Good Social Media: Constructing An Alternative Content-Ranking Algorithm for Social Network Sites

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Considering social media's wide adaptation within the last two decades, current content-ranking algorithms within social network sites have become increasingly influential. The problematic influences that content-ranking have affect societies and democracies on large scale. It, therefore, becomes increasingly relevant to research and conceptualize alternative content-ranking algorithms in order to mitigate problematic consequences. This paper utilizes literature research and expert validation in order to conceptualize such an alternative. The proposed content-ranking algorithm proposed within this research, thus, aims to further mitigate problematic consequences within social network sites.

Additional Key Words and Phrases: Social Media; Content-ranking; Algorithm; Echo Chambers; Mental Health; Misinformation.

1. INTRODUCTION

With estimates of social media platforms nearing 3 billion users [11], the effects of humanity's increasing dependency on social media functionalities become incredibly relevant. In current state, social media has extended much beyond merely a communicative tool, where platforms such as Instagram, Facebook and YouTube have additionally transitioned into entertainment platforms for users. Furthermore, traditionally non-social services such as Spotify, are expanding into social-media territory through feature additions such as `following` users and `blending` playlists. With an increase in social media usage, the effects of such usage are relevant to analyse. Particularly, the negative consequences of such increased usage and its relation to content-ranking methodologies within current social media. Research has established social medias' relation to political bias, misinformation and poor mental health [5], [9], [14]. These influences extend much beyond the individual, as social media adaptation such as YouTube, Facebook and Instagram dominate the online landscape, with 81%, 68% and 40% of surveyed United States adults, respectively, reporting ever having used these sites [3]. Its wide adaptation stresses the importance of research, as even small influences can greatly impact a large subset of the world. Ultimately, the impacts for the individual [5], [9], [14] can cause great harm for democracies and social well-being. It becomes incredibly relevant to analyse these negative effects and conceptualize a content-ranking solution as it may solve many of these issues.

2. PROBLEM STATEMENT

The increasing influence of social media, strengthened by the problematic consequences displayed in research (e.g., political bias, misinformation and poor mental health [5], [9], [14]) create a particularly vulnerable state for societies. This vulnerability becomes incredibly problematic when multinationals and governments leverage this to do harm. Additional problematic consequences may include influencing citizens to vote against their own interest and distracting voters from political participation [14]. A further legitimate concern arises when unknowing users spread misinformation, where such a spread may have harmful implications for metrics such as health literacy [12]. Overall, the problematic implications these consequences have on mental health, democracies, health literacy, freedom of thought and more, display a course of dangerous developments. The immense growth and adaptation of social media, combined with current content-ranking algorithms display a need for research to propose an alternative solution. This paper will use the identified problematic consequences to conceptualize an alternative to current content-ranking algorithms within social network sites, aiming to further mitigate problematic consequences.

2.1 Research question

In order to structure and subdivide this objective, the following research question is used:

What alternative content-ranking algorithm within social network sites can further mitigate problematic influential mechanisms?

Which is further divided into sub-questions:

I. What information fuels current social media content-ranking algorithms?
II. How do current content-ranking algorithms strengthen social medias' problematic consequences?
III. What alterations to current social media content-ranking algorithms can mitigate problematic consequences?

3. METHOD

The structure of this research can be divided into three key steps, where the model elaboration within the paper is aimed to respect the selected design science guidelines [8].

The first step pertains to conducting further literature research. This entails analysing current content-ranking algorithms, particularly how these strengthen problematic consequences [5], [9,10], [12-14]. To do this effectively, research is collected using both a systematic and non-systematic literature search. The systematic literature search utilizes Google Scholar, with key search terms "social media" or "social network site", extended throughout multiple queries using terms "political effects",

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"mental health", "effects" and "addiction". The non-systematic literature search relies on a network of teachers, researchers and university students to recommend journals and studies. The literature research conducted within this step functions to produce a thorough understanding of problematic consequences stemming from current content-ranking algorithms.

Second, an alternative content-ranking algorithm will be proposed using the findings from the previous literature research as justification. Its objective is to mitigate problematic consequences by understanding and identifying weaknesses within current content-ranking algorithms. In order to test, alter and display the functionality of the model, mathematical input functions, diagrams and a pseudocode implementation will be created. The model will be elaborated on through the use of mock-up designs and examples to display its functionality within a practical example.

The third key step pertains to the validation of the model. The constructed conceptualization discussed in the previous step, will require validation by knowledgeable experts such as scientists, policy advisors or industry experts, to ensure its viability. This step requires the finding and contacting of experts through e-mail, telephone contact or other means. This research aims to contact two experts, with expertise from a scientific and industry perspective, respectively. Furthermore, the validation and feedback acquired within this step will reflect the model implementation by continuously strengthening the algorithm in an iterative process.

4. RELATED WORK

In order to effectively deconstruct problematic consequences of current content-ranking algorithms, the analysis can be separated into two key sections. First, the observation and understanding of consequences, and second, the identification of associated causes. Several problematic consequences of social media are thoroughly documented within numerous scientific papers. For instance research displaying social media's strengthening effect on anxiety, depression and loneliness [5]. With further research displaying additional, broader negative effects of social media on mental health [10]. Problematic consequences of social media furthermore extend to instances of social media addiction [9]. By conducting two studies, the research [9] finds empirical evidence suggesting social media addiction is associated with reduced academic performance and mental health due to a lowered self-esteem. Social media's negative effects on self-esteem are also found within research studying the role of social comparison within social media [13]. After an initial baseline survey, the study sends participants five surveys per day via email with questions focused on emotional status and their social media use. The study concluded with a post-test questionnaire, followed by a statistical analysis. The research found a positive relation between increased social comparison and diminished self-esteem [13]. The reduced mental health effects displayed within a multitude of papers highlight a concerning pattern of problematic consequences. Additional negative consequences highlighted in research include the prevalence of misinformation and bias, particularly how social media relates to voting, misinformation, xenophobia and political polarisation [14]. The literature review discusses how echo chamber effects may lead to increased political polarisation and may additionally create a landscape where governments, corporations and terrorist organisations abuse misinformation to distract, manipulate and harm citizens. The paper [14] is, therefore, particularly relevant for this research as it directly discusses problematic consequences of recommender systems and content-ranking in relation to a number of causes. Namely it discusses how echo chambers (or filter bubbles), contribute to problematic consequences, giving direction with respect to what aspects of current content-ranking require attention. It infers that research analysing social media recommender systems is, therefore, additionally relevant as the cause of problematic consequences may be identifiable. Research [1], therefore, gains further relevancy as its systematic literature review discusses differences, similarities and adoption rates of social media recommender techniques. The paper highlights the popularity of data mining combined with "clustering" or "k-nearest neighbour" classification. Both being techniques that require user data to classify recommendations.

Further relevant work includes the "Solid project" [4], an open-source web decentralization project aiming to repair the internet through radically re-imagining data-managing infrastructure for applications. The project allows users to manage data permissions through a storage system using "pods". The user can manage what information is accessible to applications by granting access to partitions of a pod. The project incentivizes users to regain control of their data, aiming to mitigate problematic consequences created by the internet.

The listed research displays how social media is in great need of repair. Social media's problematic consequences relating to mental health and misinformation are particularly alarming. It stresses the importance of repair-focused initiatives such as the Solid project [4] to further help mitigate problematic consequences of the internet and social media.

5. REQUIREMENTS

In order to accurately assess the requirements for an alternative content-ranking algorithm, the sub-questions this research poses must be answered.

5.1 What information fuels current social media content-ranking algorithms?

Research displays how social network content-ranking and recommender algorithms utilize data-mining techniques to classify users and content [1]. The predictive learning capabilities of current content-ranking and recommender algorithms stem from using metrics that indicate a high likeliness of interaction. With variations per social-media platform, a shared focus to prolong user activity results in data relating to user information. Examples of such data includes the title and description of liked groups, attended events, liked pages and articles [1]. However, with an increasing complexity of algorithms and growing user bases, additional metrics including minutes of watch-time, number of comments, comment complexity, saves, click-through-rate and watch history, become increasingly relevant.

5.2 How do current content-ranking algorithms strengthen social medias' problematic consequences?

Several problematic consequences within social media are displayed to connect with echo chamber effects of social media [14]. Current content-ranking algorithms actively contribute to echo chamber effects by favourably ranking content with a high likeliness of interaction. The likelihood of “cross-cutting content” is lowered, strengthening dangers of fake news and misinformation campaigns [7], [14]. Additionally, this method of content-ranking provides a poor representation of real life. The algorithm favours high-interaction content, resulting in a timeline where only users’ highlights are shown. The positive relation between increased social comparison and reduced mental health [13], therefore, may connect to the poor representation of real life within social media timelines. Furthermore, current content-ranking algorithms focus on prolonged user activity, suggesting it may, additionally, heighten occurrences of social media addiction. Thus, leading to reduced mental health and academic performance [9].

5.3 What alterations to current social media content-ranking algorithms can mitigate problematic consequences?

Current social media content-ranking contains several factors that contribute to problematic consequences. This research identifies four key components within content-ranking that require prioritisation in order to further mitigate problematic consequences (See Table 1).

Table 1. List of Requirements

Nr	Requirement
1	Heterogeneity
2	Representativeness of real life
3	Transparency
4	User Benefit

First, the **heterogeneity** of ranked content. With the interaction-based indexing of current content-ranking algorithms contributing to echo chamber effects [14], the algorithm displays itself as non-functional. An alternative algorithm is required to preserve diversity of content, whilst still maintaining relevancy of content. Thus, a more heterogenic timeline must be constructed. Second, the **representativeness of real life** within social network sites. Rather than actively providing users a communicative tool to connect friends, family and interest, current social media content-ranking focuses on prolonged user activity and monetary profit. With timelines transforming into highlight-reels and entertainment, it infers that current social network sites fail to accurately represent real life. Third, the **transparency** of content-ranking**.** Current content-ranking and recommender algorithms can be considered a `black-box`. Social network sites provide little or no information on the exact functions used to rank and recommend user content. Additionally, often no personalisation features are provided for users to manage content-ranking and which data is used to feed the algorithm. This leaves corporations with great responsibility and power, as these algorithms influence what consumers see on a daily basis. Furthermore, users are often not aware that corporations make these decisions, further heightening its influential strength. Fourth, an inherit aim to **benefit the user**. At its core, current content-ranking algorithms strive to prolong user activity. With the problematic consequences displayed in research [5], [9,10], [12-14], the lack of regard for a user’s mental health or else, is evident. The addictive nature of current content-ranking and recommender algorithms disregards the `best-interest` of the users, as it merely prioritizes prolonging user activity in order to maximise profit.

6. MODEL

Having established the primary shortcomings and alterations needed, an alternative content-ranking algorithm can be constructed.

6.1 Pseudo-Chronological

$$\begin{aligned} &\text{x} := 36.0 + (\ 4\ /\ \text{active\_hours}\ ) + (\ 2 \\ &*\ \text{last\_online}\ ) \\ &\text{priority\_time} := \text{x} * \text{fav\_strength} \\ &\text{ppt} := \text{post\_time} - \text{priority\_time} \end{aligned} \tag{1}$$

In order to increase the **heterogeneity** of content within the content-ranking algorithm, the exclusion of content within a timeline must be prevented. For this, a chronological content-ranking solution is fully functional as it is non-discriminatory when displaying posts. However, a strictly chronological ranking system may lower the relevancy of content. In order to include a form of relevancy indexing, **transparency** and active **benefits to the user**, this research proposes a `pseudo-chronological` content-ranking algorithm. The proposed ranking algorithm is chronological in its foundation, however, additionally allows users to strengthen relevancy ranking of selected profiles by increasing a *fav_strength* variable.

Table 2. List of Variables used within Formula

Variable	Description
Fav_strength	Relevancy index, adjustable by the user.
Last_online	Number of hours since the user was last active online.
Active_hours	User activity (in hours) within the last 72 hours .
PPT (Priority Post Time)	Position index for posts in *fav_list*
Reg_list	List containing posts by non-favourited users posts or with a PPT greater than 0.
Fav_list	List containing posts by favourited users with a negative PPT.
Post_time	Passed hours since publishment of a post, additionally functions as position index for *reg_list*.
Priority_time	Number of priority hours gained if user is favourited.

This value is a priority strength factor ranging from 0 to 1, where a higher value prioritizes its position on the timeline. The *fav_strength* variable is only included in calculation for favourited profiles. Prior to this calculation, the algorithm separates posts made by favourited and regular profiles into variables *fav_list* and *reg_list*, respectively. It infers that for favourited profiles, the PPT (Priority Post Time) is its primary ranking metric, influenced by a number of variables. Both *last_online* and *active_hours* influence the factor strength of *fav_strength*. A higher *last_online* value strengthens the influence of *fav_strength*, whereas a higher *active_hours* value lowers the effects of *fav_strength* on a post's timeline ranking. Finally, both the *post_time* and *priority_time* are used to calculate the PPT. This value is leading in the ranking for the fav_list with one exception. If the calculated PPT is positive number, a post it removed from *fav_list* and appended in *reg_list*. This exception functions as a tool to clean up the timeline and limit the influence of *fav_strength*. *Reg_list* is then sorted chronologically, whereas *fav_list* is sorted ascending on PPT. Using the two sorted lists, a final timeline is constructed through alternating between *fav_list* and *reg_list*. If no items are left in either list, items of the complementing list are appended to construct the final timeline.

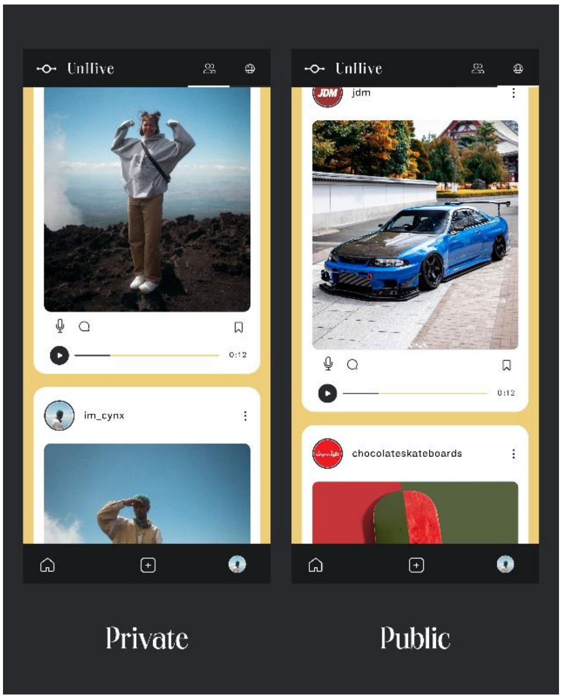

Fig1. Example Implementation of Timeline Split

6.2 Split Timeline

In order to heighten the **representativeness of real life** within content-ranking, this research must allow users to `genuinely` connect with friends and family. To ensure these connections are valued and do not drown within interaction-based ranking, this model suggests an alternative solution. To more accurately represent daily life, this model separates the conventional timeline by unidirectional and bidirectional connections (See Figure 1). In essence, two timelines are created where each represents public and private space, respectively. This separation allows for a clear distinction between user relations to profiles and user content. This method aims to separate friends and family from influencers, news outlets, celebrities and public figures. It allows users to easily check on their inner circle without losing the functionality of entertainment within social network sites. The separation of unidirectional and bidirectional content can, however, be implemented in numerous ways. One such implementation would be to differentiate between followers and friends. User classification using this method would list posts by friends within the personal timeline, whilst followers would be listed within the public timeline.

6.3 Advertisement and Suggested Content

With a corporate focus on monetary profit, it is relevant to note that a poor implementation of this model may severely lower the viability of the proposed alternative content-ranking algorithm. To preserve the model's initial objective and heighten its **representativeness of real life** within content-ranking, the integrity of the timeline split is of the utmost importance. This requires the private timeline to stay true to its functional and symbolic purpose. Both advertisements and suggested content should, therefore, be restricted to the public timeline.

7. EXPERT VALIDATION

In order to create further value in this research, the proposed alternative content-ranking algorithm requires validation. This research aims to confirm the viability of the proposed model by consulting two experts. First, Janina Pohl, a research assistant at the chair of Professor Trautmann. Pohl has reportedly worked with stream mining algorithms on social media data at the University of Münster. Second, Bart Ensink was consulted, a digital strategist at Little Rocket. Both meetings followed similar structure, for which several discussion points were key parts of the interaction (See Table 3).

Table 3. List of Key Discussion Points

Nr	Discussion point
1	State of the algorithm.
2	Viability of the model.
3	Alterations to the research approach that could improve its effects.
4	Points that should be further focused on.

7.1 Expert: Janina Pohl

The validation of the proposed content-ranking algorithm was discussed with Pohl through a 45-minute Microsoft Teams call on the 19th of December. During the meeting, the model consisted of a rough framework, rather than a complete algorithm. Within this framework two potential algorithms were discussed. First, a content-ranking algorithm, strictly focused on profiles followed by the user. Second, an additional recommender algorithm to strengthen the public timeline in order to further mitigate problematic consequences.

The framework for the content-ranking algorithm contained several objectives, namely that it:

- Show content semi-chronologically.
- Must allow users to favour profiles for timeline positioning.
- Must not stack the favourited content with frequent inactivity.

- Split the conventional timeline to represent private and public space.

The framework for the additional recommender algorithm had the following objectives, that it:

- Must suggest content beyond a user's network in order to further lower echo chamber effects of content-ranking.
- Suggest content within a category relevant to the user. For instance, Fox News followers would receive suggested content by CNN of BBC in order to display different perspectives.
- Be strictly placed within the public timeline.

Although at an incomplete state, Pohl expressed belief that the suggested content-ranking framework posed a viable solution. Particularly how allowing users to manage their own timeline would be extremely valuable, being further in line with Pohl's "ideal" content-ranking algorithm. Pohl seemed further in support of the algorithm's intent to prevent favourited content from cluttering the timeline and utilizing user activity to manage the influence of *fav_strength*. For the additional recommender algorithm, however, Pohl expressed further consideration was required. Its intent to suggest relevant content outside a user's network whilst retaining a form of category indexing would substantially increase the model's complexity. Pohl suggested that using randomization could potentially pose a solution, however, that this would require further research and consideration. An additional alteration to the research approach suggested by Pohl was the inclusion of power users to further validate the model. Such feedback could further improve the quality of the proposed model as it would give additional perspective on its viability. During the closing of the meeting, Pohl reiterated how considering the scope of this research, focusing strictly on the timeline split and pseudo-chronological algorithm would strengthen the quality of this research due to the conceptual value of the proposed alternative content-ranking algorithm.

7.2 Expert Feedback: 1

In order to strengthen the viability of the model, several implementation alterations were made due to Pohl's feedback. First, in order to sufficiently prioritize the viability of the split timeline and pseudo-chronological algorithm, the additional recommender algorithm found itself excluded. Additionally, the model implemented a combination algorithm which alternates between *fav_list* and *reg_list* to construct the final timeline. As Pohl agreed, ensuring favourited content does not stack and clutter the timeline is of high importance. The combination algorithm is, therefore, an additional precaution to ensure this cluttering is prevented.

7.3 Expert: Bart Ensink

The second validation of this research was an in-person meeting on the 18th of January with Bart Ensink at the Little Rocket office in Enschede, the Netherlands. Following a brief introduction to the scope of the research, the proposed content-ranking solution discussed in Chapter 6 was presented and discussed. A particularly interesting observation made was how Ensink considered more than merely the conceptual viability of the model. Although Ensink deemed the presented content-ranking solution viable, its practicality from a business perspective had yet to be thoroughly considered. Ensink posed questions such as "how would a business make money?" and "what value would the average consumer see in such an alternative content-ranking algorithm?". The discussion questioned how implementation of the proposed content-ranking algorithm would create a sustainable business model whilst retaining the integrity of the algorithm. Essentially, what restrictions and suggestions are worth adding in order to ensure businesses do not create additional problematic consequences by mis-interpreting the proposed model in this research. Ensink thus found the alternative content-ranking algorithm proposed in this research viable, however, lacking in its elaboration on implementation. In order to verify the model's functionality and viability, Ensink suggested creating a prototype. The created prototype could then aid with user testing or other forms of verification.

7.4 Expert Feedback: 2

Due to time constraints little alterations were implemented using Ensink's feedback. However, Ensink's business-oriented perspective proved incredibly valuable as this research failed to address restrictions and suggestions. Primarily, the elaboration of the model was expanded upon with the addition of Chapter 6.3. This chapter discussed additional implementation guidelines in order to preserve the integrity of the content-ranking algorithm proposed in this research. However, due to the limited scope of this research, suggestions such as the creation of a prototype for user testing, cannot be realised. Additional suggestions made by Ensink are, thus, valuable considerations for future research.

8. DISCUSSION AND FUTURE RESEARCH

Through the use of a pseudo-chronological structure and split timeline, this research poses a potential alternative to current content-ranking algorithms. With the use of literature research and expert validation, the model displays its potential viability to further mitigate problematic influential mechanisms. It is however evident that this research is merely a first step. Considering the scope of this research, its limitations stress a need for additional research to display the viability of this model. Future research could display test its viability through a controlled experiment or prototyping (as suggested by Bart Ensink). Further research could conceptualize a recommender algorithm that aims to mitigate problematic consequences. This could further strengthen the functionality of the public timeline elaborated on in this research. Ultimately, this research provides detailed insights into how an alternative content-ranking algorithm may further mitigate problematic influential mechanisms.

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APPENDIX A: PSEUDOCODE IMPLEMENTATION

```
function createTimeline(posts : list of posts)

    fav_list, reg_list, final_list := empty list

    // calculate ppt
    for p in posts do
        if (p.fav < 0) then
            reg_list.push(p)
        else
            priority_time := (36.0 + (4 / active_hours) + (2 * last_online)) * p.fav
            time := p.post_time – priority_time
            p.ppt := time

            if (time < 0) then
                fav_list.push(p)
            else
                reg_list.push(p)


    fav_list.sort(key:=lambda x: x.ppt)
    reg_list.sort(key:=lambda x: x.post_time)


    // combine lists
    n := length(reg_list)
    m := length(fav_list)

    for i in range(n + m) do
        if ((i-1) / 2 < n) and ((i / 2) < m) then
            if (i % 2 == 0) then
                append fav_list[i / 2] to final_list
            else
                append reg_list[(i - 1) / 2] to final_list
        else
            if ((i - 1) / 2 < n) then
                append reg_list[i - m] to final_list
            else
                append fav_list[i - n] to final_list

    return final_list
```