How Collaborative Filtering Shapes Discussion on Reddit

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Online communities are important platforms for knowledge sharing in a variety of professions, including software engineering and data science. Reddit a popular social media platform, described as a "community of communities", introduced a feature in 2013 that allowed moderators of a community to hide comment scores for a fixed period of time. By hiding comment scores communities are partially disabling the collaborative filtering system that is widespread on Reddit. Leveraging this exogenous variation we examined differences between 68 matched Reddit software development and data science communities that had either made comment scores visible or hidden in order to understand the impact of collaborative filtering on information exchange in online discussions. We found evidence that partially disabling collaborative filtering was related to more contributions of both low and high quality, however fewer contributions that required more cognitive effort. We argue that collaborative filtering helps to incentivize contributions while simultaneously increasing entry costs associated with participating in discussion.

CCS Concepts: • **Human-centered computing → Collaborative content creation**; **Empirical studies in collaborative and social computing**.

Additional Key Words and Phrases: collaborative filtering; online communities; knowledge sharing online; discussion quality

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1 INTRODUCTION

Online communities, such as Stack Overflow, Reddit and Hacker News, are important platforms for knowledge sharing in a variety of professions, including software development and data science. In these communities individuals seek professional advice, keep up with new technologies, and get answers to specific technical questions [2, 41]. Mirroring the adoption and advancement of social media, online communities increasingly utilize more sophisticated communication platforms, with more features and affordances, such as user profiles, distributed moderation, collaborative filtering, and threading [27, 31, 48]. Researchers have theorized that the adoption of social media affordances in online knowledge sharing discussions shapes the discourse and effects knowledge sharing [30, 47].

In order to address the problems of long, dense discussions with contributions of varying quality [11, 54] many platforms make use of distributed moderation and collaborative filtering [6, 27]. Users of the platform act as moderators up voting content that they perceive to be valuable and down voting content they perceive to lack value. Research has shown that there is some consensus among ratings of quality [29]. Platforms then make use of the net up and down votes given by the community to score comments, order comments, and hide comments. These collaborative filtering

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systems are a form of social navigation in which cues are left from prior users to help new users to navigate large amounts of information [6]. In principle, collaborative filtering can help to direct attention toward the most valuable information; reduce information overload; and reduce the negative effects of anti-social contributions. However, these systems are vulnerable to biases and inefficiencies, such as underprovisioning [18] and social influence [32], which can lead individuals to attend to less relevant comments at the expense of other more relevant comments [8]. For example, due to bandwagoning an early information poor reply (e.g. states an opinion) may get more up votes than a late information rich reply (e.g. discusses pros and cons supported by external sources), resulting in misdirected attention.

Online communities often display community ratings publicly and use these scores to provide a visible reputation score for each user on the site [36, 48]. Up and down votes provide feedback to a user from the community about how much the community values that individual's contributions [**?**]. Comment scores also act as an extrinsic incentive that can motivate and encourage contributions by allowing a user to build a reputation in the community [45]. Reputation building is one reason individuals make contributions to online communities in spite of the fact contributions are voluntary, they can require significant cognitive effort and are a public good [25, 50]. Researchers have shown that using a reputation system in an online forum can impact the speed and quantity of information made in response to questions [12].

In 2013 Reddit, one of the most popular social media platforms in the U.S.[1] known for being a "community of communities"[2], introduced a new feature to allow moderators to decide whether to partially disable collaborative filtering within a specific community[3]. Reddit is organized into a set of communities known as subreddits, created and maintained by users, each of which is moderated by an appointed or elected set of users given special administrative powers for that particular subreddit. The communication platform used by Reddit is typical of modern online forums. Users create posts, which can be links, pictures, videos, or text. Users comment on these posts in a threaded discussion forum. Reddit employs a distributed moderation system in which users up and down vote all content including posts and comments. By default Reddit fully enabled collaborative filtering such that a community rating is displayed next to all content, community ratings are used to order content on the page, and community ratings contribute to a reputation system. The hide comment scores setting allows moderators of a subreddit to partially disabled the collaborative filtering system by hiding these community ratings for each comment for up to 1 day after each comment is posted.

Using a quasi-experimental technique of matching subreddits that chose to fully enable versus partially disable collaborative filtering, we investigate the impact of collaborative filtering on information sharing among information focused software development and data science communities on Reddit. We ask one main research question:

Research question: *What impact does partially disabling collaborative filtering have on online knowledge sharing, including the a) quantity and b) quality of contributions; c) patterns of discourse; and d) community network structure?*

We argue that collaborative filtering may affect information sharing through three main mechanisms (Table 1). First, collaborative filtering **alters costs to enter**. Collaborative filtering increases costs to enter because not all contributions get equal attention by the community and in order to attract the more attention from the community a comment must get a high rating by the community. When the costs to enter are higher individuals make fewer contributions [23]. As a result we predict that:

[1]https://www.pewresearch.org/fact-tank/2019/04/10/share-of-u-s-adults-using-social-media-including-facebook-is-mostly-unchanged-since-2018/
[2]Fitzpatrick, A. 2013. Don't blame all of reddit for Boston bombing witch hunt. Mashable. http://mashable.com/2013/04/24/reddit-boston-bombing/
[3]https://www.reddit.com/r/modnews/comments/1dd0xw/moderators_new_subreddit_feature_comment_scores/

Prediction 1: *Partially disabling collaborative filtering will lower cost to enter encouraging more contributions of both high and low quality.*

Second, collaborative filtering **alters relative attention given to early contributions**. Comments stream into a discussion at different times and tend to be rated by the community often in real-time as they arrive. Due to social influence individuals are sensitive to the ratings given by others before them, such that they tend to up vote comments that have already been upvoted [32]. This can lead to bandwagoning in which some comments receive inflated attention due to random chance and/or the early sequence of events, such as arriving early in the discussion. Thus, collaborative filtering may bias a community toward attending to information and solutions provided early in the discussion and away from information provided later in the discussion. As a result the use of collaborative filtering may act to discourage more extensive discussion in which individuals provide additional information and solutions later in the discussion. As a result we predict that:

Prediction 2: *Partially disabling collaborative filtering will reduce attention to early contributions encouraging more extensive discussion and connection among users.*

Third, collaborative filtering **alters incentives for contributions**. When an individual receives a positive score on their comment, which is publicly displayed, it can provide positive feedback from the community that is encouraging and enables individuals to build a reputation by having their comments recognized publicly. These incentives can act to encourage contributions by providing a benefit that outweighs costs of contributing, such as cognitive effort. As a result we predict that:

Prediction 3: *Partially disabling collaborative filtering will lower incentives for contributions reducing the benefit to cost ratio of making high effort contributions.*

This study focuses on Reddit specifically because it is a popular platform in which we can evaluate the impact of collaborative filtering due to the exogenous variance introduced by the hide comment score setting. This study also focuses on software development and data science specifically because: 1) discussion in online communities focused on these topics tends to be information focused [41], 2) patterns in information sharing in online communities focusing on these topics have been studied extensively by others allowing us to draw from prior work (e.g. [2, 31, 41, 48, 53]) and 3) sharing code can easily be quantified in these discussions and is an information rich contribution that requires higher cognitive effort for both of these topics. We find that within software development and data science focused communities on Reddit partially disabling collaborative filtering had a mix of beneficial and detrimental effects on information sharing. We discuss these results and the trade offs associated with collaborative filtering; concluding with design implications for online communities focused on knowledge sharing.

2 RELATED WORK

2.1 Knowledge Sharing in Online Communities

Online communities form on many different types of communication platforms, including newsgroups, bulletin boards, email mailing lists, online forums, question and answer sites (Q&As), and common interest groups on social media sites [52]. Individuals seek and provide information in the online communities in spite of the fact that contribution is voluntary; information requested can be specialized and technical; and once provided information becomes a public good [50]. Online communities are typically open to everyone and can span geographic and social boundaries [21]. Low costs to enter make it easy for anyone to contribute to an online community allowing large communities to form [23, 25]. However, low costs to enter also make online communities vulnerable to anti-social behaviors and poor quality

Collaborative filtering enabled	Visible Fully	Hidden Partially	Prediction	Markers	Findings
Costs to enter	Higher	Lower	Partially disabling collaborative filtering will lower costs to enter encouraging more contributions of both high and low quality	Quantity and quality of contributions	Mostly supported
Attention to early contributions	Higher	Lower	Partially disabling collaborative filtering will reduce attention to early contributions encouraging more extensive discussion and connection among users	Patterns of discourse, community network structure	Little to no evidence
Incentives for contributions	Higher	Lower	Partially disabling collaborative filtering will lower incentives for contributions reducing the benefit to cost ratio of making high effort contributions	Code blocks	Supported

Table 1. Summary of predictions and findings.

contributions [11, 22, 23]. Researchers have argued that online communities face several well known problems including under contribution and regulating user behavior [24].

The affordances of the communication platforms affect how much knowledge is shared, what knowledge is shared and the characteristics of knowledge discussions [30, 47]. Platform designers selectively chose discussion forum features to improve the quality of contributions and to promote specific kinds of discussions [42]. For example, Stack Overflow made targeted design choices to promote "information over conversation", including differentiating answers from comments, organizing comments linearly rather than hierarchically, employing collaborative filtering to rank answers by votes, and adding a user reputation system [31].

Researchers apply social network methods and theories to understand community structure and knowledge sharing in online communities [14, 55]. For example, Faraj and Johnson found evidence of direct and generalized reciprocity when they examined online community communication networks [14]. Researchers also evaluate the impact on affordances of communication platforms on knowledge sharing using community network structure [3, 5].

2.2 Distributed Moderation & Collaborative Filtering

Early pioneers in online discussion platforms, like Slashdot, introduced distributed moderation systems that allowed users on the site to up vote and down vote comments on the discussion platform giving each comment a community rating to efficiently address moderation needs as the scale of online discussions grew massive [27]. Researchers have shown that there tends to be moderate agreement in the ratings given to comments by the community [27, 29]. Community ratings are used to direct users attention to higher rated content by rank ordering comments by community scores, by hiding comments that score below a certain threshold, and/or by making the score public, each of which is a form of collaborative filtering. Individuals are sensitive to social cues of popularity in making their viewing choices

[16] and direct their attention to posts given higher community ratings [6]. As a result collaborative filtering can act as an information filter, reducing information overload and increasing learning from reading online discussions [6, 26, 29].

Distributed moderation and collaborative filtering have now been widely adopted by online discussion platforms. Researchers have argued that collaborative filtering has other consequences beyond directing readers' attention. Typically online forums use community ratings to order content on a page. Researchers have shown using theoretical simulations that forums that organized content by rank ordering as opposed to using an algorithm that gives proportional attention attract higher quality contributions, but have less participation [17]. Vasilescu and colleagues [48] showed that R developers produced faster answers and more answers on Stack Exchange Q&A than on email mailing lists. While Zagalsky and colleagues [53] showed that developers produced more background information and rationales on email mailing lists than on Stack Overflow. Both sets of authors argue that these differences are due to the competitive nature of Stack Overflow enabled by community ratings. More empirical research directly evaluating the impact of community ratings on knowledge sharing in online communities is needed to resolve these discrepancies.

2.3 Social Influence Online

Social influence, the tendency of individuals to be influenced by the judgements of others, affects the perceptions and judgements of individuals in online communities. In two controlled experiments of an online music market Salganik and colleagues [38, 39] showed that when individuals could see which songs others downloaded individuals were influenced by others purported choices, such that it increased inequality–the most popular songs became even more popular–and decreased predictably–there was more variance in which songs became the most popular across different trials. Because collaborative filtering systems make the opinions of others visible and salient, such as by displaying a community score, researchers have postulated that they increase the effect of social influence on individuals own ratings of content [43]. Muchnik and colleagues [32] using a randomized controlled experiment in which they artificially increased, decreased, or kept the scores of comments the same on an online forum found evidence of an asymmetrical bias due to social influence. Comments whose scores were artificially increased received more up votes than they would have otherwise; comments whose scores were artificially decreased received compensating up votes such that they received around the same score they would have received otherwise [32]. An implication of these findings is that collaborative filtering systems may artificially increase the popularity of content that receives early up votes. However, other researchers find that while important, social influence may be less important in content ratings than other biases, such as relative position of content on a page [8, 19].

2.4 Motivation, Community Feedback, & Reputation Systems

Many researchers have studied motivations for why individuals contribute to online communities. They find that individuals are motivated by a variety of intrinsic motivations, such as altruism, helping others, learning, entertainment, and extrinsic motivations, such as reputation building and anticipated direct and/or generalized reciprocity [25, 28, 33, 50]. Using social exchange theory researchers have argued that individuals will contribute to an online community when the benefits of contributing outweigh the costs [50]. Costs can include the cognitive effort needed to contribute as well as the competitive advantage given up when knowledge is shared in an online community [52].

Attracting attention, having ones content appreciated by others, and building a reputation in a community are interrelated and thought to incentivize content creation in online communities [25, 51]. Researchers find that receiving more attention, including more views, comments, and net up votes, is associated with contributing more in the future to online communities, while receiving less attention is associated contributing less in the future [20, 37, 45, 51].

Communication platforms have quantified and made community feedback explicit and public by displaying community ratings next to content and using these ratings as part of public reputation systems. These public displays of community ratings can motivate and change behavior. A field experiment in massive open online courses's Q&As found that including a reputation system increased the rate and quantity of replies in response to posts [12].

2.5 Reddit

Reddit is a popular social media platform. A 2019 Pew Research survey estimated that 11% of U.S. adults used Reddit[4]. Reddit has been described as a "community of communities"[5], which span a diversity of topics from politics to entertainment to educational topics that increasingly center on text based discussions [40]. Communities form around different topics on subreddits, while some cultural norms are shared across Reddit individual subreddits also develop their own set of norms and rules [9, 15].

Providing information through answering questions is an important aspect of Reddit discourse [54]. Researchers find evidence of user specialization, in which some users primarily answer others' questions [7]. Researchers have shown that individuals on Reddit provide high quality comments that include information and prescriptive advice to individuals experiencing mental health issues [13]. In particular, Reddit is heavily used by software developers to exchange knowledge. Software developers use these platforms to keep up to date with new technology and to get feedback from others in their professional community [2, 41]. Well known problems that affect online communities, such as undercontribution and poor quality contributions, including misinformation, are also a problem on Reddit [18, 35].

2.6 Summary

Prior research has highlighted some important effects of collaborative filtering including directing individuals attention, helping to regulate user behavior, and acting to incentivize contributions by providing a mechanism to explicitly build reputation in the community, while also demonstrating that collaborative filtering systems can create bias and increased inequality in the estimates of value of content. Following the tradition of investigating the impact of specific affordances of communication platforms on information exchange in online communities we investigate the impact of collaborative filtering on discussion in Reddit.

3 METHOD

3.1 Data Collection

A set of software development and data science subreddits were identified using a curated list[6] and searching key words related to software development (e.g. python, java) and data science (e.g. r, data) in subreddit descriptions. Key words used for the search were generated by the authors based on the topics and using the top tags on the popular Q&As StackOverflow and Cross Validated which focus on software development and data science respectively. This initial set of subreddits was then manually coded by the first author to verify that the subreddit was appropriate to the topic. In addition, we required that subreddits be minimally active during the data collection period, which meant they had to have at least 10 posts.

[4]https://www.pewresearch.org/fact-tank/2019/04/10/share-of-u-s-adults-using-social-media-including-facebook-is-mostly-unchanged-since-2018/
[5]http://mashable.com/2013/04/24/reddit-boston-bombing/
[6]https://github.com/iCHAIT/awesome-subreddits/blob/master/README.md#programming

In total 226 subreddits were included: 192 related to software development (e.g. r/learnprogramming, r/raspberry_pi, r/javascript) and 34 related to data science (e.g. r/datascience, r/analytics, r/rstats). Data including information about the subreddit's administrative settings, moderators, posts, comments, and users was collected for these subreddits for 5.5 months from November 1, 2018 to April 15, 2019 using the Reddit API.

3.2 Data Analysis & Variables

Reddit allows moderators of a subreddit to decide whether to hide comment scores. When activating this setting moderators have to decide how long to hide comment scores with the option of hiding them from 1 minute up to 1 day[7]. This is a subreddit wide setting and cannot be adjusted by users who are not moderators of that specific subreddit. When this setting is active users who visit the subreddit cannot see comment scores for comments that have been made within the set time period (e.g. 5 hours). Users can continue to up and down vote comments and they can infer relative scores as comments can be sorted by their scores using comment display algorithms like "top" and "best". We gathered data on whether each subreddit had **hidden or visible comment scores** and the length of time for which the scores were hidden. We report on the descriptive statistics for this subreddit setting.

In order to evaluate the effect of hiding comment scores on information exchange discussions we conducted propensity score matching which is a quasi-experimental technique to control for pre-existing differences, such as subreddit popularity and subreddit topic, between subreddits that activated this setting and those that did not. We measured a set of global characteristics about each subreddit, including:

Topic: whether they were software development (or data science) related.

Popularity: the total number of posts, the number of subscribers to the subreddit, the average number of active viewers at the moment as defined by the number of people reading the subreddit at that time as measured at four time periods (Tuesday at 9am and 9pm and Saturday at 9am and 9pm EST) and the average score of the most popular post on the subreddit.

Community maturation: the number of minutes since a subreddit had been created and the number of characters used to describe the subreddit to visitors. We assumed that online communities develop and mature the longer they are active. In addition we assumed that those communities that were more mature would have more developed and longer statements describing the community.

Moderation: the current number of moderators and the average number of days moderators had held that position.

Content customization: whether the subreddit allowed images to be posted, whether the subreddit allowed videos to be posted, whether the subreddit enabled emojis to be used, whether the subreddit was set to hide threads with deleted comments, whether users could personalize their screen name using flair, and whether users could categorize posts using tags.

We report descriptive statistics about these characteristics for subreddits that had hidden versus visible comment scores and the results of logistic regression analyzing these differences with respect to the comment score setting.

We used the R package MatchIt to perform propensity score matching using the nearest neighbor matching algorithm and this set of pre-existing characteristics of subreddits to identify a balanced set of subreddits that used and did not use the comment score hiding setting. Based on the results of propensity score matching we identified a matched set of 68 subreddits for analysis 34 with comment scores **hidden** and 34 with comment scores **visible**. For each post in the matched set of subreddits we measured aspects of the discussions, including:

[7] https://www.reddit.com/r/modnews/comments/1dd0xw/moderators_new_subreddit_feature_comment_scores/

Quantity of contributions: To assess the extent to which any information was provided in response to a post we measured whether a post received any comments (**had replies**), the number of comments it received (**num. replies**), and the average number of characters in each comment it received (**avg. reply length**).

Quality of contributions: To assess the extent to which comments provided poor or high quality information we measured aspects of the content that they provided. We counted the number of comments that a post received that were deleted by moderators or received a score of 0 or less (by default comments receive a score of 1) as a measure of the **number of poor quality replies**. We counted the number of comments that included links, which are often internal or external sources of additional information, such as related Wikipedia articles and Stack Overflow Q&As, as a measure of high quality replies (num. replies with links) [49]. In addition, because code is so important to software development and data science and is often used to provide examples and to answer specific questions we measured the **number of code blocks** provided in comments replying to a post as a measure of high quality replies that require significant cognitive effort [34].

Patterns of discourse: we applied Linguistic Inquiry and Word Count (LIWC), a set of dictionaries used to count psychologically meaningful word usage, to count the average percent of words used in the two categories of assent and negate across all comments replying to a post, which can be used as proxies for **agreement** and **disagreement** respectively in groups working together [44].

Community network structure: we constructed a network for each subreddit for two time periods of equal length approximately 3 months long following the method of [14]. Nodes were included for every user who made a post or comment. Directed edges were included between user B to user A if user B made a root comment replying to a post made by user A or user B made a reply comment to a direct parent comment made by user A. We measured the **network density**, the **percent of nodes that were isolates**, **network reciprocity**, the **number of weakly connected components**, and the **size of the largest weakly connected component for each network**.

In order to understand how making comment scores visible versus hiding them affected knowledge sharing we conducted 13 mixed effects models examining the effect of hiding comment scores, as the independent variable, on the 13 measures of information sharing, patterns of discourse and community network structure, as the dependent variables using data from the 68 matched subreddits. The unit of analysis for most models was at the post level, with the exception of network variables, for which the unit of analysis was at subreddit-time period level. Because there were repeated measurements per subreddit we included it as a random effect. We used a mixed effects logistic regression model to evaluate the effect of the setting on whether a post received a reply because the dependent variable was binary; this model had 394,898 observations. The remaining variables were positively skewed. When the dependent variable was a count measure and fit the appropriate distribution, we used generalized mixed effects regression models with a poisson distribution (num. poor quality replies, num. replies with links, num. code blocks, num. of subgroups, size of largest subgroup). For the remaining variables we log normalized the variables prior to entering them into the model and used mixed effects regression. The models with network structure variables had 136 observations two per subreddit. The remaining models had 307,669 observations, because we excluded posts that did not receive any comments for these measures. We report the marginal means for both groups which are back transformed to be consistent with the original units.

Perc. subreddits hiding scores	15%
Range time hidden	5 min - 1 day
Mean hours hidden	4.6
Median hours hidden	1
Std. Dev hours hidden	7.5

Table 2. Descriptive statistics about 34 subreddits that hid comment scores.

4 RESULTS

4.1 Hidden comment scores setting

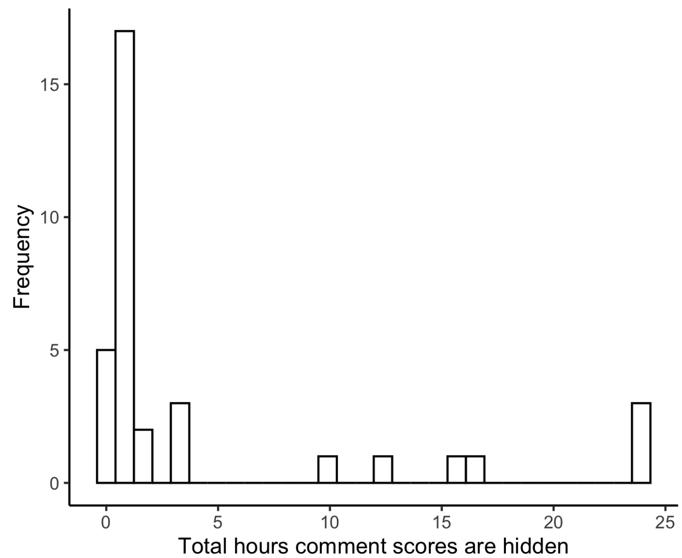

Fig. 1. The distribution of the total number of hours each subreddit hides comment scores for those subreddits that hide comment scores.

15% of subreddits (N = 34 out of 226) from our initial set of subreddits related to software development and data science had activated the setting to hide comment scores (Table 2). Hiding comment scores was less common than leaving comment scores visible for this set of information focused Reddit communities.

When subreddit moderators did activate this setting they tended to hide comment scores for short periods of time on average (Figure 1, Table 2). Moderators had the option of hiding comment scores for 1 minute to 1 day; on average they hid comment scores for 4.6 hours (Median = 1 hour). Although subreddit moderators chose to hide comment scores for as few as 5 minutes and up to the maximum allowable time, 1 day. Subreddits that were more popular, as measured by the number of posts, tended to choose shorter time periods to hide comment scores ($r(32) = -0.45$, $p = 0.008$). Presumably moderators are sensitive to the rate of activity on the subreddit in choosing the amount of time to hide comment scores. Most of the time commenting occurs immediately after a post is made; on average we found that 48% of comments were made within 1 hour of a post, 64% within 5 hours of a post, and 88% within 24 hours of a post. Unfortunately, we have no information on when voting occurs relative to when a post or comment is made, because Reddit API does not

Variable	Prop./Means (SD) Visible	Hidden	Coef.	SE	z	p
Topic						
Whether software dev. (vs. data)	85%	85%	.58	.71	0.82	0.41
Popularity						
Num. posts	2,115 (7,291)	5,517 (6,789)	-0.00003	0.00005	-0.62	0.53
Num. subscribed	66,018 (208,582)	564,637 (2,325,636)	$1.2\text{x}10^{-6}$	$1.3\text{x}10^{-6}$	0.92	0.36
Num. active viewers	169 (459)	535 (877)	0.00007	0.0006	0.12	0.91
Avg. score for most popular post	552 (3,689)	2,682 (8,644)	-0.0001	0.0001	-0.89	0.37
Community maturation						
Subreddit age	8.6 yr. (2.6)	8.0 yr. (2.5)	$-3.8\text{x}10^{-9}$	$3.3\text{x}10^{-9}$	-1.00	0.32
Len. subreddit description	96.8 (104)	138.5 (101)	0.004	0.002	1.65	0.10
Moderation						
Num. moderators	**3.74** (3.73)	**7.65** (6.54)	**0.16**	**0.08**	**2.00**	**<0.05**
Avg. moderator tenure	4.9 yr. (2.4)	3.6 yr. (1.6)	-0.0004	0.0004	-1.07	0.29
Content customization						
Whether allowed images	**90%**	**71%**	**-3.43**	**1.38**	**-2.49**	**0.01**
Whether allowed videos	91%	79%	2.47	1.43	1.73	0.08
Whether emojis were enabled	7%	24%	0.92	0.63	1.46	0.15
Whether deleted comments hidden	18%	47%	0.35	0.52	0.68	0.49
Whether users could personalize	32%	50%	-0.33	0.53	-0.63	0.53
Whether posts could be tagged	**30%**	**65%**	**1.62**	**0.57**	**2.8**	**0.005**

Table 3. Means, standard deviations, and results of logistic regression describing differences in the characteristics of subreddits that hid versus made comment scores visible. Based on observations of 226 subreddits.

provide information about the timing of votes. On other sites like Stack Exchange Q&As we know viewing and voting can occur much later than commenting [1, 46]. Therefore it is unclear whether hiding comment scores for short time periods is well calibrated.

4.2 Characteristics of subreddits that hide comment scores

We measured mostly static characteristics of subreddits relating to their topic, popularity, maturation, moderation, and content customization and evaluated whether these characteristics were different for subreddits in which moderators decided to hide comment scores. Results of the logistic regression model with all 226 subreddits suggested that there were significant differences in terms of the moderation and content customization between subreddits with visible versus hidden comment scores (Table 3). Subreddits that hid comment scores tended to have more moderators, 7.65 on average instead of 3.74 for subreddits with visible scores (Coef. = 0.16, SE = 0.08, $p < 0.05$). Subreddits with hidden comment scores were likely to be more heavily moderated than subreddits with visible comment scores. In line with this finding, we also found that the content was more restricted and allowed for more customization on subreddits with

Variable	Perc./Mean	Median	Std. Dev.
Had replies	78%		
Num. replies	11.3	3	50.8
Avg. reply length	370.6	233	564.3
Num. replies with links	0.9	0	2.8
Num. code blocks	0.4	0	3.2
Num. poor quality replies	0.5	0	10.5
Agreement	0.8%	0%	3.70
Disagreement	1.0%	0.6%	2.4
Network density	0.005	0.001	0.01
Perc. isolates	11%	8%	0.14
Reciprocity	0.48	0.48	0.10
Num. of subgroups	397.2	128.5	701.5
Size largest subgroup	6,275	1,720	12,008

Table 4. Descriptive statistics for discussion quality variables for 68 subreddits selected for analysis.

hidden comment scores, which may be the result of greater moderation on these subreddits. We found significantly fewer subreddits with hidden comment scores allowed images, 71%, compared to subreddits with visible comment scores, 90% (Coef. = -3.43, SE = 1.38, p = 0.01). A greater number of subreddits with hidden comment scores allowed posts to be categorized and filtered using tags, 65%, compared to subreddits with visible comment scores, 30% (Coef. = 1.62, SE = 0.57, p = 0.005).

To control for systematic differences between subreddits that used the hidden comment score setting we applied propensity score matching using nearest neighbor algorithm and the full set of subreddit characteristics. The algorithm selected 34 out of the 192 subreddits with visible comment scores that were most equivalent to the 34 subreddits with hidden comment scores. This provided us with a set of 68 subreddits that were substantially more balanced in terms of moderation and content customization, which helps to ensure that these variables are not acting as confounders in the evaluation of the impact of collaborative filtering on discussion.

4.3 Associations between hiding comment scores and knowledge sharing discussions

We present the results of mixed effects regression models examining the impact of hiding comment scores on information sharing, patterns of discourse, and community network structure. Table 4 provides the descriptive statistics for the measures; Table 5 provides the marginal means and results of the statistical tests; and Figure 2 graphs the effect sizes for the statistically significant results.

We predicted that collaborative filtering would discourage contributions because it increases costs to enter discussion. Therefore we expected that partially disabling collaborative filtering might increase the quantity of contributions. We found a statistically significant effect of hiding comment scores on whether a post received a reply (Coef. = 0.48, SE = 0.12, $p < 0.0001$). On average 80% of posts received at least one reply on subreddits with hidden comment scores whereas only 71% received at least one reply on subreddits with visible comment scores. However, for those posts that received at least one reply we found no statistically significant difference in terms of the number of replies received or the average length of the replies received between subreddits with hidden versus visible comment scores. These results support our prediction that partially disabling collaborative filtering results in more contributions and provides evidence in line with our argument that collaborative filtering alters costs to enter.

Variable	Visible	Hidden	Effect Size	Coef.	SE	Stat.	p
Quantity of contributions							
Had replies	**71%**	**80%**	**0.31**	**0.48**	**0.12**	**4.11**	**<0.0001**
Num. replies	4.2	4.5	0.05	0.06	0.12	0.52	0.60
Avg. reply length	196	209	0.05	0.06	0.08	0.79	0.43
Quality of contributions							
Num. replies with links	**0.92**	**1.07**	**0.13**	**0.15**	**0.07**	**2.15**	**0.03**
Num. code blocks	**0.24**	**0.14**	**-0.21**	**-0.56**	**0.09**	**-6.54**	**<0.0001**
Num. poor quality replies	**0.10**	**0.16**	**0.30**	**0.44**	**0.08**	**5.71**	**<0.0001**
Patterns of discourse							
Agreement	0.35	0.35	-0.01	-0.01	0.02	-0.33	0.74
Disagreement	0.62	0.67	0.06	0.03	0.03	0.97	0.34
Community network structure							
Network density	0.008	0.003	-0.37	-0.004	0.003	-1.55	0.13
Perc. isolates	8%	6%	-0.39	-0.32	0.20	-1.65	0.10
Reciprocity	0.48	0.45	-0.24	-0.05	0.05	-1.06	0.29
Num. of subgroups	127	144	0.07	0.13	0.38	0.33	0.74
Size largest subgroup	948	1,406	0.15	0.39	0.57	0.69	0.49

Table 5. Marginal means, effect sizes (d), and results of mixed effects statistical tests evaluating the differences between subreddits with visible versus hidden comment scores. Degrees of freedom are based on data from 68 subreddits, with 394,898, 307,669, and 136 observations for models testing whether a post has reply, other post variables, and other network variables respectively.

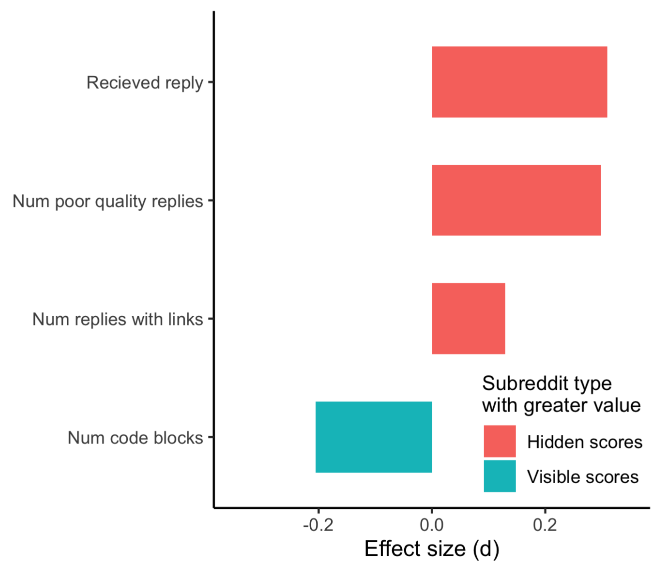

Fig. 2. Estimated effect sizes for significant differences between subreddits with visible vs. hidden comment scores.

Similarly we predicted that collaborative filtering would discourage high and low quality contributions because it increases costs to enter; however, we also predicted that it would increase high effort contributions because collaborative filtering additional incentives for contributing. Therefor we predicted that when collaborative filtering was partially disabled we would in general observe more high and low quality contributions, but fewer high quality contributions that were effortful. We found that posts on subreddits that made comment scores hidden received significantly more replies with links than posts on subreddits in which comment scores were visible (Coef. = 0.15, SE = 0.07, $p = 0.03$). Comments with links are one type of high quality contribution. On average each post received about one reply with a link, on subreddits with hidden comment scores posts received on average 1.07 replies with links whereas on subreddits with visible comment scores posts received on average only 0.92 replies with links. We also found that posts on subreddits that made comment scores hidden received significantly more poor quality replies (those that were deleted by moderators or received a score 0 or below) than posts on subreddits that made comment scores visible (Coef. = 0.44, SE = 0.08, $p < 0.0001$). When comment scores were hidden posts received 0.16 comments that were poor quality on average, whereas when comment scores were visible posts received 0.10 comments that were poor quality. However, we observed the opposite pattern for code blocks. Posts on subreddits that made comment scores visible received more code blocks than posts on subreddits that made comment scores hidden (Coef. = -0.56, SE = 0.09, $p < 0.0001$). On average posts on subreddits with visible comment scores received 0.24 code blocks, whereas posts on subreddits with hidden comment scores received 0.14 code blocks. These findings support our predictions that partially disabling collaborative filtering results in more contributions of high and low quality, but fewer contributions that require more effort and are consistent with our arguments that collaborative filtering alters costs to enter and incentives for making contributions.

We argued that collaborative filtering discourages more in depth discussion and more interaction between individuals because it biases attention toward early comments. We had predicted that when collaborative filtering was partially disabled that there would be more extensive discussion and connections among individuals. Thus, we had expected that when comment scores were hidden to see language that suggested more debate including more agreement and more disagreement and a community network structure that suggested more connection, such as higher density, fewer isolates, more reciprocity, fewer subgroups and more core members. We found no significant differences in the use of assents and negations, two markers of agreement and disagreement respectively, among subreddits that hid versus made comment scores visible. We also found no significant differences in the community network structure among subreddits that hid versus made comment scores visible, with the exception of a marginal difference for the quantity of isolates. We found a marginally significant effect of hiding comment scores on the percent of isolates in the subreddit community (Coef. = -0.32, SE = 0.20, $p = 0.10$). Subreddits with visible comment scores had a greater percentage of isolates, 8%, than subreddits with hidden comment scores, 6%. In other words when collaborative filtering was fully enabled there were slightly greater percent of individuals without connections to others. These findings provide little to no evidence to support our predictions that partially disabling collaborative filtering would be associated with more interaction and connections and little to no evidence to support our argument that collaborative filtering affects discussion because it alters attention to early contributions.

In summary we found that when collaborative filtering was partially disabled posts received more contributions of both high and low quality, however fewer contributions that required more cognitive effort. All of the observed effects were substantial, but small in magnitude with effects sizes ranging from 0.13 to 0.31. Together these results support our arguments that collaborative filtering increases costs to enter discouraging participation and increases incentives to contribute motivating high effort contributions.

5 DISCUSSION

The results of this study suggest fully enabling collaborative filtering comes with a set of trade-offs that positively and negatively impact information exchange in online discussions. We observed two positive consequences associated with collaborative filtering: 1) a higher quantity of high effort contributions in this case code blocks and 2) a lower quantity of low quality contributions. We also observed two negative consequences associated with collaborative filtering: 1) a lower likelihood of getting any contributions at all in response to a post and 2) a lower quantity of one type of high quality contribution–comments with links to other sources of information. These findings suggest that fully enabled collaborative filtering as compared to partially disabled collaborative filtering is neither completely beneficial nor completely detrimental, but has a mix of different beneficial and detrimental effects.

In addition, these findings supported two out of the three mechanisms we argued resulted from the effects of collaborative filtering on discussion (Table 1). We argued that collaborative filtering increased the costs to enter discussion in online communities. When collaborative filtering is fully enabled contributions are no longer treated equally, making it more difficult to capture the full attention of the community and thereby gaining full entry into the conversation. Consistent with this mechanism we found that posts on communities that fully enabled collaborative filtering were less likely to receive any contributions, received fewer low quality contributions and received fewer of one type of high quality contribution. Regulating anti-social behavior in online communities is important to creating a sustainable community [22]. One method to discourage anti-social behavior is to increase costs to enter using distributed moderation and collaborative filtering [27]. However, higher costs to enter have the unintended consequence of discouraging contribution in general. This finding is consistent with theoretical simulations that have shown that collaborative filtering can reduce widespread participation [17].

We also argued that collaborative filtering provides incentives to contribute which increases the benefit to cost ratio and can help to motivate contributions that require more cognitive effort, such as code blocks. Consistent with this argument we found that when collaborative filtering was partially disabled individuals contributed fewer code blocks to discussion. Social exchange theory can be used to understand why individuals share information in online communities [50]. According to this theory as it has been applied to online communities if the potential benefits to contributing outweigh the potential costs then individuals will contribute, if the benefits do not outweigh the costs then they will not. In this case direct feedback from the community in the form of a visible net positive score may act as a potential benefit. Researchers studying other online communities have shown that receiving positive feedback from the community can encourage participation and motivate more contributions [45, 57]; relatedly building a reputation in the community is one of the most important extrinsic motivations that drives participation in online communities [25]. One of the most important costs associated with contributing knowledge to an online community is the cognitive effort it takes to compose an information rich comment, such as writing a block of code [52]. Social exchange theory can help to explain why collaborative filtering may help to encourage high effort contributions. The way in which collaborative filtering is often implemented in online communities quantifies and makes visible community feedback which increases the benefits associated with making a contribution and helps to outweigh the costs associated with contributions that take more cognitive effort.

We found very little support that collaborative filtering affected patterns of discourse and community network structure. We argued that collaborative filtering discourages deeper discussions and connections among community members because it biases attention toward early comments that receive up votes [32]. In general we did not find any empirical evidence in support of this prediction, we found one marginally significant difference and no other significant differences in terms of patterns of discourse and community network structure. There are a few explanations for this lack of support. First, we cannot draw conclusions from failure to find an effect using null hypothesis testing. Second, we only evaluated the impact of *partially* not fully disabling collaborative filtering, which is a weak test of the effects of collaborative filtering on discussion. Had we been able to observe differences between communities that fully or more extensively disabled collaborative filtering we may have seen more differences in interaction patterns. Third, because collaborative filtering varies from community to community on Reddit and more communities enable it than partially disable it the norms and expectations of discussion on Reddit may supersede the more subtle effects of partially disabling it for a particular community. Future research should evaluate the impact of collaborative filtering on interaction patterns using a stronger manipulation.

5.1 Design Implications & Future Research

In this study we found evidence to suggest that collaborative filtering has a set of positive and negative impacts that make it neither completely beneficial nor completely detrimental. Therefore, these findings support Reddit's design choice to allow for selective and flexible use of the collaborative filtering system across different communities as well as their design choice to provide a feature which only partially disables collaborative filtering.

Reddit's design choice to allow moderators to decide on a community by community basis whether to fully enable collaborative filtering is sensible because different communities face different challenges and needs that affect whether or not the trade-offs associated with collaborative filtering are a net benefit to the community. For example, collaborative filtering may be a net advantage to a community that attracts more anti-social behavior, such as a popular community or a community focused on a more controversial topic, because collaborative filtering increases costs to enter, thus discouraging low quality contributions. Alternatively, collaborative filtering may be a net disadvantage to a community with users who have information needs that are highly technical and thus require contributions take more cognitive effort, such as a community focused on providing technical support.

The approach selectively and flexibly using collaborative filtering at a community level relies on moderators to make good decisions about whether collaborative filtering is beneficial to their community. However, moderators are not given tools to support making this decision. Future research should use qualitative methods to investigate how moderators are currently making a decision about whether or not to hide comment scores and how they are deciding on how long to hide comment scores in order to understand their decision process and information needs. Moderators could be given additional statistics about their communities to make a more informed and judicious decision about whether and how to enable collaborative filtering.

Another approach to selectively and flexibly using collaborative filtering on a platform is to provide a setting to enable or disable collaborative filtering on a user by user basis. From prior work we know that there are individual differences in motivation, in which some individuals are motivated by reputation building more than others [28, 33]; individual differences in sensitivity to feedback from others [4]; and individual differences in anti-social behavior [11]. This prior work suggests that there may be individual differences in sensitivity to collaborative filtering and thus a benefit from enabling collaborative filtering for some but not all individuals. This setting could be determined based on individuals's preferences and/or past behaviors.

The findings from this study also support Reddit's design choice to allow at most partial disabling of collaborative filtering. In partially rather than fully disabling collaborative filtering Reddit has created a hybrid collaborative filtering system that maintains some features of collaborative filtering while removing others. By creating a hybrid system Reddit may be able to balance some of the advantages and disadvantages of collaborative filtering. For example, even when collaborative filtering was partially disabled community ratings still provided partial incentives to contribute because they continued to contribute to a user's reputation score; thus preserving some of the benefits of collaborative filtering. Future research should evaluate the specific consequences of suites of features that blend elements of a fully enabled versus a fully disabled of collaborative filtering system.

5.2 Limitations

We used propensity score matching to control for differences between subreddits in which comment scores were hidden versus visible; this method and other quasi-experimental matching techniques can help to reduce confounds and are commonly used in studying live platforms in which experimental interventions are not possible (e.g. [10, 49, 56]). However, this method cannot remove all confounds, particularly those unknown and unaccounted for in the statistical models, and thus we cannot draw definitive causal claims based on these results.

Further, we examined the impact of collaborative filtering relying on the exogenous variation introduced by the hide comment scores setting. This setting only partially disables collaborative filtering and thus is a very weak manipulation of collaborative filtering. When the hide comment score setting was turned on comments could still be ordered by community ratings and these community ratings still contributed to a user's reputation score visible on their user page. In addition, on average comment scores were only hidden for a short period of time after which they were made visible. We may have observed larger differences in discussions between communities that hid comment scores had the manipulation of collaborative filtering been stronger.

The goal of this study was to explore multiple potential effects of collaborative filtering on discussion based on a priori predictions. For this reason we used a less conservative approach by conducting multiple statistical tests without controlling for familywise error rate. As a result we have a higher chance of a false positive. However, even if we had applied a correction, such as the Bonferroni correction 3 out of the 4 statistical tests would still have been statistically significant.

6 CONCLUSION

In this study we examined differences between 68 Reddit software development and data science communities that had either made comment scores visible or hidden in order to understand the impact of collaborative filtering on information exchange in online discussions. We found evidence that partially disabling collaborative filtering was related to more contributions of both low and high quality, however fewer contributions that required more effort. These results supported our arguments that collaborative filtering helps to incentivize contributions that require more cognitive effort, but also increases costs to enter discussion. Due to the mix of positive and negative effects of collaborative filtering on discussion communication platform designers should investigate ways to selectively and flexibly apply collaborative filtering.

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