

# USER PERSPECTIVES ON PERSONALIZED ACCOUNT- BASED RECOMMENDER SYSTEMS

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Personalized recommenders from commercial entities are a quintessential attribute of surveillance capitalism. Shoshana Zuboff's critique of personalization as prediction imperative notes "...this new form of information capitalism aims to predict and modify human behavior as a means to produce revenue and market control."<sup>1</sup> Personalization systems in the context of the surveillance capitalist have proven especially disconcerting due to their "... aims to impose a new collective order based on total certainty."<sup>2</sup> Personalized recommender systems seem to be an inextricable attribute of contemporary algorithmic culture<sup>3</sup>. As an example of this ubiquity in higher education consider the hundreds of scholarly articles on academic recommendation systems (RS) that have been published<sup>4</sup>.

Despite the volume of this scholarship, the RS research area has struggled with the problems of research replicability to determine best practices in RS.<sup>5</sup> One area in which research best practices are needed includes information on users' perspectives and needs. Their perspectives are a crucial, yet understudied, component of personalization services within academic environments specifically.

While design guidelines for RS design have been promulgated,<sup>6</sup> users have not verified them within academic personalization efforts. It also is the case that, while concern for user control<sup>7</sup> of data and user privacy<sup>8</sup> in RS has seen recent productive scholarship, a gap in the literature exists in understanding academic user preferences and perspectives on RS used in library settings; hence, input about student preferences for academic RS is particularly crucial and unavailable heretofore. This research used a rubric of interaction metrics to address this gap in users' perspectives of RS and explored the features and functionality students desire in account-based RS in information settings. The evaluative rubric's themes were drawn from a literature survey to evaluate RS from the user's perspective.

## **BACKGROUND**

Personalized recommendations for information resources in libraries is not an entirely new phenomenon, personalization services have been in vogue in the library field in the last decade.<sup>9</sup> Researchers have published a case that detailed the development of account-based recommenders in an academic library mobile app and focused on data mining transactions for account-based recommenders in open source discovery environments.<sup>10</sup> Recommendation of library content derived algorithmically is not without policy implications. For example, the mobile account-based recommender necessitated establishing a new privacy policy for VuFind-based library account recommenders in the Illinois library system.<sup>11</sup>

In addition to policy implications, algorithmic bias attributable to AI, and its subfield of machine learning, must be considered<sup>12</sup>. While not without contention,<sup>13</sup> a growing axiom in the field is that algorithms are biased.<sup>14</sup> One of the most compelling and important works on this topic is *Algorithms of Oppression*, which was notable for interrogating pervasive structural racism in the most prominent search websites and result lists.<sup>15</sup> There is ample recent scholarship

on the way automated systems that use data derived algorithmically have affected health, poverty, and national wellbeing.<sup>16</sup> Questions of replicability also have come under scrutiny, as certain types of AI that are used in RS are unable to describe completely why one system provided a result that was not replicated in another.<sup>17</sup> Other systems are a complete “black box,” wherein even those who constructed the algorithm do not understand the system’s outputs.<sup>18</sup>

Turning to the academic library sphere, commercial vendors have also decided as a matter of surveillance capitalist profit accumulation, to implement article recommenders based on user actions within their systems. These include some of the largest vendors of library content, such as Elsevier. The BX Article Recommender is one such service available from Elsevier.<sup>19</sup> BX is implemented commonly in link resolvers, but also is available in other discovery environments, including API access. The BX Article Recommender is based on data mining millions of link resolver interactions around the world. Trend MD is another article recommender that is displayed in the Emerald journal platform.<sup>20</sup> Trend MD as implemented in Emerald’s interface allows the user to select journal articles in other publications based on computed relevancy. These journal article recommendations seem to be based in part on author and keyword mining and user data. These vended article recommender services have data retention policies and procedures which implementing libraries must evaluate for their local populations.

The implementation of an account-based recommender for library accounts an academic library controls is an opportunity for libraries to implement a service that is consistent with user expectations for personal data re-use and RS transparency. Understanding students’ perspectives on such systems is critically important in stewarding an information system that both is useful for students and respects privacy and transparency. This paper reports students’ perspectives on a

mobile RS. An evaluative RS rubric from a review of RS evaluations<sup>21</sup> was adapted for structured student interviews. The rubric encompassed three key areas, including: 1) The way the RS generates recommendations; 2) The way the recommendations are displayed to the user, and finally 3) The way the recommendations can be revised based on user input. These are defined more formally in Table 1 below.

**Table 1. Areas of Inquiry for Student Perspectives of Recommender Systems<sup>22</sup>**

<b>User Perspective</b>	<b>Definition</b>
Generating recommendation from student actions	A student may browse, search, check-out, or otherwise rate items in this category.
Displaying recommendations to students	The user reviews the recommendation provided. Reviewing in the context of the mobile app occurs when users tap the Recommendation module
Revising recommendations from student input	These will encompass such feedback mechanisms as rating or selecting the recommendation.

## **METHODS**

Students were recruited to participate in interviews on RS based on their interest in accessing their library account from the library mobile app. Over 100 students log into their library account through the mobile app weekly. If students agreed to take part in the study, they visited the campus library for a structured interview that lasted no longer than thirty minutes. The students were provided a \$10 gift card to the University of Illinois campus book store for their

participation in the study. A total of nine (N=9) students participated in the interviews, which took place from February 2018 through February 2019.

This research used a structured in-person interview methodology to gather students' perceptions of RS. According to one methodology scholar, "... The structured interview employs a list of preestablished questions in a fixed order and using standardized wording."<sup>23</sup> A structured interview format allows ideas to be compared across participants and serves to help build themes based on interview questions targeted. As a further methodological consideration, the article "Interviewing Users," by user experience expert Jakob Nielsen, inspired this research. He wrote that interview data can serve several key objectives, but is most useful "...when you want to explore users' general attitudes or how they think about a problem."<sup>24</sup> Therefore, the interviews focused to a greater extent on student attitudes about RS, and therefore utilized mobile research recommender primarily as a prompt for preference elicitation in this study. The interview questions correspond to the themes identified in the rubric in Table 1, which can be found in the appendix. The interviews were structured so that questions corresponded to the three key areas of inquiry, including: 1) eliciting recommendations; 2) displaying recommendations, and 3) revising items recommended through users' feedback to the system.

Students who visited the library for the in-person interview were shown two of the library account-based recommender screenshots as prompts. These were paper screenshots printed for the interviews, in which mobile devices were not used. The image below is the first level of recommendations that users were shown, and is presented to the user in the app when they tap on the "Recommendations" module. After seeing the first image, the participants were asked to examine the detail level page, image 2, as a prompt.



Image 1. First level of recommendations in the mobile app.



Image 2. The second level provided detailed recommendation lists in the mobile app.

## RESULTS

Several students in the interview cohort held a relatively conservative perspective on the way RS in libraries should generate their results; viewing with concern and outright suspicion those key features of surveillance capitalism qua consumer data science<sup>25</sup> (e.g., practices of internet-based capitalism that exploits for maximum profit the systematic data mining of user actions irrespective of user preferences) to inform RS in an academic library setting. Most students who were interviewed tended to oppose using such contemporary techniques as data mining what the app accesses, or recording everything that is searched. One student reported that those items on which they click are for a course, and that may not be the right signal to send for what they want to have recommended. There was a certain creepiness that one student mentioned—her direct statement was that recommendation systems “... are useful but sometimes it is scary. For example, you may be browsing the web and something follows you that you searched for on your phone. That something followed you. The algorithm is listening to you.” Another student reported that she did not want the system to use her searches.

The students’ relation to the course also was nuanced. While there were students who thought recommendations based on course searches were irrelevant to a RS, a minority opinion holder commented that RS could, in fact, be based on a course and that a professor or students within the same course could benefit from recommending items to each other through the platform. There was a further dissenting opinion in this respect held less, as one student thought that one of the VuFind library catalog’s shortcomings was, “Some results for keyword searching that are not what I was looking for, even when I was logged in. The system should know my searches and my major, so that the results are not so broad. The system should know me.” However, this was not a majority opinion among the students interviewed.

More than one student mentioned that item ratings were not particularly helpful. Contemporary recommendation research also has begun to move away from recommendation systems based on ratings. Instead, students suggested other approaches to generating recommendations in addition to the way that the system is designed currently. Students suggested a start-up page on which to select topics and being able to curate the list of topics suggested. A graduate student said that a pre-defined vocabulary could be used to generate recommendations and then expanded based on user interest; she noted that the system could "...allow users to recommend a tag or a keyword. Some areas from different fields could be useful to my research, but these areas aren't known to my field. For example, help support interdisciplinary research by showing overlapping areas in different research fields."

A concern about RS transparency was evident among most students we spoke to, and one key quote indicative of the need for transparent systems was, "Of course we would want to know how recommendations are generated. Every book could have a 'recommended because you searched.' People will be interested in why these are recommended." One student offered that, while similar to Amazon, the service can distinguish itself from commercial entities through transparency, "... transparency is important. So that folks know what this is based on. The Amazon system isn't as transparent. That that could make this distinctive."

### **Recommendations' Display**

With respect to the mobile app's display of account-based recommendations, emerging themes indicated that students desired an interface that supported quick scans of recommendations. Students noted that when they look at a recommendations list, "Mostly I just want to skim through all the items," and that the recommendations presented to the user should be easy to obtain quickly. With respect to metadata elements' presentation, one student

mentioned that year of publication would be more useful to his field, as he would prefer to filter for items that are most recent because recency is an important factor in his field. Students suggested other ways to approach filtering when recommendations are displayed, noting that the system could "...provide a filter over the recommended item and provide additional context about broader fields." This provided some direction for a design that includes year and the ability to reference subject metadata in recommendations' display.

The one outlier in this need for quick bursts of recommendation interaction was a student who suggested that, rather than including book images—which are problematic for academic books as they do not provide much information—that users would be served better by including an option in the recommendation app to read reviews of the item recommended.

### **Critiquing Recommendations**

This section pertains to the way students can critique or modify the recommendations presented to them within the platform. There seemed to be general agreement among most, but not all, students we interviewed that it would be advisable to have some way to revise the recommendations. The single student who said he would not be interested in critiquing recommendations suggested that while other students might want that, he would not use the ability to revise recommendations.

Those who did want to revise recommendations suggested several approaches, including filtering tools to filter subjects that would provide only the topics or years selected in a filter. Here again, timeliness was viewed as important for what a student is researching right now, not recommendations for an assignment or paper that has been completed already. The notion of rating functionality in this venue was not conclusive; a graduate student thought that rating fiction would be acceptable, but that otherwise they distrusted reviews, noting, "People's politics

and their personal opinions are clouding too much of book reviews online.” This underscored both an undercurrent of distrust in online reviews and savviness in the graduate students’ approach to online recommendations.

### **Stewardship Levels Desired**

With respect to the storage of items recommended, there seemed to be some agreement that the system could retain recommendations that students were shown. However, several caveats were raised—that it would be helpful either to simply show the more immediate recommendations’ history or only recommendations that the user has accessed in the app. One student also indicated that he would want to control such storage with an opt-in process. The student’s direct remark in this respect was that, “I don’t want automatic retention of anything.” A final feature suggested was simply to make it easy for the students to save those parts of the search that they found useful— “Provide a checkbox to let me keep these,” was another student’s idea for functionality. Overall, the theme of data stewardship for the students was that it should support the system’s utility, from going back to see things they might have overlooked— “Automatically rediscovering could be helpful,” because “...working on a paper could take a year. It could be useful to go back and look at things that I overlooked.” These themes will be explored more in the findings section, but they do indicate the need for a broader research assistance system—one that supports the user throughout the course of his/her research project—not simply finding papers in an initial search, but being able to revisit them and conduct further searches as their project continues.

### **Unexpected Results**

Students were asked to share what had or had not worked for them in other RS they had used previously on the Internet, and they mentioned a variety of services. One student referred to

YouTube as an example of a service that did not work the way she wanted it to, and noted that “...frequently YouTube doesn’t work so good because it gives you a recommendation based on one thing you did. It should be based more on a frequently searched thing. Recommendations are sending you things you already are interested in, which might not show you newer things and that is not really a good way to learn.” Students also indicated that they did not like the fact that commerce seems to drive recommenders, for example, “...on the Internet you might be interested in finding information about something but not want to buy.” Another student took a measured approach to this problem, noting “...when they [recommenders] are trying to sell something it feels predatory, but otherwise it is good.” The findings section explores commercial elements and implications of product recommendations in greater detail because it provides several instructive areas of developments that academic libraries should avoid. These student users seemed to have strong feelings about RS, as indicated by this final quote about Internet RS that did not work as expected, “...Netflix suggests movies that I hate. Amazon is so-so. Not nearly as good as it once was. Spotify music recommendation is so-so but it does not allow genre expansion as easily as desired.”

## **FINDINGS**

The emergent themes from the structured interviews revealed issues of system transparency, the way different types of scholars conduct their work, and the need to safeguard student privacy. Overall, students believed that there is a place for RS in academic library settings. Academic library recommenders can distinguish themselves from commercial recommenders in several ways, including increased transparency beyond what is available in commercial systems, and by attending to the level of student privacy desired as a system design

issue. An academic recommender based in a library user account can support interdisciplinary research greatly regardless of commercial concerns.

### **Transparency and Privacy**

When students were asked how much system information to display, one of the consistent themes that emerged was that nearly all of them wanted to know more about the way the system decided to recommend an item. A corresponding finding was the nuance that students requested in the way the system used their data—they seemed to understand that while commercial systems could use their search history and history of clicking or tapping on the items, for a variety of reasons, they did not all agree that an academic library app would be served best by using these data. The students we interviewed believed that using item popularity and associated item topics as a way to recommend items to users through their library accounts was appropriate. However, they were opposed to datamining their searches or otherwise sharing their information without specific opt-in language. When asked about retaining items recommended for them to view later, students were most interested in looking at what they have researched previously themselves, particularly for projects that run from over several months to a year. The idea of data stewardship for algorithms has seen some recent scholarship, but it does not yet have clear answers for the way and where content derived algorithmically must be curated for preservation or re-use.<sup>26</sup>

When asked about platforms that do not work as expected, students contrasted the library account-based recommender with other personalization services online. While Netflix received mixed reviews, mention of YouTube seemed to elicit a strong response, in that the recommender showed you only more of what you already knew. This helps us understand that an RS in an academic library setting should work to expand users' interest into other areas, with novelty and serendipity as system development goals. An article in the *New York Times* last year by scholar

Zeynep Tufekci detailed her observations of the way the YouTube RS shows users consistently homogenous content. Tufekci indicated that this bias for serving extreme views for generation of advertising revenue makes YouTube the “great radicalizer,” in their efforts to derive ever more profit from users.<sup>27</sup>

### **Interdisciplinary Support**

While all users who logged into their mobile account through the app were invited to participate in interviews that focused on the library mobile RS, it was found that more graduate students were more interested in RS than were the undergraduate students who participated in the structured interviews. Graduate students in particular indicated that RS could help them see the way other research areas approach similar problems—this is a feature of academic libraries’ RS that is underappreciated—they are not simply “more like this” search engines—they also may be designed for novelty and support increased capability to browse the library collection.

### **CONCLUSION**

The field of library developed and stewarded recommenders is new as yet, but such implementations as the mobile account-based recommender that prompted this research are growing. Recent scholarship in the related field of learning analytics<sup>28</sup> may inform and guide ethical considerations associated with data re-use in part, which, as a data-intensive trend in academic librarianship, has seen scholarship on the ethical need for user privacy, among other codified ethical standards,<sup>29</sup> and a foundation of professional ethics. The ethical considerations associated with algorithms are both a system design issue and, in the focus of this research, user-defined. Research from this study was able to find ample support among the cohort to which we spoke that the system should provide ways to incorporate the user’s ethical preferences. Scholars in the ethics of algorithms have argued that, “... The design of the algorithm must allow the user

to choose the circumstances in which she situates herself,” that “... it is necessary that the designer leaves it to the user to specify what ethical parameters to choose,” and that, “when this is not possible, the ethical assumptions in the algorithm should at least be transparent and easy to identify by users.”<sup>30</sup> Because library-based recommenders are still emerging, these aspects of ethical design and preferences can be a distinctive part of a student’s library experience.

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## **APPENDIX: STRUCTURED INTERVIEW QUESTIONS**

### **Display Recommendations**

1. According to our records, you are a previous user of the Minrva mobile app – have you used the Recommendation module previously?
  - a. Show participant printed screens of what the recommender does if they haven't already used it or to remind them if they used it in the past.
2. How useful do you find a recommendation service?
3. Is the presentation of the recommendations easy to understand?
4. Can you recall a specific instance within the Minrva mobile app Recommendation module or any other Internet resource in which a recommendation service worked particularly well?
5. Are there any instances where recommender services did not work as expected in this app or elsewhere on the Internet?
6. The system does not currently retain past recommendations. If the system were to store these historical recommendations, would you ever want to go back and view previous recommendations that were provided at an earlier time?

### **Revise**

Do you have a preference for a recommendation system to include functionality to rate the recommendations that you are provided?

- a. What types of feedback would you prefer to offer: ratings, clarification, or something else?

### **Preference Elicited**

7. How do you prefer your book recommendations to be generated?
  - a. Should the system generate recommendation based on browsing behavior (what is tapped on in the app) or with ratings (what is checked out or favorited)?
  - b. How much information do you prefer to know about how the recommendations are generated in the recommendation module?

## NOTES

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