Detecting Obstacles to Collaboration in an Online Participatory Democracy Platform: A Use-case Driven Analysis

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ABSTRACT

Massive online participatory platforms are an essential tool for involving citizens in public decision-making on a large scale, both in terms of the number of participating citizens and their geographical distribution. However, engaging a sufficiently large number of citizens, as well as collecting adequate contributions, require special attention in the functionalities implemented by the platform. This paper empirically analyzes the existing flaws in participatory platforms and their impact on citizen participation. We focus specifically on the citizen consultation "*République Numérique*" (Digital Republic) to identify issues arising from the interactions between users on the supporting platform. We chose this consultation because of the high number of contributors and contributions, and the various means of interaction it proposes. Through an analysis of the available data, we highlight that contributions tend to be concentrated around a small set of proposals and contributors. This leads us to formulate a number of recommendations for the design of participatory platforms regarding the management of contributions, from their organization to their presentation to users.

CCS CONCEPTS

• **Applied computing** → **E-government**; • **Human-centered computing** → **Empirical studies in interaction design**; *Collaborative and social computing systems and tools*; • **General and reference** → Empirical studies.

KEYWORDS

Citizen participation, E-government, Empirical study, Graph analysis, Interaction design, PageRank, Collaboration

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1 INTRODUCTION

The direct participation of citizens in the political life of their city, province or country has gained considerable popularity in recent decades, especially at the local level [12, 23]. These systems aim to empower citizens to contribute to their local or national policies. In addition, the rise of the *civic tech* field of study and innovation has led to the emergence of new digital alternatives to the more traditional approaches involving face-to-face meetings. Web-based platforms for participatory projects manage the participation of a much larger and more diverse population than their physical counterparts, without ending up in a cacophonous situation where the number of participants is too high for the good of the participation. Participatory platforms address various applications, e.g., participatory budgeting [28], releasing open data for civic purposes [5], gathering and processing the opinions of large groups of citizens [29], and citizen consultation and deliberation, to name a few. We focus on an example of the fourth case: the "*République Numérique*" (Digital Republic, *RepNum* for short in the following) online consultation (§ 2). Online consultations aim at allowing citizens to directly express their opinions on a particular topic –in our use case, the different articles of a bill– outside of any electoral context. They are frequently considered as a way to improve the participation of citizens in a representative political system although they are non-binding for the organizing institution. Technically, online consultation platforms can be seen as CSCW platforms allowing users to collaboratively edit a set of independent proposals by adding new elements or by discussing previously added ones. They generally implement at least the three following forms of contributions:

(1) User A submits a proposal, detailed or vague, to the platform.
(2) User B comments on a proposal formerly submitted by User A.
(3) User B votes for, against, or neutrally, on A's proposal.

The *RepNum* platform has already been the subject of several academic papers, notably in the French-speaking social science community. Existing analyses focus mainly on the discourse accompanying the implementation of the platform [2] and on the interaction possibilities offered to citizens by the platform design [20]. However, to the best of our knowledge, there does not exist any publication focused on the technical analysis of the impact of platform design on the way users contributed to the *RepNum* consultation. There exist technical analyses of the user contributions to similar platforms such as Decidim [3] or more general collaborative systems like Google Docs [26]. These studies focus on the inference of collaboration models from the users' interactions. Instead, we aim at eliciting recommendations mitigating bias in the platform's design to enhance the engagement of citizens in online participatory platforms. Our objective is to help build more equitable participatory platforms based on the data produced by previous experiences. To do so, we analyze the users' contributions and interactions in the *RepNum* platform. This specifically leads us to investigate the following Research Questions out of which we draw recommendations for the design of participatory platforms:

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Table 1: Possible types of replies for a contribution

Initial contribution \ Can be replied with...	Argument	Modification	Source	Vote
Argument				×
Modification	×		×	×
Proposal	×	×	×	×
Source				×

RQ1: How is the attention distributed among proposals and are platform-related factors at the origin of the distribution? (§ 3)
RQ2: How do the most active contributors use the different types of contributions (proposal, modification, argument, source, vote) and how can we mitigate their influence on the consultation? (§ 4)
RQ3: What is the impact of the presentation of proposals on the participation? (§ 5)

All code used in the production of the analyses is available at *https://github.com/WilliamAboucaya/repnumbehavioranalysis*.

We then analyze the threats to validity (§ 6) and position our contributions with respect to related work (§ 7). A summary of our contributions and perspectives for future work conclude the paper.

2 THE RÉPUBLIQUE NUMÉRIQUE CITIZEN CONSULTATION

The consultation for the *RepNum* bill was held from 09/26 to 10/18 2015 and primarily took place through the dedicated online platform [8]. The main objective of the (essentially online) consultation was to allow contributors to propose amendments –called *Proposals*– to the bill before its examination by the French Parliament, while giving no guarantee that the amendments would be integrated.

The *RepNum* platform builds upon the proprietary solution for online consultations of the Cap Collectif company. Using the *RepNum* platform, contributors register using their real name or a pseudonym. They also specify their *profile*, that is, whether they are *citizens*, *institutions*, *non-profit* or *for-profit* organizations. Over the last few years, other consultations have taken place in France, particularly concerning vaccination [21, 32], and in other countries such as Australia [6] and Canada [22]. However, we chose to analyze the *RepNum* consultation because it received a large number of contributions, and the platform allows more diverse types of contributions (see Table 1) compared to its main alternatives, e.g., CONSUL [11] or Decidim [13]. Distinguishing features include the addition of a source (e.g., a newspaper article) to a pre-existing proposal, and the amendment of a proposal through a modified version. We argue that such functions are vital in a collaborative and confrontational situation to help solve potential disagreements and help everyone form an informed opinion on a particular topic, as described in [24]. We further highlight that the functions offered by the *RepNum* platform match the ones of the generic interaction workflow supporting participatory budgeting presented in [28].

Statistics indicate that the consultation has reached a diverse audience larger than only experts in IT and companies of the field [7, 15, 16]. However, the way users have contributed varies greatly depending on their profile. Table 2 illustrates how the different types of contributions are distributed among the different user profiles.

```
Consultation
└── Part 1: Flow of data and knowledge
│   └── Chapter 1: Data economy
│   │   └── Section 1: Opening public data
│   │   │   └── Proposal 1
│   │   │   └── Proposal 2
│   │   │   └── ...
│   │   └── Section 2: Public data service
│   │   └── ...
│   └── Chapter 2: Knowledge economy
│   └── ...
└── Part 2: Protection in the digital society
└── ...
```

Figure 1: Organization of proposal categories with examples of categories from the *RepNum* bill (translated from French)

For example, it emphasizes that certain profiles, particularly non-profit organizations and the French government, have published many more *Proposals* than others per individual, especially citizens.

All the contributions to this consultation and related metadata are available online as open data at *https://www.data.gouv.fr/fr/datasets/consultation-sur-le-projet-de-loi-republique-numerique*. This allows us to analyze in-depth how users engage with respect to their profile and contribution types, from which we are able to derive platform pitfalls and recommendations for the platform design so as to enhance the user engagement. *Contributions* relate to one of the bill *categories* (i.e., the specific part, chapter, and section, according to the overall structure of the bill depicted in Figure 1). As detailed in Table 2, the dataset gathers 156,121 contributions from 21,464 unique authors. However, the dataset omits exhibiting a key feature of the platform: it pins the *Proposals* from the government –i.e., part of the initial law bill– on top of every section of the consultation, while the government profile is of type "*institution*" in the dataset. Thus, to distinguish the government *Proposals*, we pre-processed the dataset to replace their profile "*institution*" by "*government*".

3 RQ1: DOES THE PLATFORM INFLUENCE HOW USERS CONTRIBUTE?

3.1 Analyzing how contributions distribute across users

In order to identify which contributors have received the most attention, we apply the PageRank algorithm [27] that measures the importance of vertices in a directed graph through the number of edges pointing towards them. Various papers introduce PageRank adaptations to detect influential users in social networks, while accounting for the specifics of the underlying platform [4, 33]. We specifically use the weighted PageRank algorithm [34] that fits well the interactions implemented in the *RepNum* platform. We built four weighted directed graphs representing the interactions between contributors using the four types of replies (i.e., *Argument*, *Source*, *Modification*, *Vote*) to a contribution –*Proposals* are ignored since they cannot follow from another contribution. We distinguish the different types of contributions to avoid giving the same weight to two different contributions that do not have the same purpose and effort-requirement (e.g., a 1-click vote *vs* a detailed argument). It also allows us to analyze if the PageRanks of a user correlate for different types of contributions (see § 3.2). Hence, each of the four graphs focuses on a single type of contribution where: the vertices are the users/contributors to the platform, and a directed edge from

Table 2: Number of contributions of all types by user profile

Profile	Users	Proposals	Modifications	Sources	Votes	Arguments
Citizen	13,492	400	950	369	112,322	4,627
	62.99%	57.803%	68.493%	88.916%	76.080%	77.245%
Non-profit organization	393	110	157	14	1,955	291
	1.831%	15.896%	11.319%	3.373%	1.324%	4.98%
Institution	199	22	47	11	1,141	62
	0.927%	3.179%	3.389%	2.651%	0.773%	1.035%
For-profit organization	154	13	27	4	1,043	66
	0.717%	1.879%	1.947%	0.964%	0.706%	1.102%
Government	1	30	0	0	0	0
	0.005%	4.335%	0%	0%	0%	0%
Others	7,225	117	206	17	31,176	944
	33.661%	16.908%	14.92%	4.096%	21.117%	15.760%
Total	21,464	692	1,387	415	147,637	5,990

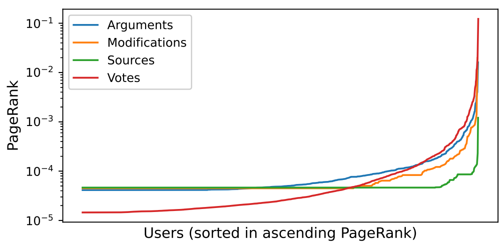

Figure 2: PageRank of users in ascending order

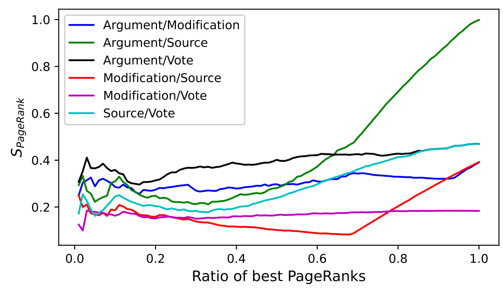

Figure 3: PageRanks correlation for different reply types

a contributor A to a contributor B represents a reply contribution of the given type from A to a contribution from B. Each graph is defined as $G(V, E)$ with V (resp. E) denoting the set of vertices (resp. edge). Then, $w : E \longrightarrow \mathbb{R}$ returns the weight of a given edge where the weight of an edge e outgoing from a vertex v is computed as:

$$\forall v \in V, e \in E^{+}(v) : w(e) = \frac{1}{|E^{+}(v)|}$$

After applying the PageRank algorithm to the four graphs, we filtered each one of them by removing the users who did not publish any contribution that can generate replies of a given type from the associated graph (e.g., a user who did only publish *Sources* cannot receive an *Argument*). We then ordered the PageRanks in ascending order (see Figure 2). For each graph, we can clearly identify a small minority of contributors whose activities generate the most replies, as represented by an exponential growth of the PageRank. We argue that the existence of this small minority whose *Proposals* centralize the vast majority of replies of a specific type tends to alter the nature of the consultation for most users. Indeed, since most users receive little to no feedback to their contributions, they could disengage from the consultation. The satisfaction survey conducted by Cap Collectif[9] supports the claim as it indicates that 81.4% of the respondents have visited the platform less than 5 times. This may also prompt users to change their behavior, from proposing new articles for a bill project to commenting and approving preexisting *Proposals*. This leads us to make the following recommendation:

Rec. 1. *To give voice to a wider part of the audience, we recommend to highlight the newest Proposals, in a way similar to the layout proposed by platforms such as StackOverflow, to improve the share of initial Proposals that receive attention and feedback. The RepNum platform already offers to sort the Proposals of a section chronologically; however, this is not the default selection.*

3.2 Analyzing the factors influencing the contributions

After obtaining the different PageRanks of the consultation, we investigate whether the highlighted centralization of contributions is directly related to contributors with high PageRanks and their individual influence, or depends on the *Proposals* themselves, independently of their authors. To do so, we first investigate whether or not the PageRank of a user for a given type of contribution is correlated to their PageRank for the other types. This correlation allows us to know if the contributions of two different types are centralized around the same initial contributors, and therefore to identify if the users who tend to receive the most replies of a given type also receive the most replies of other types. Let:

- $type_a$ and $type_b$ denote types of contributions among {*Argument*, *Modification*, *Source*, *Vote*};
- PR_{type_a} (resp. PR_{type_b}) denotes the list of users sorted by ascending order depending on their PageRanks for $type_a$ (resp. $type_b$) contributions –the list refers to all the unique users contributing to the consultation;
- $r \in [0, 1]$ denotes the ratio of users taken from the end of the lists PR_{type_a} and PR_{type_b} (i.e., $r = 0.05$ means we compute the

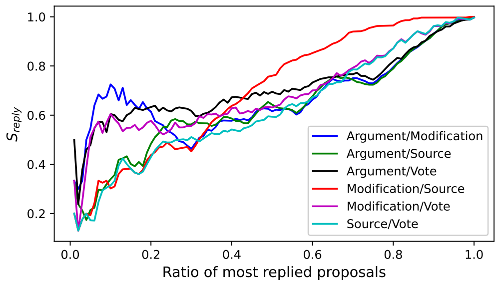

Figure 4: Correlation of the amount of replies to a proposal for different contribution types

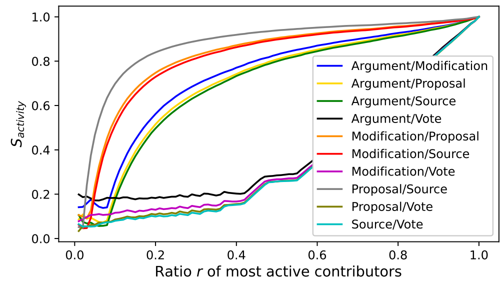

Figure 5: Correlation of activity for each contribution type

similarity of the most active 5% contributors for $type_a$ and $type_b$ contributions); and

- $PR_{type_a,r}$ (resp. $PR_{type_b,r}$) denotes the sublists of PR_{type_a} (resp. PR_{type_b}) obtained after picking the r share of the highest PageRanks in both lists.

The similarity ratio $s_{PageRank}$ provides the level of similarity between $PR_{type_a,r}$ and $PR_{type_b,r}$ (i.e., at $s_{PageRank} = 0$, none of the users in $PR_{type_a,r}$ are in $PR_{type_b,r}$, and at $s_{PageRank} = 1$, both lists are identical):

$$s_{PageRank} = \frac{|PR_{type_a,r} \cap PR_{type_b,r}|}{|PR_{type_a,r} \cup PR_{type_b,r}|}$$

We compute the similarity ratio between two contribution types using the filtered PageRanks lists computed in § 3.1. The result depicted in Figure 3 shows that the degree of similarity remains under 0.5 for the low values of r ($r < 0.2$). For certain pairs of contributions (e.g., the *Argument/Modification* and *Argument/Vote* pairs), the similarity remains stable between 0.3 and 0.4. Consequently, we argue that PageRanks for these types of contributions are correlated. The correlation is weaker for other pairs (e.g., *Modification/Source* and *Modification/Vote*) that seem to be independent. The fact that the *Argument/Source* curve of the graph is the only one that converges towards 1 for the highest values of r is due to the fact that both *Arguments* and *Sources* can only be used as replies to *Proposals* and *Modifications*, i.e., $PR_{Argument}$ and PR_{Source} contain the same users after filtering. We can conclude that the users who receive most of the *Argument* replies tend to also centralize other types of replies, but this centralization does not apply for most other types.

Although contributors tend to weakly centralize contributions of different types in most cases, we want to know if this centralization is stronger around *Proposals*. This leads us to compute the similarity of the *Proposals* receiving the most replies of each type. Let:

- P_{type_a} (resp. P_{type_b}) denotes the list of *Proposals* in ascending order depending on the number of replies of $type_a$ (resp. $type_b$)
- $P_{type_a,r}$ (resp. $P_{type_b,r}$) denotes the sublist of P_{type_a} (resp. P_{type_b}) obtained after picking the r (r defined as before) share of the *Proposals* with the most replies.

The similarity ratio s_{reply}, which provides the level of similarity between $P_{type_a,r}$ and $P_{type_b,r}$, is defined as:

$$s_{reply} = \frac{|P_{type_a,r} \cap P_{type_b,r}|}{|P_{type_a,r} \cup P_{type_b,r}|}$$

The results of the computation (see Figure 4) highlights two main results. First, for the lowest values of r (i.e., $r < 0.2$), the levels of similarity for pairs of reply types follow two tendencies. The *Argument/Modification*, *Argument/Vote* and *Modification/Vote* pairs have a high level of similarity ($s_{reply} > 0.5$) while this correlation is clearly weaker for all the pairs that contain the *Source* type of reply, i.e., the *Argument/Source*, *Modification/Source* and *Source/Vote* pairs. The computation becomes less relevant as r grows since P_{type_a} and P_{type_b} contain the same users, i.e., s_{reply} converges towards 1 for the highest values of r. In other words, although the *Proposals* that gather the most replies of a given type tend to also receive the most replies of other types, the correlation does not apply to the *Source* reply type that appears independent from the others. However, we mitigate this absence of appearant correlation as it may result from the low number of *Source* replies in the dataset (see Figure 2) and must not be interpreted as an inverse correlation or a decorrelation.

Second, the comparison of the filtered version of the correlation of PageRanks (see Figure 3) with the graph obtained from the computation of s_{reply} evidences that the similarity level grows faster for the latter. This difference in the shape of the curves may be related to a low impact of initial authors on the concentration of replies around a single contribution. Therefore, replies would be sent to a contribution due to its content rather than its author.

Our analysis shows that *Proposals* that receive the most replies of a certain type –excluding *sources*– tend to also centralize replies of the other types. This can lead to situations where a *Proposal* receives, e.g., a great number of *Votes* and very few *Sources*, becoming de facto a subject that both meets a great interest from the contributors and proposes very few material to form an opinion. We derive the following recommendation:

Rec. 2. *We recommend to give the opportunity to users to add tags to Proposals such as "sources needed" or "lacking arguments" to attract potential contributors who may enrich their least complete parts. As part of our ongoing work, we are also investigating the automated labeling of contributions depending on the types of contributions they lack using a machine learning approach based on, inter alia, the number of replies of different types to a Proposal or their content, like proposed in [17].*

4 RQ2: HOW TO MITIGATE THE INFLUENCE OF THE MOST ACTIVE USERS?

In order to further understand the behavior of contributors, we analyze the correlation between the activity of a user for different types of contribution. This correlation allows us to know whether the most active contributors for a type of contribution are also very active in another type, or the two behaviors are independent. Let:

- U_{type_a} (resp. U_{type_b}) be the list of users sorted by ascending order depending on the number of contributions of $type_a$ (resp. $type_a$) they have published;
- $U_{type_a,r}$ (resp. $U_{type_b,r}$) be the sublist of U_{type_a} (resp. U_{typeb}) obtained after picking the r (r defined as before) share of users with the highest number of contributions in the list.

The $s_{activity}$ ratio, which provides the level of similarity between $U_{type_a,r}$ and $U_{type_b,r}$, is defined as:

$$s_{activity} = \frac{|U_{type_a,r} \cap U_{type_b,r}|}{|U_{type_a,r} \cup U_{type_b,r}|}$$

Figure 5 highlights two different kinds of evolution of the similarity depending on r. The first group includes pairs of contribution types for which the level of similarity does not significantly increase while $r < 0.4$, and raises significantly afterwards. This group is composed of all the pairs containing the *Vote* contribution type. Here, the similarity level increases only because the wider both sublists are, the more likely a user is to be found in both of them. Therefore, we cannot declare that there is a correlation between the activity in *Vote* and other types of contributions.

The second group contains the pairs for which the level of similarity is low for $r < 0.1$ but drastically increases afterwards and finally remains almost equal to 1 after the first half of the graph, resulting in a square root-shaped curve. This group contains all the pairs containing two text-based contribution types, i.e., any type except *Vote*. For these pairs of contribution types, even if the 5-10% most active contributors are completely different, we can see that their top 20% is very similar. The most visible example of this group is the *Proposal*/*Source* curve of the graph. We conclude that, for pairs in this group, there is a correlation between the activity in both contribution types. This type of behavior is similar to the one identified by Vasilescu *et. al.* [31] in StackOverflow and GitHub. However, we also identify that the most active contributors ($r < 0.05$) in one type tend to be specialized in this type and do not produce as many contributions of other types.

The analysis further indicates that, for text-based contributions, even though the 10 to 20% most active contributors for a specific type of contribution tend to also contribute to other types above the average, there is a small minority of specialized contributors who focus on producing contributions of one specific type.

This leads us to infer that the presence of extremely active contributors, whether they are specialized in one type of contribution or versatile, can be a potential source of bias in participation. Indeed, these kinds of behavior can lead to situations where, for a given *Proposal*, most reply contributions of one or more types are submitted by a specific opinion group. This kind of situations could reduce the capability of contributors to form an informed opinion on a *Proposal* and bias their final (dis)approval. Consequently, we introduce the following recommendation:

Rec. 3. *To reduce the risks induced by the centralization of contributions of a given type around a small set of contributors, it is necessary to identify the Proposals whose replies are made by a small set of active contributors. Such a detection can be achieved using graph-based anomaly detection [1] where: contributors and Proposals are two different types of vertices, and a contributor is linked to a Proposal by an edge if they have submitted a contribution related to the said Proposal. The Proposals that are detected as receiving an abnormally high number of replies from a few contributors are then highlighted to other contributors, so that they can provide new perspectives. This detection could lead to a reduction of the bias induced by the original contributors' perspective.*

5 RQ3: DOES THE POSITIONING OF *PROPOSALS* HAVE AN IMPACT ON PARTICIPATION?

In order to better understand which users and which *Proposals* tend to receive the most replies, we now hypothesize that the positioning of *Proposals* on the consultation's user interface has an impact on their popularity. Indeed, the *RepNum* platform displays *Proposals* according to the two following criteria:

Categorization: *Proposals* are grouped according to the categories of the consultation's structure (see Figure 1). As a result, contributors have easier access to the the content related to the categories at the top. This potentially creates a bias toward these categories and thus an impact on replies to content in lower categories.

Pinning: Within each category, the first *Proposals* displayed are always the ones composing the initial bill project, that is, the ones proposed by the government. These *Proposals* are "*pinned*" at the top of their category. The other *Proposals* can be sorted according to different criteria (e.g., date of publication, number of *Votes*, etc.) but are sorted randomly by default. This layout implies that the *Proposals* made by the government are more accessible to the contributors. This is a potential source of bias that can lead users to focus on government *Proposals* at the expense of public participation.

To assess the actual impact of this design choice of the *RepNum* platform, we statistically analyze the number of replies of each type to the *Proposals*, according to the two above criteria. In our first analysis, we group *Proposals* according to their categorization (see Figure 1). We then compute the quartiles and median for the number of replies of each type to a *Proposal* depending on the three levels (see Table 3 in Appendix). Regardless of the categorization level chosen, we notice small variations in the three statistical values. These variations tend to be wider for *Votes* than for other types of replies, with peaks identified in Part II–Chapter 2–Section 2, and Part III–Chapter 3–Section 1. However, we cannot identify any clear decrease or increase in the number of replies depending on the positioning of the category in the user interface. Nevertheless, we can see that the way categories are presented has a clear impact on the number of *Proposals* submitted within a section. Indeed, the number of *Proposals* per section tends to decrease as the category is positioned lower in the user interface. This tendency is more significant for coarser levels. Therefore, we consider that even though the impact of the positioning of contributions based on categorization is not significant enough to be identified as a bias generator in the contribution of replies to a *Proposal*, it has an impact on the number of *Proposals* submitted in a section and reduces the participation for the related subjects. We make the following recommendation:

Rec. 4. *The number of Proposals related to the topmost categories –as displayed– being higher than that of the lower categories, we recommend either to sort categories randomly so that each contributor is exposed to different topics of the consultation, or to implement another method to display categories of Proposal on a more horizontal layout.*

The second analysis compares the popularity of all the *Proposals* of the consultation with those made by the government alone. First, we group the *Proposals* made by the government according to their part, chapter and section (see Table 3 in Appendix). The number of *Proposals* from the government being particularly low (between 1 and 6 per section), we only compute the median for the number of replies of each type. Then, we compare these values to the associated medians and quartiles for the whole set of *Proposals* computed previously. The comparison shows that for every type of reply and category level, the median of replies to government *Proposals* of a category is always higher or equal to the third quartile of the number of replies to *Proposals* in this category. We conclude that pinning *Proposals* has a significant impact on the number of replies received, and consequently is a bias generator and centralizes the participation around the *Proposals* made by the government. This leads to the following recommendation:

Rec. 5. *As the pinning of Proposals tends to centralize the replies around a small set of pinned Proposals, we recommend either not to implement this option or to change the criteria of selection to pin Proposals which would benefit the most from high number of replies (e.g., highly controversial Proposals).*

6 THREATS TO VALIDITY

For the analysis of the centralization of contributions around contributors and *Proposals* (§ 3.2), we did not take into account the relevance of contributions. Indeed, certain contributions can be out of the scope of the consultation, mischievous, or duplicates of pre-existing *Proposals*. This factor could be meaningful to explain why a *Proposal* receives many replies or not, as the least relevant *Proposals* are likely to be ignored by contributors. This should be considered to balance the contributions received by *Proposals*, so as to not highlight irrelevant *Proposals* that receive little attention.

We focus this study on a specific consultation. It is therefore subject to a demographic bias concerning the studied population and our findings could differ in other consultations. We mitigate this risk by choosing the largest dataset we have found, concerning the number of both contributors and contributions. However, reproducing similar work on different datasets is worth investigating to generalize our recommendation to other participatory platforms.

When we evaluated the impact of the positioning of *Proposals* on participation (§ 5), our conclusions and recommendations were based on the default positioning of *Proposals* on the user interface. However, we were not able to get statistics about the percentage of contributors using this default interface. Still, lacking this information has no impact on the validity of Rec. 4 since, regardless of the modifications of the interface proposed by the platform, categories are always displayed in the same order. Nevertheless, if most users did choose a non-default positioning of *Proposals* which would not put pinned *Proposals* forward, then the centralization of contributions around the said pinned *Proposals* would be only caused by the fact that they have been issued by the government. In that case, Rec. 5 would not effectively solve the identified problem since it would not be induced directly by the user interface.

7 RELATED WORK

Ben Jabeur *et al.* [4] introduce three new algorithms based on PageRank to characterize the specific behavior of three different groups (*influencers*, *leaders* and *discussers*) of key users in Twitter. Weng *et al.* [33] present another PageRank-based algorithm, also targeting Twitter but focused on the detection of influencers depending on the topic. Our work distinguishes from the above studies by addressing participatory platforms. However, their analysis identifies different types of following behaviors depending on the topical similarity between users, in a way similar to ours. This work suggests that the dedicated customization of PageRank would allow the detection of influential contributors according to the given use of online citizen participation platforms, which is area for our future work.

Conover *et. al.* [10] propose to use label propagation [30] to identify clusters of users belonging to the same opinion group. Their approach allows to identify the patterns of interaction between users from the two clusters they identify –left- and right-leaning users– for the different types of interactions proposed by the platform. This method can be relevant in our case, especially as a mean to improve the reliability of Rec. 3 in the detection of opinion groups centralizing the discussion around a specific proposition.

Khan *et al.* [18] present a requirement engineering approach based on the extraction and evaluation of arguments from end-users feedbacks. They apply an argumentation theory and machine learning-based approach to establish requirements for a Google Maps feature. Our approach differs greatly from theirs since we draw our recommendations based on users' behavior and on the flaws they highlight on the platform we study. We argue that our approach has the advantage of directly relying on users' interactions with the platform rather than on the declaration of a subset of users. Therefore, our approach allows the identification of issues even if users are not aware of their existence. However, argument mining-based approach has the advantage of directly giving voice to platform users and therefore could be used to improve online participatory platforms based on arguments provided by citizens.

While this paper has concentrated on informing the design and/or enhancement of participatory platforms based on the analyses of a past consultation, related studies are concerned with questioning the overall development process of these platforms. For instance, Knutas *et al.* [19] present a case study of the software development processes that emerged from the "*Code for Ireland*" initiative. They provide a description of the implemented practices together with their achievements. They also identify specific challenges in the development process, notably concerning the specification of requirements or the engagement of stakeholders, and propose a set of recommendations to solve the problems identified.

Finally, the study of the *RepNum* consultation has received much attention from the French-speaking social science community. This includes the work of Laurent *et al.* [20] who analyze the graphic design of the *RepNum* platform and the interactions it enables with the platform. They highlight the inadequacy of the contribution means offered by the platform with respect to the diversity of the points of view expressed. They also investigate the use of the platform in the context of the French representative democracy. Alexis *et al.* [2] also analyze the functionality of the *RepNum* platform, taking into account the tools offered to the user for the consultation and investigating the types of discourse induced. They highlight a depoliticization of the discourse through the neutralization[1] of the subject. These studies are complementary to ours and discuss other keys to understand how the *RepNum* consultation worked.

8 CONCLUSION

We analyzed the different flaws of the *RepNum* platform regarding citizen participation. Our findings show a high degree of centralization of contributions around a small set of *Proposals*. This centralization is more related to the content of *Proposals* themselves than to the identity of their authors. We also highlight the existence of extremely active contributors, with some of them being specialized in a specific type of contribution and others being more versatile. Finally, we identify the impact of the positioning of *Proposals* on the number of related contributions submitted. These different situations constitute threats to participation, and therefore to the inclusion of citizens in public decision making. To solve the problems arising from them, we propose five recommendations oriented towards the design of participatory platforms.

We conclude that the design of participatory platforms should be considered as a vector of bias to the participation itself, and the behavior of contributors is a meaningful indicator to identify such issues. However, to the best of our knowledge, contemporary participatory platforms do not implement certain modern software features, which could be used to improve their existing features, involve citizens deeply in the process and respond to new use cases. For example, modern CSCW tools such as collaborative editing would help participants elaborate collective proposals, and NLP-based topic extraction would help recommend proposals to potential contributors depending on their topics of interest and expertise. Social recommendation [14] could also be leveraged to highlight relevant topics for contributors or help them find co-writers for common proposals. As part of our current and future work, we focus on feature-oriented action levers available to participatory platform designers to improve online participation. We start this work with an analysis of the impact of adding collaborative editing elements to help contributors elaborate and discuss proposals. We also aim at integrating the objectives pursued by platforms maintainers to our study through a panel of semi-directed interviews.

REFERENCES

[1] Leman Akoglu, Hanghang Tong, and Danai Koutra. 2015. Graph based anomaly detection and description: a survey. *Data Mining and Knowledge Discovery* 29, 3 (01 May 2015), 626–688. https://doi.org/10.1007/s10618-014-0365-y

[2] Lucie Alexis, Christine Chevret-Castellani, and Sarah Labelle. 2017. Enjeux sociopolitiques d'un nouvel ordre de discours autour des dispositifs de participation en lien avec la loi pour une «République numérique». *Cahiers du CRICIS* [Méta]morphoses numériques de la culture et des médias : quelques pistes de réflexion, Special Issue (2017), 56–67.

[3] Pablo Aragón, Andreas Kaltenbrunner, Antonio Calleja-López, Andrés Pereira, Arnau Monterde, Xabier E. Barandiaran, and Vicenç Gómez. 2017. Deliberative Platform Design: The Case Study of the Online Discussions in Decidim Barcelona. In *Social Informatics*, Giovanni Luca Ciampaglia, Afra Mashhadi, and Taha Yasseri (Eds.). Springer International Publishing, Cham, 277–287.

[4] Lamjed Ben Jabeur, Lynda Tamine, and Mohand Boughanem. 2012. Active Microbloggers: Identifying Influencers, Leaders and Discussers in Microblogging Networks. In *String Processing and Information Retrieval*, Liliana Calderón-Benavides, Cristina González-Caro, Edgar Chávez, and Nivio Ziviani (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 111–117. https://doi.org/10.1007/978-3-642-34109-0_12

[5] Kirsten Boehner and Carl DiSalvo. 2016. Data, Design and Civics: An Exploratory Study of Civic Tech. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 2970–2981.

[6] Axel Bruns and Jason Wilson. 2010. *Citizen Consultation from Above and Below : The Australian Perspective.* IGI Global, Hershey, PA, USA, 332–346. https://doi.org/10.4018/978-1-61520-933-0.ch020

[7] Cap Collectif. 2015. *Bilan de la consultation nationale sur le projet de loi pour une république numérique.* Cap Collectif. https://www.republique-numerique.fr/media/default/0001/02/2377a996950cadd5a093dc9e3a621c0e1f9a19f5.pdf

[8] Cap Collectif. 2015. *Consultation sur le projet de loi pour une République Numérique.* https://www.republique-numerique.fr/

[9] Cap Collectif. 2015. *Résultats du questionnaire de satisfaction de la consultation nationale sur le projet de loi pour une république numérique.* Cap Collectif. https://www.republique-numerique.fr/media/default/0001/02/52587d44cde47eacdba246c5625232454c06e33a.pdf

[10] Michael Conover, Jacob Ratkiewicz, Matthew Francisco, Bruno Goncalves, Filippo Menczer, and Alessandro Flammini. 2011. Political Polarization on Twitter. *Proceedings of the International AAAI Conference on Web and Social Media* 5, 1 (Jul. 2011), 89–96. https://ojs.aaai.org/index.php/ICWSM/article/view/14126

[11] CONSUL. [n. d.]. *The CONSUL Project.* https://consulproject.org/

[12] BOAVENTURA de SOUSA SANTOS. 1998. Participatory Budgeting in Porto Alegre: Toward a Redistributive Democracy. *Politics & Society* 26, 4 (1998), 461–510. https://doi.org/10.1177/0032329298026004003 arXiv:https://doi.org/10.1177/0032329298026004003

[13] Decidim. [n. d.]. *Free open-source participatory democracy for cities and organizations.* https://decidim.org/

[14] Bairan Fu, Wenming Zhang, Guangneng Hu, Xinyu Dai, Shujian Huang, and Jiajun Chen. 2021. Dual Side Deep Context-Aware Modulation for Social Recommendation. In *Proceedings of the Web Conference 2021* (Ljubljana, Slovenia) *(WWW '21)*. Association for Computing Machinery, New York, NY, USA, 2524–2534. https://doi.org/10.1145/3442381.3449940

[15] Insee. 2020. *Age pyramid in France (French).* Insee. https://www.insee.fr/fr/statistiques/2381472

[16] Insee. 2020. *Socio-professional category by gender and age in France (French).* Insee. https://www.insee.fr/fr/statistiques/2489546

[17] Rafael Kallis, Andrea Di Sorbo, Gerardo Canfora, and Sebastiano Panichella. 2019. Ticket Tagger: Machine Learning Driven Issue Classification. In *2019 IEEE International Conference on Software Maintenance and Evolution (ICSME)*. 406–409. https://doi.org/10.1109/ICSME.2019.00070

[18] J. A. Khan, Y. Xie, L. Liu, and L. Wen. 2019. Analysis of Requirements-Related Arguments in User Forums. In *2019 IEEE 27th International Requirements Engineering Conference (RE)*. 63–74. https://doi.org/10.1109/RE.2019.00018

[19] Antti Knutas, Victoria Palacin, Giovanni Maccani, and Markus Helfert. 2019. Software Engineering in Civic Tech a Case Study about Code for Ireland. In *Proceedings of the 41st International Conference on Software Engineering: Software Engineering in Society* (Montreal, Quebec, Canada) *(ICSE-SEIS '19)*. IEEE Press, 41–50. https://doi.org/10.1109/ICSE-SEIS.2019.14

[20] Victoria Laurent, Romain Badouard, Clément Mabi, Cécile Méadel, and Guillaume Sire. 2018. Les outils numériques gouvernementaux au service de la loi: le design de la plateforme République numérique. *Terminal. Technologie de l'information, culture & société* 122 (2018). https://doi.org/10.4000/terminal.2071

[21] Daniel Lévy-Bruhl, Jean-Claude Desenclos, Sylvie Quelet, and François Bourdillon. 2018. Extension of French vaccination mandates: from the recommendation of the Steering Committee of the Citizen Consultation on Vaccination to the law. *Eurosurveillance* 23, 17 (2018), 18–00048.

[22] G. Longford and C. Hurrell. 2007. *Online Citizen Consultation and Engagement in Canada.* IGI Global, Hershey, PA, USA, 1261–1267. https://doi.org/10.4018/978-1-59140-789-8.ch191

[23] Arthur Lupia. 1994. Shortcuts Versus Encyclopedias: Information and Voting Behavior in California Insurance Reform Elections. *American Political Science Review* 88, 1 (1994), 63–76. https://doi.org/10.2307/2944882

[24] Brendan Luyt. 2015. Debating reliable sources: writing the history of the Vietnam War on Wikipedia. *Journal of Documentation* 71, 3 (01 Jan 2015), 440–455. https://doi.org/10.1108/JD-11-2013-0147

[25] Claire Oger. 2013. *Fondements et formes de l'autorité en discours.* Habilitation à diriger des recherches. CELSA, Université Paris-Sorbonne, Paris, France.

[1] Erasure of oppositions between different points of view and the production of signs of the evidence of a single point of view, assumed transparent (translated from [25]).

[26] Judith S. Olson, Dakuo Wang, Gary M. Olson, and Jingwen Zhang. 2017. How People Write Together Now: Beginning the Investigation with Advanced Undergraduates in a Project Course. *ACM Trans. Comput.-Hum. Interact.* 24, 1, Article 4 (March 2017), 40 pages. https://doi.org/10.1145/3038919

[27] Lawrence Page, Sergey Brin, Rajeev Motwani, and Terry Winograd. 1999. *The PageRank Citation Ranking: Bringing Order to the Web.* Technical Report 1999-66. Stanford InfoLab. http://ilpubs.stanford.edu:8090/422/

[28] Cristhian Parra, Christelle Rohaut, Marianne Maeckelbergh, Valerie Issarny, and James Holston. 2017. Expanding the Design Space of ICT for Participatory Budgeting. In *Proceedings of the 8th International Conference on Communities and Technologies* (Troyes, France) *(C&T '17)*. Association for Computing Machinery, New York, NY, USA, 213–221. https://doi.org/10.1145/3083671.3083702

[29] The Computational Democracy Project. [n. d.]. *Polis.* https://compdemocracy.org/Polis/

[30] Usha Nandini Raghavan, Réka Albert, and Soundar Kumara. 2007. Near linear time algorithm to detect community structures in large-scale networks. *Phys. Rev. E* 76 (Sep 2007), 036106. Issue 3. https://doi.org/10.1103/PhysRevE.76.036106

[31] Bogdan Vasilescu, Vladimir Filkov, and Alexander Serebrenik. 2013. StackOverflow and GitHub: Associations between Software Development and Crowdsourced Knowledge. In *2013 International Conference on Social Computing*. 188–195. https://doi.org/10.1109/SocialCom.2013.35

[32] Jeremy K Ward, Florian Cafiero, Raphael Fretigny, James Colgrove, and Valérie Seror. 2019. France's citizen consultation on vaccination and the challenges of participatory democracy in health. *Social Science & Medicine* 220 (2019), 73–80.

[33] Jianshu Weng, Ee-Peng Lim, Jing Jiang, and Qi He. 2010. TwitterRank: Finding Topic-Sensitive Influential Twitterers. In *Proceedings of the Third ACM International Conference on Web Search and Data Mining* (New York, New York, USA) *(WSDM '10)*. Association for Computing Machinery, New York, NY, USA, 261–270.

[34] W. Xing and A. Ghorbani. 2004. Weighted PageRank algorithm. In *Proceedings. Second Annual Conference on Communication Networks and Services Research, 2004.* Institute of Electrical and Electronics Engineers, Fredericton, NB, Canada, 305–314.

APPENDIX: DATA TABLES FOR SECTION 5 (ALSO AVAILABLE ON THE GIT REPOSITORY)

Table 3: Amount of replies to contributions of all types for each category of the consultation

Part	Chapter	Section	Nb. of Proposals	Arguments			Modifications			Sources			Votes		
				Q1	Med	Q3	Q1	Med	Q3	Q1	Med	Q3	Q1	Med	Q3
Part I	Chapter 1	Section 1	160	1	2	5	0	0	1	0	0	0	14	24	81
		Section 2	47	1	2	5	0	0	1	0	0	0	7	23	48
		Section 3	33	1	3	6	0	0	1	0	0	0	9	23	75
		Whole chapter	240	1	2	5	0	0	1	0	0	0	11	23	76
	Chapter 2	Section 1	59	0	2	5	0	0	0	0	0	0	10	24	52
		Section 2	25	1	2	6	0	0	1	0	0	1	8	26	203
		Whole chapter	84	0	2	5	0	0	1	0	0	1	10	24	81
	Whole part		324	1	2	5	0	0	1	0	0	0	10	24	77
Part II	Chapter 1	Section 1	30	1	4	6	0	0	1	0	0	0	11	24	62
		Section 2	19	0	1	2	0	0	1	0	0	0	4	14	21
		Section 3	23	1	2	6	0	0	0	0	0	0	8	15	29
		Section 4	31	0	1	4	0	0	0	0	0	0	8	12	39
		Whole chapter	103	1	2	6	0	0	1	0	0	0	8	16	48
	Chapter 2	Section 1	82	0	1	3	0	0	0	0	0	0	4	9	27
		Section 2	19	0	2	10	0	1	1	0	0	1	8	42	248
		Whole chapter	101	0	1	4	0	0	1	0	0	0	4	11	43
	Whole part		204	0	2	5	0	0	1	0	0	0	6	13	48
Part III	Chapter 1	Section 1	60	0	1	3	0	0	1	0	0	0	3	8	30
		Section 2	30	1	2	5	0	0	1	0	0	0	4	10	28
		Whole chapter	90	0	1	4	0	0	1	0	0	0	4	9	28
	Chapter 2	Section 1	19	1	3	5	0	0	1	0	0	1	5	13	37
		Section 2	12	0	3	5	0	0	1	0	0	0	4	25	83
		Whole chapter	31	1	3	5	0	0	1	0	0	1	5	16	83
	Chapter 3	Section 1	13	2	3	6	0	1	1	0	0	0	23	114	396
		Section 2	14	0	3	4	0	0	1	0	0	0	3	13	76
		Section 3	16	1	4	10	0	0	3	0	0	0	12	52	174
		Whole chapter	43	1	4	6	0	0	1	0	0	0	12	51	185
	Whole part		164	1	2	5	0	0	1	0	0	0	4	13	70

Table 4: Amount of replies to governmental contributions of all types for each category of the consultation

Part	Chapter	Section	Nb. Proposals	Med. Arguments	Med. Modifications	Med. Sources	Med. Votes
Part I	Chapter 1	Section 1	3	44	32	3	1319
		Section 2	1	38	30	3	892
		Section 3	3	23	19	1	777
		Whole chapter	7	38	27	1	892
	Chapter 2	Section 1	1	25	49	2	822
		Section 2	2	40	12	1	706
		Whole chapter	3	40	49	2	822
	Whole part		10	38	27	1	822
Part II	Chapter 1	Section 1	1	40	24	1	1426
		Section 2	1	47	38	0	796
		Section 3	2	24	16	1	379
		Section 4	1	31	24	2	488
		Whole chapter	5	38	24	1	669
	Chapter 2	Section 1	6	23	16	0	495
		Section 2	1	35	26	1	853
		Whole chapter	7	25	26	1	561
	Whole part		12	28	24	1	561
Part III	Chapter 1	Section 1	1	22	41	2	368
		Section 2	2	9	7	5	226
		Whole chapter	3	13	7	5	368
	Chapter 2	Section 1	1	21	10	5	392
		Section 2	1	81	30	6	1380
		Whole chapter	2	21	10	5	392
	Chapter 3	Section 1	1	19	24	7	498
		Section 2	1	45	22	5	408
		Section 3	1	24	11	5	833
		Whole chapter	3	24	22	5	498
	Whole part		8	21	11	5	392