Personalized Algorithms: AI's Role in Information Overload

Personalized Algorithms: AI's Role in Information Overload

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Abstract

In today's always-connected society, AI-driven recommendations in social media have become a staple of internet usage, significantly shaping users' consumption experiences. This research investigates the extent to which such personalized algorithms may induce information overload and anxiety in regular users, contrary to their intended purpose. Drawing on prior literature exploring the potential negative effects of personalized algorithms, this paper presents findings from a controlled lab experiment conducted using the TikTok platform. Participants (N=44) engaged with their own personalized For You Page, as well as a neutral, human-curated feed, over the course of two separate days; measures of perceived state anxiety and information overload, as well as pre- and post-experiment heart rate, were recorded for each session. In support of the hypothesis, results indicate that participants experienced significantly higher levels of overload and anxiety when exposed to the personalized AI-driven recommendations, compared to the control condition. These findings emphasize the importance of understanding prominent algorithms and their effects on users' well-being, essential both for platform development and the formation of technology policy.

Introduction

How do AI-driven recommendations and algorithms in social media contribute to information overload and anxiety? This research question is central to today's digitally connected media world, with the proliferation of online content and growing reliance on artificial intelligence powered algorithms that personalize information consumption. While information overload is not a new phenomenon, the ability to consume mass amounts of information in mere minutes brings it to the forefront of current technology design challenges. Constantly being bombarded with personalized suggestions, especially on platforms such as TikTok that boast extremely personalized algorithms, may actually lead to increased information overload and anxiety, contrary to their intended purpose. Information overload can lead to fatigue, anxiety, reduced decision making ability, and difficulty evaluating information, so by investigating this question we can understand how to mitigate these negative effects via effective design principles.

Background

The issue of information overload began receiving increased attention with the widespread adoption of the internet and social media. In the early days of sites such as Facebook, users' feeds followed a chronological order, until innovative algorithms were developed to personalize information consumption and keep users engaged, as well as reduce overload (Raza et al., 2022). Previous research claims that accurately identifying user interests and providing relevant content is a critical component of algorithmic success; accurate filtering and ranking of information are essential for personalized recommendations to effectively alleviate information overload on social networking sites (Koroleva et al., 2012). While some research does suggest that user satisfaction is greater when recommended content accurately aligns with user interests, uses and gratifications theory, as proposed by Elihu Katz in 1959, suggests that user satisfaction varies depending on the user's motivation for using the personalized service (Liang et al., 2006). Uses and gratifications theory claims that media users access information with a purpose, and play an active role in selecting a specific source and certain information to consume. Accordingly, previous research has found that platform satisfaction is higher when the user is actively searching for social interaction, but lower when using the site for escape or entertainment (Liang et al., 2006). This discrepancy leaves room to investigate when personalized recommendations may be ineffective, or even harmful.

Prior research indicates that personalized recommendations are effective in mitigating overload (Liang et al., 2006, Koroleva et al., 2012, Feng et al., 2021). However, there is a research gap that fails to address the potential negative effects of such algorithms. From the limited amount of previous research on such negative effects, the following has been proposed. Despite the expectation that personalized recommendation algorithms efficiently alleviate information overload by filtering out information deemed irrelevant to each individual, users may still be overloaded by the sheer volume of recommended information (Huang et al., 2020). In a 2016 survey study in which the researchers hypothesized that higher perceived relevance would correlate with lower perceived levels of information overload, no such relationship was actually found (Lee et al., 2016). One potential explanation for these findings is that information consumption that exceeds one's cognitive capacity, regardless of relevance, distracts one from real life, which then results in anxiety surrounding one's inability to "disconnect." Another potential explanation is that an information quantity threshold exists, at which the relationship between information relevance and information overload reverses. Below this threshold, increased relevance reduces overload, but above the threshold a greater quantity of information intensifies overload. Regardless of which theorized explanation is accurate, or a different explanation altogether, it is clearly demonstrated here that greater relevance does not always result in reduced overload. The researchers of this study also hypothesized that greater information overload would increase social networking service fatigue, and, as predicted, found that information overload was in fact a significant stressor influencing fatigue. This finding emphasizes the importance of studying information overload in the context of social media.

Also contrary to more prominent literature, research using the stressor-strain-outcome framework found that the greedy recommendation feature characteristic of TikTok's algorithm can actually induce information overload (Ma et al., 2021). A greedy recommendation algorithm is one that selects the choice most immediately rewarding on each step, without considering potential long-term consequences. The stressor-strain-outcome framework, as proposed by Koeske and Koeske in 2010 to reevaluate the burnout phenomenon, claims that stressors from information systems or technology induce strain on the individual, eventually affecting the outcome of user behavior. A stressor is a stimuli perceived to be disruptive, and the strain is the actual disruptive influence of the stressor on one's mental or emotional well-being. The outcome is then the individual's response to the strain. In the case of this study, the stressors were information narrowing, redundancy, and overload, the strain was user exhaustion, and the outcomes were psychological reactance and discontinuance intention. The experimenters used an online survey to collect data from users of the Chinese short-form video platforms Douyin, Kuaishou, and Bilibili. Douyin is the Chinese version of TikTok. The survey included questions regarding user discontinuance, psychological reactance, exhaustion, information narrowing, information redundancy, information overload, and greedy recommendation. Analysis found that greedy recommendations were positively related to information narrowing, redundancy, and overload – all of which were positively related to user exhaustion. User exhaustion predicted psychological reactance, which was then positively related to discontinuance intention. This research not only revealed the potential ineffectiveness of greedy recommendations in minimizing overload, but also demonstrated a correlation between such recommendations and increased overload in the context of short-form video platforms. The additional relationships between exhaustion, psychological reactance, and discontinuance intention once again underscore the importance of understanding the potential adverse effects of personalized recommendation algorithms.

Though this perspective has received less attention in traditional information overload discourse, there is clearly a subset of research suggesting personalized recommendation algorithms are not as effective as they are touted to be. As discussed above, technology overload, which ecompasses information, communication, and system feature overload, contributes significantly to social networking service fatigue, and thus is critical to understand in order to implement effective design strategies that minimize negative user effects (Lee et al., 2016).

The decision to implement a personalized recommendation algorithm is a design choice made in an attempt to keep users engaged with the platform, however, these algorithms may be exacerbating the issue of information overload in the internet age. In this way, information overload can be viewed as a design issue itself, caused by the misuse of information technology (Roetzel, 2018). In exploring potential solutions to this issue, ideas that have been proposed include the development of selective-exposure and diversity-aware algorithms, the improvement of information seeking self-efficacy in users, and informational nudging by the system itself (Raza et al., 2021; Schmitt et al., 2017; Fabbri, 2023).

Aims & Objectives

Previous research investigating the negative side of recommendation algorithms relies primarily on survey methodology, using Likert scales for participants to rate their perceived overload based on regular usage. To expand previous research, the current study used an experimental design that closely emulated real-world consumption habits by exposing participants to their personal TikTok "For You" pages. TikTok is the optimal platform for this experiment since prior research found a relationship between the greedy feature characteristic of TikTok's recommendation system and information overload (Ma et al., 2021). It was hypothesized that when exposed to personalized AI-driven recommendations (Experimental Condition), participants would experience greater information overload and anxiety than when exposed to a neutral, human-curated feed (Control Condition) because content that is so precisely tailored to the user's interests may lead them to feel overwhelmed by suggestions of what to do, buy, or believe, that actually apply to their lives. While this approach does incur some limitations – including the fact that individual participants will scroll at varying rates, resulting in a different amount of total videos viewed – by not controlling this aspect, it was possible to more accurately replicate regular consumption habits, placing a greater focus on how users engage with the TikTok algorithm itself.

Methods

Design & Participants

This experiment used a within-subjects design comparing two conditions, that is a personalized, AI-driven feed, and a neutral, human-generated feed. According to G*Power, in order to obtain a medium effect size (.5), this experiment required a sample size equal to or greater than 44 participants. A total of 50 participants were recruited from the Lehigh University student population. Ultimately, 44 participants were included in the analysis, all of whom were compensated with two $10 Amazon gift cards. The participants consisted of 30 female participants and 14 male participants between the ages of 18-23. From the original 50 participants recruited, six were excluded from analysis due to missing their second experimental session. No participants with prior awareness of the experiment's hypothesis were included, and all participants regularly use TikTok for at least two hours per week. This time requirement was imposed to ensure that the user is active enough on the platform for the algorithm to closely tailor itself to their interests.

Materials

In order to establish the conditions, participants engaged with their own "For You" pages on their personal smartphones for the Experimental Condition, since the TikTok algorithm specifically tailors content to each individual user. While each participant viewed a different set of videos, this approach was the most precise way to measure the effects of the greedy personalized recommendation algorithm characteristic of the TikTok platform. For the no-recommendations Control Condition, a random selection of TikTok videos was compiled, accessible from the user's personal smartphone, ranging widely in topic and length that, in its entirety, had a run-time of at least two hours. This feed was developed by manually searching for and selecting each video and adding it to a "liked" folder under an account called @personalizedalgorithms; the "liked" videos were made publicly visible, and thus could be accessed via the participant's own TikTok account. The user experience of scrolling through this "liked" selection of videos mimics the experience of scrolling on the For You Page. The two hour timeframe accounted for the fact that participants were unlikely to watch the entirety of every video, and avoided the potential for participants to run out of videos before the experimental period was over. Participants underwent each condition for a duration of one hour. The length of this interval was chosen in an attempt to ensure that participants were engaging with the platform for enough time to observe potential trends in overload, anxiety, and heart rate.

Participants' perceived overload and anxiety were measured using established instruments that prompted them to respond to a series of questions on a Likert scale. Questions assessing information overload were modified from Karr-Wisniewski and Lu (2010), and those assessing state anxiety were adapted from the State-Trait Anxiety Inventory, developed by Spielberger et al. (1983). All survey questions are detailed in the Appendix. Participants' heart rates were measured using a pulse oximeter and recorded with their participant code immediately prior to and following each experimental session, acting as a physiological measure of overload and anxiety. It has been previously demonstrated that information overload causes anxiety, and state anxiety has been seen to manifest in an elevated heart rate and a decrease in heart rate variability, making heart rate a suitable supplementary measure of overload and anxiety (Renjith, 2017; Spielberger, 1979; Dimitriev, 2016).

Procedure

Upon arriving at the lab, participants were directed to a private room, separate from any other participants. Participants were then instructed to thoroughly read and sign an informed consent form, and ask any questions they may have prior to participating. Participants' heart rates were measured and recorded immediately prior to the start of the scrolling session.

Participants were then instructed to begin the experimental period, either by accessing their personal For You Page, or by navigating to the curated collection of videos, which was accessible via their personal device. Participants were instructed to scroll through the videos as they would regularly do outside of the lab for the entire duration of the experimental period. An alarm was set to accurately time the experimental session. This study employed a within-subjects design, with all subjects engaging in both conditions over the course of two days, with at least one week between the two sessions. The order of conditions was counterbalanced across participants. The one week delay accounted for the potential that the For You Page of participants who engaged with the control (human-generated) feed first may have been affected by their hour of scrolling through non-personalized videos. Since each participant uses TikTok for at least two hours each week, this delay allowed enough time for the algorithm to re-adjust to their preferences.

Participants' heart rates were measured and recorded again immediately following the completion of the scrolling session. Following the experimental period, participants completed a questionnaire via Qualtrics, consisting of questions measuring current perceived information overload and state anxiety (see Appendix). Responses were made using a 7-point Likert scale (*1 = strongly agree, 7 = strongly disagree).* Participants were then compensated, thanked, and reminded to return for the second session. At the conclusion of the second session, participants were debriefed.

Results

Outcomes were analyzed using Paired Samples t-Tests to determine differences between the experimental and control conditions in levels of perceived information overload, state anxiety, and pre-and post-experiment heart rate. A significant effect of condition was predicted for all outcome measures. A significant difference was predicted in pre- and post- differences in heart rate between the two conditions. In sum, heightened information overload and anxiety were expected as a result of engaging with the personalized AI-driven recommendations.

Results of Paired Samples t-Tests revealed significant differences between the experimental (*M*=106.80, *SD*=13.98) and control conditions (*M*=100.84, *SD*=15.62) in state anxiety levels as measured by the STAI ($t(43)=2.39$, $p=0.02$, $d=0.36$). Results also demonstrated a significant difference in feelings of overwhelm due to the amount of information processed ($t(43)=2.11$, $p=0.04$, $d=0.32$) between the experimental (*M*=5.11, *SD*=1.40) and control conditions (*M*=4.64, *SD*=1.62). These findings are visually represented in Figures 1 and 2, respectively.

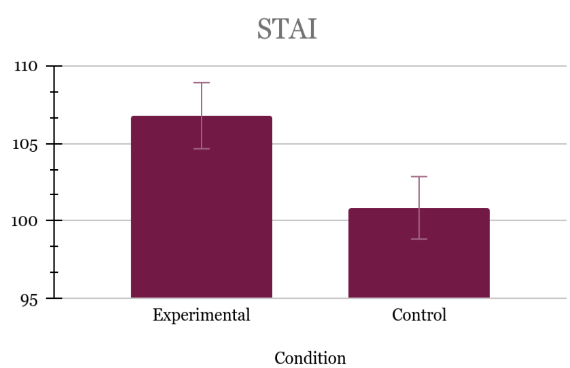

Figure 1. State Anxiety Levels. Comparison of state anxiety levels between experimental and control conditions.

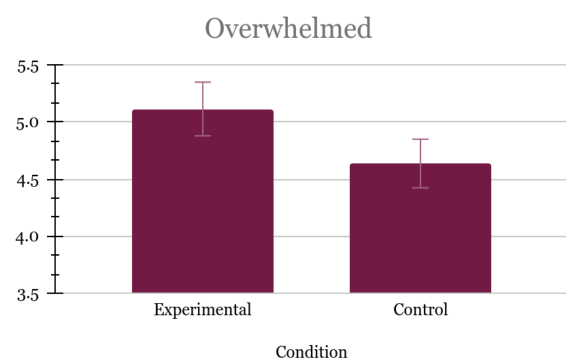

Figure 2. Feelings of Overwhelm. Comparison of feelings of overwhelm between experimental and control conditions.

There was also a marginally significant difference between the experimental (*M*=4.16, *SD*=1.82) and control conditions (*M*=3.64, *SD*=1.81) in feelings of having viewed too much information to synthesize and put to use ($t(43)=1.76$, $p=0.09$). This comparison is depicted in Figure 3.

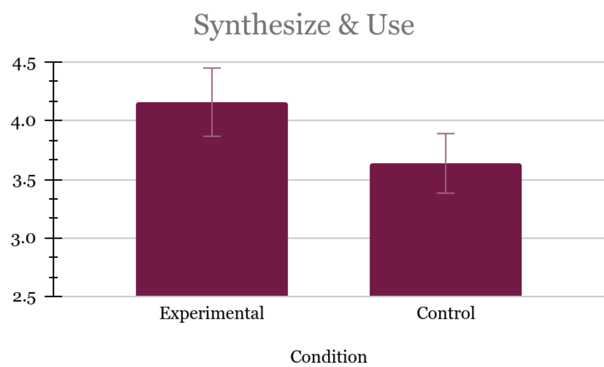

Figure 3. Feelings on Synthesis and Use. Comparison of feelings of having viewed too much information to synthesize it and put it to use between experimental and control conditions.

No significant difference was found between the experimental (M=-4.14, SD=17.34) and control conditions (M=-7.21, SD=14.61) in pre-post heart rate ($t(43)=1.09$, $p=0.28$).

These results support the hypothesis that participants experience greater overload and anxiety when exposed to personalized AI-driven recommendations than when exposed to a neutral, human-curated feed.

Discussion

The results of this study provide valuable insights into the complex nature of integrated AI, specifically in the realm of algorithmic personalization. Contrary to the majority of current information overload discourse, exposure to the hyper-personalized TikTok For You Page was associated with higher levels of anxiety, overwhelm, and feelings of an inability to synthesize and use the information one consumed. While personalized recommendation systems may have been developed in part to combat information overload, it is clear that their role is not quite that straightforward.

It is unclear exactly why hyper-personalization was found to be associated with higher levels of anxiety and overwhelm, but one potential reason is that users feel suffocated by suggestions that actually apply to their own lives. When viewing a random selection of videos, it is likely that a large number of the videos will be disregarded, as they are not found to be of any interest to a particular individual. However, when viewing a selection of videos that is highly curated to one's tastes, it is likely that the user is actively engaging with a higher proportion of the videos, and more carefully considering the information in each one, thus increasing cognitive load. Additionally, following from uses and gratification theory, social media often serves as an escape, implying the desire for surprise. However, personalized recommendations reinforce existing preferences, reducing novelty and blurring the line between information and entertainment seeking.

The discrepancy highlighted here between the perceived and actual effects of personalized recommendation algorithms underscores the importance of reevaluating how media platforms are designed. TikTok's algorithm maximizes engagement by keeping users entertained with a personalized feed, but platform designers should consider the broader effects of these algorithms on users' well-being. As mentioned previously, design strategies that promote diverse content and facilitate information seeking self-efficacy in users may help to combat information overload and anxiety in online environments. Since it is possible that a less personalized feed may reduce engagement on certain platforms, the implications of this study's findings must be considered by those in a position to create technology policy, in order to protect users for whom these sites are ingrained in their daily lives.

According to Eric Schmitt, former CEO of Google, as of 2010 we were creating just as much information every two days as humans did from the start of civilization until 2003 (Siegler, 2010). Fourteen years later, the exponential growth of online content continues, making information overload and anxiety critical to mitigate in order to avoid a parallel growth of mental exhaustion and decision making impairment, among other effects. This research highlights the need for a more nuanced understanding of the algorithms filtering this content, and by demonstrating the potential for negative consequences of hyper-personalization, also informs ongoing discussions about the design and regulation of social media platforms.

Limitations

The use of a within-subjects design and standardized procedures, along with the control condition and counterbalancing the order of conditions across participants, helped to ensure internal validity. This study also had high ecological validity, as the lab experiment closely emulated real-world consumption habits. However, future research replicating this study across diverse platforms, timeframes, and age-groups would help to establish the generalizability of findings.

Other limitations include potential confounding variables that may have affected heart rate measurements and self-report questionnaire responses. Lehigh University is located on a mountain, so participants' heart rates may have been elevated when they arrived, depending on how they traveled to the lab. Seeing as there was no significant difference in pre-post heart rate between the experimental and control conditions, such effects may have invalidated heart rate as a supplementary measure of anxiety. Additionally, external stressors may have influenced participants' responses to the questions regarding state anxiety. Future research might consider including secondary assessments such as a cognitive load or implicit association test, in order to further capture overload and anxiety.

A final limitation that should be considered is whether the participants considered their For You Page to be precisely personalized, and the curated feed to be truly random. It is possible that a participant actually found the curated feed to be relatively personalized to their tastes, despite efforts to compile a diverse selection of videos. Since participants knew what condition they were engaging with during each session, this may have reduced said potential effect by creating an expectation for the level of personalization they were about to experience. It is also possible that a participant's personalized content itself was objectively more anxiety inducing than the control content, contributing to the resulting effects. Future research may want to include a manipulation check to ensure that the correct level of personalization was achieved for each condition.

Conclusion

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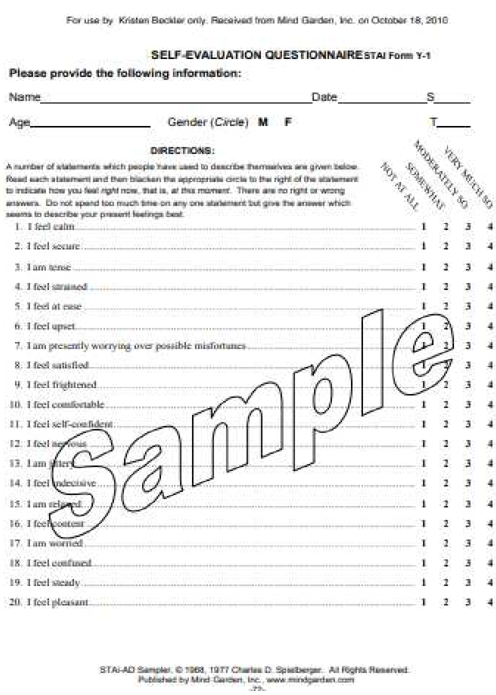
Appendix

Questions assessing information overload are modified from Karr-Wisniewski and Lu, 2010.

1. I feel disoriented by the excessive amount of information consumed during this TikTok scrolling session.
2. I am overwhelmed by the amount of information that I just processed during this TikTok scrolling session.
3. I just viewed too much information during this TikTok scrolling session to synthesize it and put it to use.

Questions assessing state anxiety are adapted from Spielberger et al., 1983.



For use by Kristen Beckler only. Received from Mind Garden, Inc. on October 18, 2010

SELF-EVALUATION QUESTIONNAIRE STAI Form Y-1

Please provide the following information:

Name________ Date________ S____

Age________ Gender (*Circle*) **M** **F** T____

DIRECTIONS:

A number of statements which people have used to describe themselves are given below. Read each statement and then blacken the appropriate circle to the right of the statement to indicate how you feel right now, that is, at this moment. There are no right or wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe your present feelings best.

	NOT AT ALL	SOMEWHAT	MODERATELY SO	VERY MUCH SO
1. I feel calm	1	2	3	4
2. I feel secure	1	2	3	4
3. I am tense	1	2	3	4
4. I feel strained	1	2	3	4
5. I feel at ease	1	2	3	4
6. I feel upset	1	2	3	4
7. I am presently worrying over possible misfortunes	1	2	3	4
8. I feel satisfied	1	2	3	4
9. I feel frightened	1	2	3	4
10. I feel comfortable	1	2	3	4
11. I feel self-confident	1	2	3	4
12. I feel nervous	1	2	3	4
13. I am jittery	1	2	3	4
14. I feel indecisive	1	2	3	4
15. I am relaxed	1	2	3	4
16. I feel content	1	2	3	4
17. I am worried	1	2	3	4
18. I feel confused	1	2	3	4
19. I feel steady	1	2	3	4
20. I feel pleasant	1	2	3	4