and some evidence for the decrease in objective policing-oriented moderation. While volunteers' moderation on objective tasks did not change significantly after adopting bots under the conventional significance level, as the number of moderation tasks automated by AutoModerator increased, objective rule-oriented policing significantly decreased. Possibly, bots could not *fully* automate policing over some objective rules that are not yet encoded in the algorithm due to their innate complexity; therefore, objective policing tasks may still require volunteer moderators' efforts to enforce compliance on novel rule infractions. Moreover, as the AutoModerator is adopted to automate largely objective moderation tasks, volunteers' moderation scope expands, likely to more subjective policing. Overall, we observe the significant increase in volunteers' policing efforts after adopting bots comes from enforcing subjective rules. Volunteer moderators therefore complement bots by accomplishing more nonautomated tasks.

**Table 5. Subjective and Objective Rule Enforcemnt**

| Variables | Moderation Focus (SUR) | | Moderation Focus (SUR) | | Moderation Scope |
|---|---|---|---|---|---|
| | Num _Policing_Obj | Num _Policing_Sub | Num _Policing_Obj | Num _Policing_Sub | Policing_Scope |
| BotAfter | -0.017<br>(0.043) | **0.093****<br>**(0.044)** | - | - | **0.072****<br>**(0.035)** |
| AutomatedTasks | - | - | **-0.017*****<br>**(0.006)** | **0.051*****<br>**(0.006)** | - |
| Num_User_Cmts | 0.059***<br>(0.014) | 0.063***<br>(0.015) | 0.058***<br>(0.014) | 0.069***<br>(0.015) | 0.067***<br>(0.023) |
| Num_Mods | 0.592***<br>(0.032) | 0.815***<br>(0.033) | 0.605***<br>(0.032) | 0.778***<br>(0.033) | 0.523***<br>(0.041) |
| Constant | -0.646***<br>(0.233) | -0.382<br>(0.240) | -0.661***<br>(0.233) | -0.343<br>(0.238) | -0.534**<br>(0.205) |
| Subreddit fixed effects | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes |
| No. Observations | 3,744 | 3,744 | 3,744 | 3,744 | 3,744 |
| R-squared | 0.685 | 0.759 | 0.685 | 0.763 | 0.778 |

Note: (1) Seemingly unrelated models (SUR) for the moderation focus analysis; standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; (2) For all dependent variables and control variables, we use natural log transformation (i.e., ln(x+1)) to accommodate skewed distribution and zeros.

To gain a deeper insight into the changes in volunteers' policing, we further supplement the findings in Table 5 by performing text analysis on the actual rules enforced by the volunteer moderators, reported in Table 6. Evidence from Tables 5 and 6 collectively lends support for H1a and H1b.

With the identified rule in each moderation comment, we aggregated volunteers' policing on each rule before and after utilizing bots. We find three groups of rules with different patterns. Specifically, the first group in Tabel 6 comprises enforced rules and associated policing tasks with decreased volunteer efforts, such as removing content that contains prohibited keywords and content with incorrect title format. These rules are mostly simple and objective; thus, bots are likely to detect rule violations with a high accuracy rate. Overall, the decreased volunteer efforts on these rules show evidence of the machine substitution effect. Bots substitute volunteers in policing such tasks and reduce their associated effort.

**Table 6. Rule-level Exploration**

| Group | Example Rules in the Group | Volunteers' policing activities before using bots. Mean (Std.) | Volunteers' policing activities after using bots. Mean (Std.) | *t*-stat | *p*-value |
|---|---|---|---|---|---|
| Group 1- Reduced volunteer moderation (99 rules) | • Content that contains prohibited links or keywords.<br>• Content with incorrect title format. | 112.272 (49.454) | 21.818 (9.009) | 1.800 | 0.074 |
| Group 2- Increased volunteer moderation (50 rules) | • Content with personal information in texts or images.<br>• Content with non-concise title and low quality. | 56.720 (22.239) | 201.120 (75.344) | -1.838 | 0.069 |
| Group 3- Emerging volunteer moderation (85 rules) | • Content that may cause unexpected consequences and damage community quality and integrity, such as satire content, vote manipulation, and posts seeking medical advice. | 0.000 (0.000) | 42.127 (15.005) | -2.808 | 0.006 |

The second group in Table 6 consists of rules that involve increased volunteer moderators' policing efforts after adopting bots. Example policing tasks in this group include removing personal information in texts/images and low-quality content (e.g., unconcise titles and content). These tasks are associated with a mix of subjective and objective rules that are difficult to code with simple and consistent patterns. The rule violations can occur in diverse content types (e.g., disclosing personal information through texts, images, or linked websites), and it is difficult to detect the violation automatically. Enforcing these rules requires more subjective judgment and a better understanding of the contextual details. The increased volunteers' policing efforts on these rules imply the machines' augmentation effects. Automation augments volunteer moderators by enabling them to take on more nonautomated tasks.

The third group in Table 6 shows emerging tasks volunteer moderators did not enforce until utilizing bots in their subreddit. Rules and associated policing tasks in this group mainly focus on community content quality and integrity, such as removing content that seeks medical advice, satire content, and vote manipulations. The violation of these rules may be in various forms. Enforcing these rules usually requires a good understanding of the content and more cognitive effort. As such, it is challenging to fully automate the moderation of these rules. Interestingly, we observe this group also includes some bot-automated tasks, such as removing spam and memes. Researchers present qualitative evidence showing that automatic moderation tools such as AutoModerator can stimulate volunteer moderators' efforts to manage rules that they did not tackle in the past and address potential errors caused by automated moderation (Jhaver et al. 2019a). The increased volunteer efforts in the emerging rules are also consistent with extant machine augmentation literature (Acemoglu and Restrepo 2018; Dixon et al. 2021), indicating that automation can lead to increased human labor because of the growing need for new tasks that complement automation.

### *5.1.2 Complementary Role of Community-nurturing to Community-policing*

As discussed in Section 2.4, two key factors might underlie the increased community-nurturing efforts by volunteers subsequent to bot implementation: (1) the attention reallocation effect from automated policing on objective rules and (2) the increased need for complementary nurturing-oriented moderation for subjective rule enforcement. To examine which mechanism drives the results in Table 3, we construct two sets of measures based on the interplay between community-nurturing and -policing activities. The first set of measures (i.e., *Num_Explanation_Alone*, *Num_Suggestion_Alone*) indicates the number of standalone nurturing-oriented comments that do not occur together with policing activities; these measures capture organic and proactive volunteer efforts to build and support their communities. In contrast, the second set of measures (i.e., *Num_Explanation_After_Policing*, *Num_Suggestion_After_Policing*) indicate the number of nurturing-oriented comments created to accompany policing activities; these measures capture the complementary role of community-nurturing to policing. If the effort reallocation from automating objective rules by bots drives the increased community-nurturing efforts, we expect to see increased proactive, stand-alone nurturing-oriented moderation. If the increased need for the complementary nurturing effort for the increased (subjective) policing induces the results, we expect more increased reactive nurturing activities following policing actions.

**Table 7. The Interplay Between Policing and Nurturing-oriented Moderation**

| Variables | Num_Explanation_ After_Policing | Num_Suggestion_ After_Policing | Num_Explanation_ Alone | Num_Suggestion_ Alone |
|---|---|---|---|---|
| BotAfter | 0.159***<br>(0.051) | 0.162***<br>(0.053) | 0.147*<br>(0.083) | 0.068<br>(0.071) |
| Num_User_Cmts | 0.023<br>(0.022) | 0.009<br>(0.022) | 0.113***<br>(0.038) | 0.106***<br>(0.036) |
| Num_Mods | 0.576***<br>(0.059) | 0.595***<br>(0.059) | 1.571***<br>(0.084) | 1.712***<br>(0.074) |
| Constant | -0.376**<br>(0.190) | -0.263<br>(0.191) | -0.944***<br>(0.319) | -0.770**<br>(0.304) |
| Subreddit fixed effects | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | Yes | Yes | Yes |
| No. Observations | 3,744 | 3,744 | 3,744 | 3,744 |
| R-squared | 0.698 | 0.700 | 0.833 | 0.856 |

Note: (1) Cluster-robust standard errors in parentheses, clustered at the subreddit level; *** p<0.01, ** p<0.05, * p<0.1; (2) For all dependent variables and control variables, we use natural log transformation (i.e., ln(x+1)) to accommodate skewed distribution and zeros.

We used the newly constructed measures as the dependent variables in Equation (1) and performed the analyses again. We observed several interesting results in Table 7. We did not see significant changes in volunteer moderators' proactive nurturing efforts in offering suggestions to community members (last column). However, while considering the interdependence between policing and nurturing, we find significant increases in volunteers'

nurturing activities accompanying policing decisions. The results in the first two columns indicate the number of explanations and suggestions following policing activities increased by 15.9% and 16.2% after bot adoption, respectively. Overall, the results in Table 8 suggest that the increased community-nurturing efforts are primarily driven by the complementary role of nurturing to policing-oriented moderation.

**Table 8. Nurturing-oriented Moderation Following Policing Actions**

| Variables | Num_Explanations_ After_Sub_Policing | Num_Explanations_ After_Obj_Policing | Num_Suggestion_ After_Sub_Policing | Num_Suggestion_ After_Obj_Policing |
|---|---|---|---|---|
| BotAfter | 0.102**<br>(0.042) | 0.001<br>(0.020) | 0.109** (0.042) | -0.001<br>(0.022) |
| Num_User_Cmts | 0.017<br>(0.019) | 0.012<br>(0.008) | 0.010<br>(0.017) | 0.015*<br>(0.009) |
| Num_Mods | 0.337***<br>(0.054) | 0.095***<br>(0.019) | 0.320***<br>(0.049) | 0.104***<br>(0.023) |
| Constant | -0.228<br>(0.162) | -0.114<br>(0.071) | -0.160<br>(0.144) | -0.154*<br>(0.080) |
| Subreddit fixed effects | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | Yes | Yes | Yes |
| No. Observations | 3,744 | 3,744 | 3,744 | 3,744 |
| R-squared | 0.665 | 0.445 | 0.689 | 0.383 |

Note: (1) Cluster-robust standard errors in parentheses, clustered at the subreddit level; *** p<0.01, ** p<0.05, * p<0.1; (2) For all dependent variables and control variables, we use natural log transformation (i.e., ln(x+1)) to accommodate skewed distribution and zeros.

Zooming in on the nurturing efforts surrounding policing decisions, we further differentiated these nurturing efforts based on the subjectivity of the enforced rules. Specifically, we generated more granular measures to calculate the number of nurturing-related comments following the policing actions for subjective (i.e., *Num_Explanation_After_Sub_Policing*, *Num_Suggestion_After_Subj_Policing*) and objective rules (i.e., *Num_Explanation_After_Obj_Policing*, *Num_Suggestion_After_Obj_Policing*) enforcement. Considering that policing over subjective rules involves a more complex decision process and human discretion compared with policing over objective rules, we expect that the increased nurturing activities from volunteer moderators primarily come from the enforcement of subjective rules. We again estimated Equation (1) with these newly created measures as dependent variables. The results are displayed in Table 8. As expected, the results show that the increased nurturing efforts are associated with policing activities related to subjective rather than objective rule enforcement.

In addition, we perform text analysis on volunteers' nurturing-related comments to gain a deeper understanding of how volunteers contribute to community-building. We categorize volunteers' nurturing activities into different groups and list the main focus of each group in Table 9.

Regarding explanation, we find that a vast majority of the explanations focus on (1) explaining rules and policing decisions, (2) answering users' individual requests, in particular, requests for more elaboration on policing decisions, and (3) clarifying the community governance system and moderation procedure. Overall, the explanations supplement policing decisions by enhancing the transparency of community rules and content moderation.

**Table 9. Example Subjective and Objective Rules**

| Nurturing Type | Summary | Example Rules |
|---|---|---|
| Explanations | Explain rules and policing decisions. | Hate speech, bigotry, and personal attacks are not allowed. |
| | Answer user requests and elaborate the rules. | Even if you give credit to the original post, it is still a repost; against the rules. |
| | Address confusion about governance and moderation procedure. | We did not delete anything. The user deleted it. |
| Suggestions | Recommend alternative communities. | A good home for this question is r/AskScienceDiscussion. Try posting there! |
| | Answer user requests. | You need to contact the administrator about your account; message r/reddit.com ASAP. |
| | Offer detailed guidance to users after policing. | Just let me know when you edited the textbox, and be aware of using the 'edit' and not 'delete' button. |
| | Send reminder. | Please remember to keep responses on-topic and free of jokes or speculation. |

Regarding volunteers' suggestions, we find it primarily focuses on offering personalized guidance to users after their content gets removed. For example, moderators recommend alternative communities to users if their originally posted content does not fit the community theme. Moreover, moderators offer suggestions to answer users' specific requests, such as addressing account suspension and navigating the resources on the platform. Moderators also offer suggestions proactively by sending users reminders. These reminders aim to stress community rules and facilitate users' rule compliance. Together with our results in Table 7, we see that nurturing-oriented moderation complements policing and assists moderators in building a more transparent and supportive community environment.

### *5.2 Moderator Retention*

Further, we investigate a downstream outcome of volunteer moderators' effort change. Specifically, centered around the sustainability concern of online platforms primarily relying on volunteers for content moderation (Zheng et al. 2019, Dosono and Semaan 2019, Matias 2019b), we further examine how bot adoption affects volunteer moderators' retention in a community. A broad range of management and volunteerism literature has suggested several work-related factors that influence voluntary labor retention (Griffeth et al. 2000, Cuskelly et al. 2006, Hidalgo and Moreno 2009). Based on the changes bots bring to volunteers' moderation, we expect that bots can positively affect volunteer moderator retention in the community for several reasons. First, when bots replace volunteers in processing simple objective policing tasks, it reduces volunteers' overall workload and enables them to perform a broader range of moderating tasks. Prior literature suggests that non-repetitive tasks (Hidalgo and Moreno 2009) and nonexcessive workload (Griffeth et al. 2000) contribute to employees' and volunteers' intention to remain in the organization. Second, as discussed in Section 2.4, the relief from routine tasks may enable volunteer moderators to engage in more community-nurturing activities, such as responding to community members' [redacted] individual requests and achieving more fulfilling work. Tasks that are gratifying and benefit others can positively influence volunteers' retention (Hidalgo and Moreno 2009). Given the increased positive interaction with users and engagement in community-building activities, volunteer moderation would have a higher intention to stay in their moderator role.

We empirically examine how bots affect volunteer moderators' retention in a subreddit. We reconstructed our data as the moderator-month panel and labeled moderators who stopped performing any type of moderation in three consecutive months as exiting the moderator team. The average length of moderators' retention in the studied communities is over nine months (the standard deviation is about seven months). We use three different models to conduct the retention analysis. The first column in Table 10 shows the results using OLS estimation. Here, we can see that volunteers remain in the moderator team for approximately six more months after automating tasks through bots. As shown in the second column of Table 10, we also observe consistent results using the Poisson regression. We further verify our results by utilizing survival analysis. The estimation of the survival analysis implies the risk of leaving the moderator team, and we can see that automating moderation reduces the hazard rate of exit. In other words, volunteer moderators are more likely to stay in the moderation team after the community adopts bot moderators. Overall, our results suggest that automating moderation tasks can positively influence volunteer moderators' retention in the subreddit and make volunteer-based content moderation more sustainable.

**Table 10. The Impact of AutoModerator on Volunteer Moderator Retention**

| Variables | OLS<br>Retention Month | Poisson Retention<br>Month | Survival Model (Cox) |
|---|---|---|---|
| BotAfter | 6.459*** (0.804) | 1.066*** (0.173) | -1.629***<br>(0.158) |
| Constant | 3.055*** (0.703) | 1.255*** (0.164) | - |
| Subreddit fixed effects | Yes | Yes | Yes |
| No. Observations | 1,752 | 1,752 | 1,174 |

Note: (1) Robust standard errors in parentheses; for OLS and Poisson, standard errors are clustered at the subreddit level; *** p<0.01, ** p<0.05, * p<0.1.

## 6. Robustness Checks

We conduct several robustness checks that combine quantitative and qualitative approaches. Table 11 summarizes all tests and findings. We present the analysis description and the results in Appendix G.

Specifically, we conduct a relative time model to examine the parallel trend assumption for the main model specification. Since communities gradually adopted the AutoModerator during the observational period, we apply alternative model estimations (two-stage DiD and doubly robust DiD) to validate results. Further, we apply several alternative methods, such as look-ahead matching and instrumental variable approaches, to address the general endogeneity concern in our analyses. Last, to eliminate the concern that the changes in volunteer moderators' behavior after adopting AutoModerator are caused by external factors, such as community requests, we interviewed several experienced moderators on Reddit. We confirmed that moderators' contributions remain voluntary without any mandatory schedule or plans.

Overall, the results from various robustness checks remain consistent with our main analyses.

**Table 11. Summary of Robustness Tests**

| Concerns | Test | Finding | Additional Details |
|---|---|---|---|
| Pre-adoption parallel trend assumption. | Relative time model | Results remain consistent. | Table G1<br>Figure G1 |
| The correlation between error terms in<br>related to four types of Table G2<br>moderator activity. | Seemingly unrelated regression model | Results remain consistent. volunteer | analyses |
| Whether the changes in volunteer moderators' activity are driven by timeunvarying and unobserved community factors? | Look-ahead matching | Results remain consistent. | Tables G3 & G4 |
| General endogeneity concerns (e.g., | | | |
| Whether changes in volunteer moderators' behavior after the adoption of Automoderator are strategically managed by the community? | Interviews with volunteer moderators | Volunteers' moderation were always voluntary. | Available upon request |
| unobserved motivation to adopt AutoModerator, unobserved confounding factors).<br>The measurement errors in the dependent variables derived from the BERT-based classification. | Whether the estimates are robust?<br>Instrument variables<br>Doubly robust DiD<br>Two-stage DiD<br>Counterfactual estimators | Results remain consistent. | Tables G5-G8<br>Figure G2 |

## 7. Discussions

### *7.1 Key Findings*

In this study, we focus on the increasing adoption of algorithm-based moderators (bots) into content moderation in online platforms. This research identifies the focus of modertation activities to be centered primarily on policing and nurturing. In both the activities, there is a certain amount of routineness or context complexity embedded into the tasks that moderators handle. Our findings show how bot adoption shifts and expands volunteer moderators' efforts from routine policing to a broader nurturing-oriented moderation activities. Combining econometric analyses of archival moderation records from 156 communities on Reddit and qualitatitive interviews with the community moderators, we find that incorporating bots augments volunteer moderators and contributes to satisfying the increased needs for community-nurturing activities following the policing actions. Furthermore, our results suggest that bot moderators lead to more sustainable volunteer-based governance as it increases volunteer moderators' retention in a community.

### *7.2 Theoretical Implications*

Our work contributes to three streams of research. First, we contribute to platform governance literature (Sambamurthy and Zmud 1999, Tiwana et al. 2010). Whereas prior literature has discussed the role of technology in platform governance (Perscheid et al. 2020) and community management (Kraut and Resnick 2012, Ren and Kraut 2014), our work empirically investigates an emerging and yet understudied type of platform governance model on digital platforms: human-machine collaborative content moderation. Based on the functionality behind the moderation (Ruckenstein and Turunen 2020, Jiang 2020; West 2018), our study

differentiates moderation and moderators' roles as policing- and nurturingoriented. Our results suggest that such differentiation is helpful for gaining more insights into the dynamics of moderation activities. In contrast to the prevailing literature's view of policing and nurturing as independent activities, however, our study points to the need for viewing these as interrelated activities.  As such, bots' automation of policing over simple and objective tasks leads to greater needs for volunteers' corresponding nurturing efforts. Viewing them as independent activities may neglect nuanced changes in bots' and volunteers' moderation focus and contributes to an incomplete understanding of augmentation benefits.

Second, our work also sheds light on machine substitution and augmentation research (Autor and Dorn 2013, Acemoglu and Restrepo 2018, Dixon et al. 2021, Rai et al. 2019, Fügener et al. 2022, Tarafdar et al. 2023). This line of research suggests that task characteristics are one of the key factors for such relationships. Our study extends the human-machine collaboration literature from contexts centering on compensated labor to online content moderation that generally rely on voluntary labor. In our context, bots augment rather than substitute volunteer moderators in both policing and nuturing activities. However, by leveraging the interplay between moderators' functional roles (Seering et al. 2018, Tarafdar et al. 2023) and the subjectivity of enforced rules, we show that both substitutional and augmentative relationships can manifest due to augmentation. Our proposed dimensions of moderator role (policing vs. nurturing) and task subjectivity (subject vs. objective) is a valuable analytic frame for future content moderation studies.

Third, our work also contributes to the growing content moderation literature. There has been increasing attention surrounding human-bot collaborative moderation and the sustainability of volunteerbased governance in recent years (Dosono and Semaan 2019, Matias 2019b, Zheng et al. 2019). Prior work, however, primarily focuses on the qualitative perspectives of human and bot roles. We extend content moderation research by providing quantitative empirical evidence confirming that bots and human moderators tackle different content moderation tasks. Most importantly, we find bots can serve as a technological solution to motivate more volunteer-driven and desirable community-nurturing efforts, leading to more sustainable volunteerism in platform governance.

### *7.3 Practical Implications*

Our work shows several aspects of practical implications. First, for online platform managers, our research suggests that algorithm-based content moderation tools are critical and effective in coping with the scale and sustainability challenges, particularly for those heavily relying on volunteer moderation. On the content management side, equipping volunteer moderators with more automatic moderation tools will stimulate volunteers to perform more desirable community-nurturing activities in addition to greater rule enforcement. On the volunteer side, the assistance of automated moderation tools enables them to cope with a larger scope of work and extend their retention in the moderator role.

Moreover, our results suggest that online community managers should better design their community rules and moderation tasks to utilize the limited attention of volunteer moderators. For example, by creating and separating moderation tasks based on their subjectivity, community managers can more effectively identify tasks suitable for automation and better direct volunteer moderators' attention to tasks that require human discretion.

Further, given the increasing need for volunteer moderators' community-nurturing efforts surrounded by policing decisions, in addition to policing-oriented bots, platform designers should pay attention to users' follow-up requests and offer more automatic tools to assist volunteer moderators' community-nurturing activities. For example, platform designers can provide bots that can point users to potentially relevant community rules or alternative community resources following the enforcement of subjective rules. Such nurturing-oriented bots would help further reduce the demand for volunteer moderators' nurturing efforts and create a more supportive community environment.

### *7.4 Limitations and Future Research Opportunities*

We acknowledge several limitations of our research. First, moderation records on Reddit are stored in three ways: public moderation comments, submission flair, and private conversations with content creators (Jhaver et al. 2019c). Given the data availability, our data only comes from public moderation records. We therefore may miss some moderation recorded in submission flair and private messages. However, we do not consider this to be a severe issue in our study for several reasons. First, more than 80% of moderation records are present in the form of public comments (Jhaver et al. 2019c). Second, public moderation records represent an essential dimension of platform governance—transparency. As calls for transparent content moderation continue to be raised (Jhaver et al. 2019c), public moderation will become the dominant regulation approach on Reddit. Therefore, studying the impacts of machines on transparent moderation is also meaningful for platforms.

Meanwhile, we also open this avenue for future researchers to extend the work if the private moderation records are accessible. It would also be interesting to investigate the impacts of bots on moderators' choice of communication channels for content moderation.

Second, our study only investigates the human-machine collaboration from the angle of changes in volunteers' moderation, which represents the direct interaction with community members. We did not consider the new effort and time that volunteer moderators spent creating and maintaining this collaboration, such as designing bots, fixing errors, and updating bots (Jhaver et al. 2019a). However, these costs occur in the backend and are unfortunately impossible for us to observe in this context. Nevertheless, such backstage effort would be an intriguing topic for future research. It will generate valuable insights into moderation teams' work design and management.

Third, while Reddit has become a giant online platform with a large user base, other platforms may have different platform regulation structures, and they may apply different approaches to integrate algorithms into daily content moderation (Yang et al. 2019). Therefore, it is necessary to go beyond our research context and assess the external validity of the findings using data from other platforms.

Several important directions for future research have recently emerged with the adoption of more powerful techniques such as large language models (LLMs). These machine learning models show improved capabilities in further augmenting responses to context-specific communications. Empowering bot moderators through more advanced techniques like LLMs may further accentuate the interaction phenomenon between the two dimensions of moderator role (policing vs. nurturing) and task subjectivity(subject vs. objective). While LLMs significantly expand machines' capabilities and yet have some limitations in handling certain tasks (OpenAI 2023),  the applications of LLMs for content moderation will be an important future research direction for this research stream.

Further, the emergence of LLMs and other generative AI models enables rapid scale up in the production of AI-generated content (AIGC), which adds more complexity and challenges to platform content governance when LLMs may potentially play both content producer and content moderator roles in online platforms. As this phenomenon evolves, platform governance will need to define and establish mechanisms for fair and ethical conduct. Theoretical framework for such environments would need to distinguish between identified/unidentified machine generated content and its policing. In other words, the dimensionality and complexity of the task space will increase dramatically with the the prevalence of LLM usage in online platforms.

Last but not the least, in addition to machine substitution and augmentation, AI alignment perspective will need to be introduced to understand the interplay between bots and volunteer moderators in policing- and nurturing-related activities (Gabriel 2020). Encoding community-policing and -nurturing goals into the design of bots may help achieve greater alignment between bots and volunteers, leading to reduced volunteer efforts in content moderation. In contrast, failures of AI alignment may contribute to increased demand for volunteer moderators' times and harm platform's ability to provide a nurturing environment. In essence,

AI alignment may offer us a new theoretical frame to understand how to coordinate the interests of different parties in the platforms, such as content producers, consumers, and moderators, and guide better governance design. We hope our study paves the way for future researchers in these emerging contexts, and we anticipate development of deeper insights into effective human machine collaborative governance across a diverse set of platforms.