# Information Overload and User Satisfaction: Balance Between Reliance on Recommendations and Deliberate News Selection

Zhixin Pu<sup>1</sup>, Michael A. Beam<sup>2</sup>

<sup>1</sup> The Pennsylvania State University, 8 Carnegie Building, State College, United States <sup>2</sup> Kent State University, 334 Franklin Hall, Kent, United States

#### Abstract

High content relevance of news recommendations is a key factor for personalized user experiences. Personal factors, such as seeking/scanning and goal commitment, also impact information overload and user satisfaction in news recommender systems. This experimental study using data from 669 Amazon MTurk workers tests a theoretical process of news selection in news recommender systems. We manipulated two key elements of the news recommendation system: relevance of news article recommendations and the presence of a search bar. Results indicated that recommendation systems providing more irrelevant news recommendations results in users selecting more irrelevant articles and reporting higher information overload and lower satisfaction. Though we did not find evidence that seeking news with a search bar would positively influence goal commitment compared with those scanning a news recommendation overload and user satisfaction.

#### **Keywords**

Information overload, news selection, personalization, news recommender systems, user satisfaction, goal commitment

## 1. Introduction

The internet opens access to a flood of news information to users, leading to difficulties of news information processing and decision making. Recommendation systems and personal news portals are frequently used sources of health-related news, such as Google searching. These systems reorder and prioritize news information to maximize relevance to the user [1, 2]. The pre-selection of information in recommendation systems alters traditional information processing process via algorithm-selected news information, which may reduce information overload. Research on recommendation systems in different contexts has resulted in contradictory findings relative to reduced information overload [3, 4]. For example, recommendation systems can offer users a way to seek specific information using a search bar or scan for specific information after presenting several linked items. The potentially differential impact of information seeking and scanning has not been investigated relative to information overload. This study aims to compare seeking and scanning to clarify the effectiveness and elucidate the theoretical process of recommendation systems on information processing.

Algorithmically personalized systems prioritize the most relevant information [1,2] and have been related to information overload reduction [5,6]. However, other work on personalized recommendation systems has found overall relevance on SNSs [7] or personalized news portals [8] as not significantly predictive of information overload. Although past studies have indicated the benefits of relevant recommendations on combating information overload, the relationship between recommendations and

ORCID: 0000-0002-2293-0845 (A. 1); 0000-0003-2425-2010 (A. 2); © 2021 Copyright for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).



INRA'21: 9th International Workshop on News Recommendation and Analytics, September 25, 2021, Amsterdam, Netherlands EMAIL: <u>zmp5110@psu.edu</u> (A. 1); mbeam6@kent.edu (A. 2).

the information selection process remain understudied. This paper also explores how the relevance of recommendations impacts information overload and user satisfaction through users' news selection choices in the context of two common information behaviors: information scanning and seeking.

Although high relevance of recommendations decreases information overload, users still experience difficulties selecting certain articles to read when facing several related-article recommendations [9]. Relying on the ranking of recommender systems may mitigate choice overload. However, the efficacy of recommender systems and users' reliance on the recommender systems to help select relevant articles for decision making is under studied. Our study offers a 2x2 experiment where we manipulated the relevance of recommendations and whether users are scanning or seeking in the recommendation system. We rely on two metrics of selection behaviors. First, we measured the number of articles selected by users at the top of the recommended list. Second, we measured the number of irrelevant articles selected by users. Taken together, we use these selection metrics to explore to what extent users rely on the recommendation system for filtering. In addition, we argue that goal commitment is a key individual difference that should impact information overload.

In sum, this study adds to the literature by illustrating the process of how the efficacy of news recommendation systems impact news selection, which in turn affects information overload and user satisfaction. We explore how this process differs in the context of news seeking and news scanning. The study enhances our theoretical understanding of how people select and consume information with the aid of filtering recommendation systems with quantitative evidence about the impact of relevance in recommender systems on users' news consumption. The study also provides practical suggestions regarding leveraging recommender systems efficiently. The study also indicates the importance of relevance and goal commitment in the design of news recommender systems.

## 2. Literature Review

## 2.1 Information Overload

Scholars have not reached a consensus on a universal agreed definition of information overload [10, 11,12]. Some scholars refer information overload as exposure to diverse issues [13, 14, 15]. For example, Klapp [16] described the concept as the rate of information that is too high for individuals to digest, which triggers distraction, stress, errors in information processing stage. Hiltz and Turoff [17] claimed people are overloaded without the capability of filtering useful information among a plethora of information. One consistent explanation of information overload is that people are overwhelmed when they can't process excess information. Thus, we define information overload as the sensation experienced when people encounter excess information that they cannot process.

Prior researches have shown that several variables trigger information overload including demographics [18], levels of internet use [19], frequency of news access, level of attention to news, and interest in news [18].

#### 2.2 Relevance, news selection, and information overload

Relevance refers to any pattern that attracts our attention and requires interpretation by individuals .We define relevance in recommender systems similar to the definition proposed by Pazzani et al. [20], which refers to the information vector between individuals' topic interests and suggested news items. Relevance of an item is widely discussed and applied in the design of news recommender systems to predict and offer useful and accurate content to users. Collaborative filtering [21] and content filtering were approaches to recommend relevant news articles to users.

Another common technique for filtering is "top N" recommendations, which aims to provide a small set of relevant articles to each user [22]. Content listed in the "top N" position was selected based on a highest predicted ratings approach [23], and was predicted to be the ones that are be of interest to users

and are more likely to be clicked by users. Relevant recommendations were believed to assist with news selection process. Top articles and relevant articles are the ones that are predicted to receive high click rates. Relevant recommendations were also believed to reduce information overload and increase user satisfaction. That is to say, relevance impacts news selection. Highly relevant recommendations predict more top articles and less irrelevant articles selected by users. News selection further impacts information overload and user satisfaction. More top articles and less irrelevant articles selected by users predict lower information overload and lower user satisfaction in high relevance condition, while the situation might not hold true in low relevance condition. Thus, we propose that:

H1: Highly relevant recommendations are a) negatively correlated with the number of irrelevant articles read, and b) positively correlated with the number of top articles read.

H2: More irrelevant articles read by users are correlated with a) higher information overload and b) lower user satisfaction.

H3: More top articles read by users are correlated with a) lower information overload and b) higher satisfaction for those who receive more relevant recommendations.

H4: High relevance of recommendations is directly correlated with a) lower information overload and b) higher user satisfaction.

H5: High relevance of recommendations is indirectly correlated with a) lower information overload and b) higher user satisfaction.

### 2.3 Scanning/Seeking, news selection, and information overload

Seeking information and scanning information are two actions that are related to one basic need [24]. Information seeking, defined as goal-oriented information searching [24], differs from information scanning when individuals may read information without clear information seeking purposes in opportunistic browsing [25]. Existing research about news recommender systems rarely explores the difference between scanning and seeking on news selection. Though browsing articles on a certain topic and searching for information might not determine levels of information overload, the goal commitment of finding answers for questions might influence news selection, further impacting information overload and user satisfaction. Uses and gratifications theory [26] illustrated that users choose specific media to satisfy their needs. Users are satisfied when their information need is met by finding information on the recommender systems. High goal commitment is more likely to increase user satisfaction and decrease information overload when the information needs are met. However, low goal commitment indicated low information needs and thus may not lead to higher user satisfaction or impact information overload.

In addition, news selection mediates users' satisfaction and information overload. People with high goal commitment are more determined to find certain information and thus may read fewer irrelevant articles and read more top articles as suggested by the system. The phenomenon of relying on the recommendations is named algorithm dependence, similar to media dependency [27], where users are dependent on media to select news information. People with algorithm dependence are more likely to consume the news articles suggested by recommender systems, including consuming more top articles. Thus, we propose:

H6: Information seeking is correlated with higher goal commitment compared with information scanning.

H7: Higher goal commitment is correlated with a) fewer irrelevant articles read and b) more top articles read.

H8: Higher goal commitment is directly correlated with a) lower information overload and b) higher user satisfaction.

H9 Higher goal commitment is indirectly correlated with a) lower information overload and b) higher user satisfaction.

## 3. Method

## 3.1 Experimental Design, Manipulation, and Experimental Materials

The study contained a 2 (information behavior: seek/scan) X 2 (relevance: high / low) experimental design to test the impacts on information overload and user satisfaction. Participants in the information scanning group scanned twenty articles while participants in the information seeking group were required to type keywords in a search bar and search for articles (see Figure 1). Participants were randomly assigned to seek/scan articles on one of the two topics, which were "Why am I so tired?" and "What causes high blood pressure?" The two topics were both listed in the top 10 health questions people searched on Google in 2017 [28] and 2018. No certain causes were affirmed by Google while multiple causes of tiredness and several risk factors of high blood pressure were introduced in the articles. 10 news irrelevant to either topics were selected from the health section of Google news. Articles were between 500-600 words long.

**News Portal** 



Figure 1: First page of the web portal from the scanning condition.

Participants in high relevance group were exposed to sixteen articles relevant to their topic and four articles irrelevant to their topic, among them the top three articles were all relevant articles. Correspondingly, the low relevance group were exposed to ten relevant articles and ten irrelevant articles, where two of the top three articles were irrelevant articles. All the articles were randomly selected and sorted despite manipulating the number of relevant articles presented on the page. In other words, the manipulation controlled the relevance of articles in the top three positions rather than specifying a position for a certain article. For instance, the top three articles were relevant articles in high relevance condition. The three relevant articles were randomly selected from the dataset and the top three articles were randomly sorted. The rest of the articles were also randomly selected from the dataset and randomly sorted.

Regardless of the experimental conditions, all participants were required to choose 3 articles from the news portal to read. They were given instructions before entering the portal (See Figure 2). Once in the portal, participants could see news article headlines with a small preview of the article and were required to click "Read More" if they wanted to select the article to read (See Figure 3). Three pop-ups were designed to remind participants about their reading status. For instance, a popup after participants

selected the second article that said, "You just selected the second article. Please read the article then select 1 more article most relevant to the causes of being tired" (See Figure 4). A button "click here to go to survey" appeared at the bottom of the third article selected by the participants. Participants were then sent to a questionnaire in Qualtrics. Users answered a manipulation check question and an attention check question then proceeded to answer the survey measures detailed below.

News Portal



## Figure 2: Second page of the web portal.

#### News Portal

#### Common Causes of Fatigue

By Nancy Schimelpfening, Verywellmind. If you find yourself sleeping until the last possible second before dragging yourself out of bed, you may be wondering, "Why am I always tired?" Or maybe you just don't have the energy to get things done the way you once did. Fatigue and a lack of energy are a big problem for many people, but these problems can only be addressed if you know what is wrong. If you are feeling constantly tired, the first thing you should do is see your personal physician for a checkup. Your doctor can take a careful history, perform a physical exam, and...

Read More

#### Sleep and tiredness

By NHS Staff, NHS. Why am I tired all the time? Feeling exhausted is so common that it has its own acronym, TATT, which stands for "tired all the time". We all feel tired from time to time. The reasons are usually obvious and include: too many late nights long hours spent at work a baby keeping you up at night. But tiredness or exhaustion that goes on for a long time is not normal. It can affect your ability to get on and enjoy your life. Why you might be tired all the time Before you see a GP, you may want to… Read More

#### Why you feel tired all the time

By Jasmin Collier, Medical News Today. Do you often ask yourself, "Why am I so tired all the time?" If so, this article may be the perfect read for you; we have compiled a list of some of the most common reasons for tiredness and what you can do to bounce back into action. Everyone feels tired at some point in their lives — whether it's due to a late night out, staying up to watch your favorite TV show, or putting in some extra hours at work. Often, you can put your finger on the reason you're not feeling... Read More

#### Figure 3: General view of the news page.

Read Less	
Sleep and tiredness	
We all feel tired from time to time. The reasons are usua	
<ul> <li>too many late nights</li> <li>long hours spent at work</li> <li>a baby keeping you up at night</li> </ul>	You just selected the second article. Please read the article then select 1 more article most relevant to the causes of being tired.
But tiredness or exhaustion that goes on for a long time enjoy your life.	ok
Why you might be tired all the time	
<ul> <li>parts of your life, such as work and family, that m</li> <li>any events that may have triggered your tirednes</li> <li>how your lifestyle may be making you tired</li> </ul>	

Figure 4: Second pop-up instructing users to read one more article.

Eight web portals were designed to conduct the experiment. The information seeking group were directed to type in keywords in a search bar to proceed to the portal. All the participants were required to read three articles. Afterwards, they proceeded to the questionnaire in Qualtrics. The content was set to be 70% width on desktop browsers and full width in mobile browsers. Web log data was inadvertently collected by the experimental news portal software, including the condition, the sequence of articles selected, the specific articles selected, time reading each article, and search term for those in the seeking condition.

## 3.1.1. Experimental Materials

The materials were gathered from an actual Google search using the queries "Why am I so tired?" and "What causes high blood pressure?" separately. All the articles returned on the first two pages were collected on June 24, 2019 and July 4, 2019 and tailored. In total, nineteen articles about being tired and sixteen articles about high blood pressure were collected. Ten articles irrelevant to either topic were also collected on June 24, 2019 and July 4, 2019 from Google News under the category of health news (sorted by date). Topics that contained information that might elicit strong negative emotions were excluded. The lengths of all articles were tailored to vary from 510 to 599 words. Sixteen articles relevant to each topic and the ten irrelevant articles were retained.

## 3.1.2. Participants

G\*Power recommended a minimum sample size of 619 to test the proposed hypothesis. 834 participants were recruited from Amazon MTurk. Survey data with wrong answers to the attention check question, duplicate IP, and incomplete ones were filtered out. After merging the web log data and the survey data, incomplete ones, such as the cases that do not contain web log data, were deleted. In

addition, 14 cases from the seeking condition that did not follow the instructions to type in relevant keywords in the search bar were deleted. The final dataset contains 669 participants. Participants were 18-74 years old. 35.7% of them were males, and 62.3% were females. 44.1% of participants have college and above education level and 75.8% were white.

## 3.1.3. Manipulation Check

Participants answered manipulation check questions when they entered the questionnaire after they completed reading the news articles in the experimental news portal. Participants answered three questions regarding the scanning and seeking condition including, "I typed in keywords and searched for information about [certain topic]", "The web portal retrieved news about [certain topic] after I typed in keywords", and "The web portal presented information about [certain topic] without asking me to type in keywords". The scanning score was calculated by the average of the reversed score of the first questions. As expected, the scanning condition showed a significantly higher score (M = 5.09, N = 333) on scanning than seeking group (M = 2.61, N = 336) (F(1, 665) = 334.56, p < .000). For the same groups, the seeking condition showed a significantly higher score (M = 3.37, N = 333) (F(1, 665) = 394.96, p < .000).

Participants were also asked two manipulation check questions regarding the news article relevance manipulation including, "A majority of articles I saw on the web portals are relevant to the topic of [certain topic]", and "The first three articles on the top of the web portal are all relevant to the topic of [certain topic]". Answers vary from strongly disagree to strongly agree. The score of relevance is the average of the two questions. Participants in the high relevance condition (conditions 1-4) showed a higher score (M = 5.99, N = 262) than low relevance condition (M = 4.03, N = 272). The difference between groups is significant (F(1, 665) = 299.54, p < .000).

### 4. Measures

### 4.1 Information Overload

Information overload (M = 2.80, SD = 1.22) was measured using a four-item measure adapted from Stephens and Rains [29]. Participants rated statements indicating that the information they received through seeking or scanning needed too much explanation to be useful, the information they received was too much information to process, the information they received was more information than they needed, and the information they received was about the right amount of information participants needed. Information overload was reported in a seven-point Likert-scale ranging from 1 = strongly disagree to 7 = strongly agree. The last item was reversed coded. The scale was reliable ( $\alpha = .78$ ).

## **4.2 Goal Commitment**

Goal commitment (M = 5.13, SD = .88) was measured by the scale created by Hollenbeck, Williams and Klein [30]. The scale contained nine items, asking participants their feelings of finding information in the news portal. Sample Items included "It is hard to find news information", and "It was unrealistic for me to expect to find news information I'm interested in.". Several items were reverse coded guided by the scale instructions. However, one item in the scale was removed due to lack of reliability ( $\alpha = .55$ ). After deleting the item "It was quite likely that the process of finding news information may need to be revised, given how the information process went", the scale was reliable ( $\alpha = .72$ ). The final scale used in the paper had eight items.

## 4.3 Satisfaction

Satisfaction (M = 5.34, SD = .86) was measured by the Psychological Need Satisfaction and Frustration Scale [31]. The scale consisted of four subscales measuring satisfaction of autonomy, frustration of autonomy, satisfaction of competence, and frustration of competence. Each sub-scale contained four items and the overall scale contained sixteen items. Examples of the items were "I felt a sense of choice and freedom when I was looking for information on the news portal." and "I felt that my decision of selecting certain news information reflected what I really wanted.". Items in the subscales of frustration of autonomy and competence were reverse coded ( $\alpha = .89$ ).

## 4.4 Top Articles Selected by Users

Top articles selected was calculated using the participants' digital trace from the web portals. The web portals recorded the sequence of news articles and the article number selected by the users sequentially. The top articles refer to the number of the top three randomly displayed articles in the web portal that were selected by the participant. The number ranged from 0 - 3. Participants read 1.43 top articles on average (SD = .91).

### 4.5 Irrelevant Articles selected by Users

Similar to top articles selected by users, irrelevant articles selected by users were calculated based on the number of irrelevant articles selected by the user from the digital trace data. Results ranged from 0-3. Participants read .34 irrelevant articles on average (SD = .68).

### 5. Data Analysis Plan

The data analysis was completed using OLS regression. The indirect effects in the mediation models were calculated using the PROCESS macro v3.4 within SPSS Statistics 26 (Hayes, 2018). Four mediation model analyses were examined by PROCESS (model 4). The first two models started with the independent variable relevance, mediators a) numbers of irrelevant articles selected and b) numbers of top articles selected, ended with dependent variables information overload (model 1) and user satisfaction (model 2). The other two models started with mediator information seeking/scanning that impact goal commitment, independent variable goal commitment, two mediators a) numbers of irrelevant articles selected, and b) numbers of top articles selected, ended with dependent variable information overload (model 3) and user satisfaction (model 4).

### 6. Results

Four models were tested. The results and statistics of the models are reported in figures 5-8. The first two models tested the relationship between relevance of recommendations, the number of irrelevant articles read, the number of top articles read and information overload (see Figure 5) and user satisfaction (see Figure 6). The results showed a negative relationship between relevant recommendations and the number of top articles (H1a) and a positive relationship between relevant articles read by users was positively related with information overload (H2a) and negatively related with user satisfaction (H2b). H2 was supported. More top articles read by users was not related with information overload (H3a) or user satisfaction (H3b) as predicted. H3 was not supported. Relevance was positively related with information overload (H4a), while is not related to user satisfaction (H4b). H4 received partial support. High relevance of recommendations indirectly correlated with lower information overload (H5a) and higher user satisfaction (H5b). H5 was supported.



Figure 5: Model 1: How relevance impacts information overload. Note: \* p < .05; \*\* p < .01; \*\*\* p < .001



Figure 6: Model 2: How relevance impacts user satisfaction.

Note: \* p <.05; \*\* p < .01; \*\*\* p < .001

Models with seeking/scanning as the independent variable related to goal commitment, the number of irrelevant articles read, the number of top articles read and information overload (see Figure 7) and user satisfaction (see Figure 8) were also tested. The results did not indicate a relationship between seeking and goal commitment (H6). H6 was not supported. Goal commitment was negatively correlated with irrelevant articles (H7a) and positively correlated with top articles read (H7b). H7 was supported. Goal commitment is directly negatively correlated with information overload (H8a) and positively correlated with user satisfaction (H8b). H8 was supported. Goal commitment was also indirectly negatively correlated with information overload (H9a) and positively correlated with user satisfaction (H8b). H8 was supported. H9a) and positively correlated with user satisfaction (H9b). H9 was supported.



**Figure 7**: Model 3: How seeking/scanning impacts information overload. Note: \* p <.05; \*\* p < .01; \*\*\* p < .001



**Figure 8**: Model 4: How seeking/scanning impacts user satisfaction. Note: \* p <.05; \*\* p < .01; \*\*\* p < .001

## 7. Discussion

The paper explored the impacts of news recommendation relevance, information scanning vs. seeking, and goal commitment on information overload and user satisfaction via news selection. Existing research has rarely indicated how news selection processes are impacted by both algorithmic settings and personal factors, such as individual information behaviors or goal commitment, leaving a blank in sequential recommender systems research. The research also provides findings on user behaviors the context of in search engine recommendations.

Overall, high news recommendation relevance and high goal commitment predicts low information overload and high user satisfaction via news selection. Reading behaviors including scanning and

seeking did not impact goal commitment, contrary to our expectation. However, goal commitment positively impacted news selection, information overload, and user satisfaction. In addition, the design of the recommender systems, including the relevance for the top three articles and overall relevance in the recommendations impacted users' news selection. Users' news selection predicted information overload and partially user satisfaction. These results indicate that the design of recommender systems should consider focusing on user motivations, such as goal commitment.

The first finding was regarding news recommendation relevance, news selection, information overload, and user satisfaction. The results indicated that users read fewer irrelevant articles when being exposed to a great proportion of highly relevant recommendations. The finding is consistent with the existing literature that has found that recommendations influence users' news selection where users are more likely to read popular stories in the recommendation condition [32]. However, the finding also illustrated that user selection might be limited by recommended content since users can only select from the recommendations. We expand the existing literature, by illustrating the significant impacts of relevant recommendations on users' news selection and subsequent information overload and satisfaction perceptions. What's more, the finding indicated that when being exposed to more irrelevant articles, users selected more irrelevant articles. This, in turn, led to greater information overload perceptions. The reason for this finding might be choice overload, where users confronting similar related-articles recommendations and experience difficulties selecting certain articles for use [9]. Another explanation might be the reliance on news recommendations. The peripheral processing route in the dual process theories [33] helps explain the mechanism when users limits cognitive effort to make a decision on news selection. Users are more likely to rely on recommendations when making news selection to minimize cognitive load.

Surprisingly, users did not incline to select more top articles when being exposed to high relevant recommendations. Although existing research found the significant impacts of ranking on user's news selection [34], and the merits of top N recommendations on identifying items fit users' tastes [35], the current study found that users might not always select top articles in more relevant recommendation conditions. Users actively select news articles with more relevant recommendations, which can be explained by the central route of dual processing model, where users are aware of and deliberately make choices. That is, when news recommendations are more relevant, users may have greater cognitive resources to peruse the full list of articles. More relevant recommendations might be a key factor to more freedom in news selection. Trust towards recommendations may cause more top articles selection as well. More trust on the recommendations led to more top articles selection. Cognitive load might be another cause of more top articles selection. Users with high cognitive load were more likely to select more top articles to save energies. We recommend future research explore trust as another potential explanatory variable.

Second, users' news selection in high or low relevance conditions impacted perceptions of information overload and satisfaction. Users are more likely to be more information overloaded, and less satisfied with their information autonomy when they read more irrelevant articles and more top articles. Consistent with existing research [3], the study also found the correlation between news recommender systems use and perceived information overload. Users might show self-doubt of their ability of online seeking/scanning, which caused higher information overload and less user satisfaction. Users in the low relevance conditions might have experienced frustration towards the recommendations, which also might have led to higher information overload and less user satisfaction.

In addition, the study also showed that users' news selection was correlated with information overload and user satisfaction, providing a more detailed description between news recommender systems and user interaction as proposed by [36]. Contradicting our prediction, reading more top articles lead to less user satisfaction. User autonomy of news selection might explain it, where users are unlikely to continue their interests in exploring the same topic with top N recommendations design.

Third, indirect correlations between relevance of recommendations and information overload were found. These indirect effects indicated that both recommendations and user's news selection impacted user experience in recommender systems. To design a personalized sequential recommender system, both algorithmic rules and users' news selection choices, which is also called the implicit user feedback, should be considered.

Browsing style (seeking or scanning) was proposed to indirectly impact information overload and user satisfaction via goal commitment. These relationships were not found in the study's results. In other words, users seeking or scanning news recommendations in search engines or web portals did not show different levels of information overload and user satisfaction. This finding might indicate that users spend similar amounts of effort looking for information when seeking or scanning for certain topics. Different recommender rules for seeking or scanning behaviors might not be a necessary.

Interestingly, the study found that users with higher goal commitment is correlated with fewer irrelevant articles and fewer top articles read. Uses and gratifications theory helps explain the news selection that users with high goal commitment were more likely to meet their information requirement when reading fewer irrelevant and top articles. Users might enjoy the exploration process of finding relevant information in either high or low recommendation conditions. It also indicates that recommender systems design needs to consider the level of users' goal commitment to provide a more personalized information retrieval atmosphere either with more top N recommendations or not. Consequently, users with high goal commitment are more likely to be less information overload and high user satisfaction. These results support the notion that users exerting control over recommendations [37] help relieve information overload.

The paper explored how users' news selection were impacted by both algorithmic rules and goal commitment, and impacted information overload and user satisfaction. It provided empirical evidence regarding how relevant impacts information overload and user satisfaction. What's more, it illustrated the detailed news selection process that increased the understanding about the interactions between users and recommendations. The study provided practical guidance to users that a higher goal commitment and agency leads to a more satisfied online information experience. We recommend system designers find ways to motivate their users' to be more deliberative while using their online recommendation systems. The study also contributed to the design of recommender systems, where users' news selection and personal factor, such as goal commitment could be considered as potential input of personalized algorithms. In addition, top recommendations, which calls for more user satisfaction. The study also found the potential reliance on recommendations, which calls for more user behavior studies.

Like all the other studies, the study owns its limitations, and we hope to conduct future research to fill in the gaps. First, we didn't manipulate goal commitment, while we did find it to be a key variable driving satisfaction and information overload. Future studies should focus on how to manipulate goal commitment. Second, we only consider news recommendation relevance. Future research could examine diverse conceptualizations of relevance and its impacts. Third, we only consider content filtering. Future studies could look at collaborative filtering and other filtering rules. Forth, future studies could explore when seeking and scanning differ in the outcomes of information behaviors. Fifth, future studies could also include more news selection measures and explore how user react to homogenous content and cognitive load. The study could also be further expanded to include sequential reading pattern where users' reading pattern is linked to information overload and user satisfaction. The exploration could provide a direct picture of first-hand user interactions towards the news recommendations. The study could also be replicated in other contexts, such as political news recommendations, for generalization.

### 8. Conclusion

In summary, the study explored how relevance of news recommendations and information scanning or seeking impact users' news selection, and information overload and user satisfaction. The study found the potential user reliance on recommendations and vulnerability of users receiving low quality recommendations. Recommendation relevance is a key factor impacting information overload and user satisfaction in the recommendation system. High relevance leads to lower information overload. In addition, user control is one factor to consider when designing a recommender system. Lastly, individual differences, such as differing goal commitment during the information selection process, is worth considering in recommendation system designs.

## 9. Acknowledgements

The research was funded by the John Paul Jones Memorial Trust Award in the Department of Communication at the University of Wisconsin-Milwaukee.

## **10.References**

- J. Freyne, S. Berkovsky, E. M., Daly, and W. Geyer, Social networking feeds: Recommending items of interest, in: Proceedings of the Fourth ACM Conference on Recommender Systems, 2010, pp. 277-280.
- [2] K. Koroleva, A. J. B. Röhler, Reducing information overload: design and evaluation of filtering & ranking algorithms for social networking sites, in: ECIS 2012 Proceeding, 2012, pp.12.
- [3] Jörg Matthes, Kathrin Karsay, Desirée Schmuck, and Anja Stevic. "'Too much to handle': Impact of mobile social networking sites on information overload, depressive symptoms, and well-being." Computers in Human Behavior 105 (2020). https://doi.org/10.1016/j.chb.2019.106217
- [4] Ramondt, Steven, and A Susana Ramírez. "Assessing the impact of the public nutrition information environment: Adapting the cancer information overload scale to measure diet information overload." *Patient education and counseling* vol. 102,1 (2019): 37-42. doi:10.1016/j.pec.2018.07.020
- [5] R. Cohen, N. Sardana, K. Rahim, D. Y. Lam, M. Li, and O. Maccarthy, Reducing information overload in social networks through streamlined presentation: a study of content-centric and person centric contexts towards a generalized algorithm, in: 3rd Workshop on Incentives and Trust in E Communities, 2014, pp.13-18.
- [6] M. Chen, Y. Chen and C. Tseng, "SocFeedViewer: A Novel Visualization Technique for Social News Feeds Summarization on Social Network Services," in 2013 IEEE 20th International Conference on Web Services, Honolulu, HI, USA USA, 2012 pp. 616-617. doi: 10.1109/ICWS.2012.76
- [7] Ae Ri Lee, Soo-Min Son, Kyung Kyu Kim. Information and communication technology overload and social networking service fatigue: A stress perspective. *Computers in Human Behavior*,vol. 55(A) (2016): 51-61.https://doi.org/10.1016/j.chb.2015.08.011
- [8] Beam, Michael A., and Gerald M. Kosicki. "Personalized News Portals: Filtering Systems and Increased News Exposure." Journalism & Mass Communication Quarterly, vol. 91, no. 1, Mar. 2014, pp. 59–77, doi:10.1177/1077699013514411.
- [9] Felix Beierle, Akiko Aizawa, and Joeran Beel. Exploring Choice Overload in Related-Article Recommendations in Digital Libraries. 2017. ArXiv:1704.00393 [Cs]. <u>http://arxiv.org/abs/1704.00393</u>
- [10] Bawden, David, and Lyn Robinson. "The Dark Side of Information: Overload, Anxiety and Other Paradoxes and Pathologies." Journal of Information Science, vol. 35, no. 2, Apr. 2009, pp. 180– 191, doi:10.1177/0165551508095781.
- [11] H. Butcher, In meeting managers+ information needs. 1998. pp. 53. London: CIMA.
- [12] Angela Edmunds, and Anne Morris. "The problem of information overload in business organizations: a review of the literature." International Journal of Information Management, vol. 20, no.1, 2000, pp.17–28, doi: <u>https://doi.org/10.1016/S0268-4012(99)00051-1</u>.
- [13] Elizabeth J. Burge. Learning in computer conference contexts: The learners' perspective. Journal of Distance Education, vol. 9, 1994, pp.19-43.
- [14] Joel Rudd, and Mary Jo Rudd. "Coping with information load: User strategies and implication for librarians". College and Research Libraries, vol. 47, no.4, 1986, pp. 315-322.
- [15] Saima Khalid, Mihammad Saeed, and Sehrish Syed. "Impact of information overload on students' learning: An empirical approach." FWU Journal of Social Sciences, vol. 10, no.1, 2016, pp. 58–66.
- [16] O. E. Klapp, Overload and boredom: Essays on the quality of life in the information society. Connecticut: Greenwood Press. 1986.

- [17] S. R. Hiltz, and M. Turoff. "Structuring computer-mediated communication systems to avoid information overload." Communications of the ACM, vol. 28, no.7, 1985, pp. 680-689.
- [18] S. K. Lee, K. S. Kim, and J. Koh. "Antecedents of news consumers' perceived information overload and news consumption pattern in the USA." International Journal of Contents, vol. 12, no.3, 2016, pp. 1-11.
- [19] C. E. Beaudoin. "Explaining the relationship between Internet use and interpersonal trust: Taking into account motivation and information overload." Journal of Computer-Mediated Communication, vol. 13, no. 3, 2008, pp. 550-568
- [20] M. Pazzani, M. uramatsu, and D. Billsus, Syskill & webert: Identifying interesting web sites. In: Proceedings of the 13thNational Conference on Artificial Intelligence, 1, 1996, pp. 54-61.
- [21] F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, Recommender Systems Handbook. Springer US, 2011.
- [22] Z. Zolaktaf, R. Babanezhad, and R. Pottinger, A generic top-N recommendation framework for trading-off accuracy, novelty, and coverage, in:2018 IEEE 34th International Conference on Data Engineering (ICDE), 2018, pp. 149–160. doi: <u>https://doi.org/10.1109/ICDE.2018.00023</u>.
- [23] L. Coba, P. Symeonidis, & M. Zanker, Replicating and improving top-N recommendations in open source packages, in Proceedings of the 8<sup>th</sup> International Conference on Web Intelligence, Mining and Semantics, 2018, pp.1–7. doi:https://doi.org/10.1145/3227609.3227671.
- [24] D. O. Case, Looking for information: A survey of research on information seeking, needs, and behavior (2<sup>nd</sup> edition), UK: Elsevier Ltd, 2007.
- [25] O. D. Bruijn, and R. Spence, "A new framework for theory-based interaction design applied to serendipitous information retrieval." ACM Transactions on Computer-Human Interaction, vol. 15, no.5, 2008, pp. 1-38.
- [26] E. Katz , J. Blumler, and M. Gurevitch. "Uses and gratifications research." The Public Opinion Quarterly, vol. 37, no.4, 1973, pp 509-523.
- [27] S. J. Ball-Rokeach, and M. L. DeFleur. "A Dependency Model of Mass-Media Effects." Communication Research, vol. 3, no. 1, Jan. 1976, pp. 3–21, doi:10.1177/009365027600300101.
- [28] R. H. Shmerling, Dr. Google: The top 10 health searches in 2017. Harvard Health Blog. URL: https://www.health.harvard.edu/blog/google-top-10-health-searches-2017-2018022113300
- [29] Stephens, Keri K., and Stephen A. Rains. "Information and Communication Technology Sequences and Message Repetition in Interpersonal Interaction." Communication Research, vol. 38, no. 1, Feb. 2011, pp. 101–122, doi:10.1177/0093650210362679.
- [30]John Hollenbeck, Charles Williams, and Howard Klein. (1989). "An Empirical Examination of the Antecedents of Commitment to Difficult Goals." Journal of Applied Psychology. 74.(1989): 18-23. 10.1037/0021-9010.74.1.18.
- [31] Beiwen Chen, Maarten Vansteenkiste, Wim Beyers, Liesbet Boone, Edward L. Deci, Jolene Van der Kaap-Deeder, Bart Duriez, Willy Lens, Lennia Matos, Athanasios Mouratidis, Richard M. Ryan, Kennon M. Shldon, Bart Soenens, Stijn Van Petegem, and Joke Verstuyf. 'Basic psychological need satisfaction, need frustration, and need strengh across four cultures." Motivation and emotion 39 (2015): 216-236.
- [32] JungAe, Yang. (2016). "Effects of Popularity-Based News Recommendations ("Most-Viewed") on Users' Exposure to Online News." Media Psychology, 19.2 (2016): 243–271. https://doi.org/10.1080/15213269.2015.1006333
- [33] R. E. Petty, and J. T.Cacioppo, (1986). The elaboration likelihood model of persuasion, in: L. Berkowitz (Ed.), Advances in Experimental Social Psychology. Academic Press, 1986, vol. 19, pp. 123–205. https://doi.org/10.1016/S0065-2601(08)60214-2
- [34] Julian Unkel, and Alexander Haas, "The effects of credibility cues on the selection of search engine results." Journal of the Association for Information Science and Technology, vol.68, no.8, 2017, pp. 1850–1862. https://doi.org/10.1002/asi.23820
- [35] Chen, Y. (n.d.). Learning for top-N recommendations. Retrieved August 5, 2021, from

https://dare.uva.nl/personal/pure/en/publications/learning-for-topn-recommendations(16d7f634-6cdf-4d45-a6d4-523be2098930).html

- [36] Donghee Shin, "How do users interact with algorithm recommender systems? The interaction of users, algorithms, and performance." Computers in Human Behavior, Vol. 109, 2020.
- [37] Sarah Dean, Sarah Rich, and Benjamin Recht. 2020. Recommendations and user agency: the reachability of collaboratively-filtered information. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency (FAT\* '20). Association for Computing Machinery, New York, NY, USA, 436–445. DOI:https://doi.org/10.1145/3351095.3372866