ep

ANCILLARY REVIEWS

DO NOT DELETE. Submit the completed checklist below with your protocol.

Which ancillary reviews do I need and when do I need them? Refer to HRP-309 for more information about these ancillary reviews.			
Select yes or no	**Does your study…**	*If yes…*	**Impact on IRB Review**
☐ **Yes** ☒ **No**	Include Gillette resources, staff or locations	*Gillette Scientific review and Gillette Research Administration approval is required. Contact:* *research@gillettechildrens.com*	**Required prior to IRB submission**
☐ **Yes** ☒ **No**	Involve Epic, or Fairview patients, staff, locations, or resources?	*The Fairview ancillary review will be assigned to your study by IRB staff* *Contact:* ancillaryreview@Fairview.org	**Approval must be received prior to IRB committee/ designated review.**
☐ **Yes** ☒ **No**	Include evaluation of drugs, devices, biologics, tobacco, or dietary supplements or data subject to FDA inspection?	*STOP – Complete the Medical Template Protocol (HRP-590)* *The regulatory ancillary review will be assigned to your study by IRB staff* *Contact: medreg@umn.edu* *See https://policy.umn.edu/research/indide*	**Consider seeking approval prior to IRB submission.**
	Require Scientific Review? Not sure? See guidance in the Investigator Manual (HRP-103).	*ONLY REQUIRED BIOMEDICAL RESEARCH REVIEWED BY FULL COMMITTEE*	
☐ **Yes** ☒ **No**	Relate to cancer patients, cancer treatments, cancer screening/prevention, or tobacco?	*Complete the CPRC application process.* *Contact: ccprc@umn.edu*	

☐ **Yes** ☒ **No**	Include the use of radiation? (x-ray imaging, radiopharmaceuticals, external beam or brachytherapy)	*Complete the AURPC Human Use Application and follow instructions on the form for submission to the AURPC committee.* *Contact: barmstro@umn.edu*	**Approval from these committees must be received prior to IRB approval;** **These groups each have their own application process.**
☐ **Yes** ☒ **No**	Use the Center for Magnetic Resonance Research (CMRR) or MR at Masonic Institute for the Developing Brain (MIDB) as a study location?	*Complete the CMRR pre-IRB ancillary review* *Contact: ande2445@umn.edu*	
☐ **Yes** ☒ **No**	Include the use of recombinant or synthetic nucleic acids, toxins, or infectious agents?	*STOP – Complete the Medical Template Protocol (HRP-590)*	
☐ **Yes** ☒ **No**	Include the use of human fetal tissue, human embryos, or embryonic stem cells?	*STOP – Complete the Medical Template Protocol (HRP-590)*	
☐ **Yes** ☒ **No**	Include PHI or are you requesting a HIPAA waiver?	*If yes, HIPCO will conduct a review of this protocol.* *Contact: privacy@umn.edu*	
☐ **Yes** ☒ **No**	Include the use of a controlled substance?	*If yes, University Health and Safety Compliance for controlled substances will review the protocol.* *Contact: cshelp@umn.edu*	**Approval must be received prior to IRB approval.** **These groups do not have a**
☐ **Yes** ☒ **No**	Plan to use CTSI Monitoring services, and/or have an IND, IDE, or designated NSR-IDE by the UMN IRB?	*The CTSI monitoring ancillary review will be assigned to your study by IRB staff.* *Please note eligibility criteria here.* *Contact: fencl003@umn.edu*	

☐ **Yes** ☒ **No**	Use data from CTSI Best Practices Integrated Informatics Core (BPIC) Formerly the AHC Information Exchange (AHC-IE)?	*The Information Exchange ancillary review will be assigned to your study by IRB staff* *Contact: bpic@umn.edu*	**separate application process but additional information from the study team may be required.**
☐ **Yes** ☒ **No**	Use the Biorepository and Laboratory Services to collect tissue for research?	*STOP – Complete the Medical Template Protocol (HRP-590)* *The BLS ancillary review will be assigned to your study by IRB staff.* *Contact: Jenny Pham* *Pham0435@umn.edu*	
☐ **Yes** ☒ **No**	Have a PI or study team member with a conflict of interest?	*The CoI ancillary review will be assigned to your study by IRB staff* *Contact: becca002@umn.edu*	
☐ **Yes** ☒ **No**	Need to be registered on clinicaltrials.gov?	*If you select "No" in ETHOS, the clinicaltrials.gov ancillary review will be assigned to your study by IRB staff* *Contact: fencl003@umn.edu*	
☐ **Yes** ☒ **No**	Require registration in OnCore?	*If you select "No" or "I Don't Know" in ETHOS, the OnCore ancillary review will be assigned to your study by IRB staff* *Contact: oncore@umn.edu*	**Does not affect IRB approval.**

PROTOCOL COVER PAGE

Protocol Title	NSF CCRI 2232551: A Research News Recommender Infrastructure with Live Users for Algorithm and Interface Experimentation
Principal Investigator/Faculty Advisor	Name: Joseph A. Konstan
	Affiliation: ☒ UMN ☐ Fairview ☐ Gillette
	UMN Home Department: Computer Science and Engineering
	UMN Home Dept ID: 11115
	Telephone Number: 612-625-1831
	Email Address: konstan@umn.edu
Student Investigator	Name: N/A
	Current Academic Status (Student, Fellow, Resident): N/A
	Department: N/A
	Telephone Number: N/A
	Institutional Email Address: N/A
Scientific Assessment	Already funded by NSF CCRI grant, no need for further scientific assessment.
Version Number/Date:	Version 2: July 31st, 2024

REVISION HISTORY

Revision #	Version Date	Summary of Changes	Consent Change?
2.0	July 31st, 2024	Update language of qualified participant age.	No

Table of Contents

ABBREVIATIONS/DEFINITIONS

- POPROX: Platform for OPen Recommendation and Online eXperimentation
- RecSys: Recommender System
- AP: Associated Press
- CAB: Community Advisory Board
- Experimenters: researchers who propose study plans and conduct user experiments with POPROX
- Data use researchers: researchers who only use public dataset released by POPROX and not conduct any user experiments

1.0 Objectives

1.1 Pointer to 6-minute overview video

This is a very unusual protocol describing a research infrastructure with human participants rather than a study itself.

After discussion with Advarra staff, we are providing a link to a 6-minute introductory video that we believe will be helpful in preparing you to read and review this protocol.

Link to video: https://z.umn.edu/POPROX-IRB .

1.2 Purpose:

We are not proposing a single study, but rather the support system to conduct an entire stream of research on an experimental news recommendation infrastructure we are developing for general computer science and social science researchers. When operational, we will recruit a set of participants who subscribe to a personalized daily newsletter (with news articles based on content from AP and eventually other news producers). These participants will have consented to participate in studies that vary the contents, layout, and interactivity of the newsletter. Researchers (including researchers other than us) will be able to conduct experiments delivering recommendations and/or related interactive functionalities to the system's participant base. It is our intent to start recruitment in Summer 2024, but likely to operate the infrastructure in test mode for several months before we open to actual experiments.

We are seeking a review of the infrastructure being developed and our operation of that infrastructure to support experimenters. What we propose here is a set of policies that define the scope of experiments we will conduct, and that experimenters would obtain whatever approvals are needed from their own institutional IRBs, but that this protocol approval would cover our operating the system, recruiting and consenting participants, and doing our part in administering those experiments on behalf of the researchers who use the platform without further review.

In particular, these policies include a number of protections for the participants in this research, including:

- That user identity is shielded from the researchers; only our infrastructure team will have contact information for users (an e-mail address to which we deliver the newsletter and any compensation, and that can be used to opt out).

Researchers must agree not to attempt to re-identify users from de-identified data and not to attempt to contact users directly. Any survey questions asked will be screened by our team to ensure that they are neither identifying nor potentially triggering.

- That experiments are limited to ones that seek to assess potential improvements in the newsletter and that are not deceptive, misleading, or potentially harmful.
- That any compensation offered fits within our pre-approved framework (designed to limit both distortions in user behavior and potential coercion). This framework permits experimenters who deliver surveys or other time-intensive experiments to compensate participants at a level comparable to the prevailing wage.

We should note that the studies to be conducted in this infrastructure are nearly all studies that (based on prior IRB-reviewed experiments) would be determined to be not human participants research or exempt from IRB review. A few might fall into expedited review. Given the researchers' inability to engage in deep study of individual participants, nearly all studies are focused not on questions about participants per se, but rather on questions about algorithms, interface presentations, etc. Nonetheless, in view of the novel form of research infrastructure and participant experience here, we feel it is important and appropriate to have this overarching protocol receive full IRB review. If as part of that full review the IRB determines that the platform itself is not human subjects research, or is exempt, we will proceed accordingly.

2.0 Background:

2.1 Significance of the Proposed Project (the Research Infrastructure):

The field of recommender systems (RecSys) was initiated to address the challenge of information overload. In the early years of the field, most research was conducted using studies of real participants, and many studies followed participants for an extended period of time to evaluate the usefulness of their innovations. Today, however, few academic researchers can afford to build systems and recruit participants. Most studies are conducted using only offline evaluation against data collected by others.

This IRB protocol does not address a specific research question but rather provides a platform to facilitate experiments with actual users. As researchers with deep roots in the Recsys research community, we've talked with scores of recommender systems researchers, and they agree on three points. First, this focus on offline evaluation is bad for the field; it leads to optimizing things that are easy to measure (ability to recover "hidden" values) rather than taking on big questions of how to support participants as they explore and evaluate challenging information and product spaces [1]. Second, it is too expensive and difficult for individual researchers and groups to

develop and maintain not only the software infrastructure but also the communities of end participants that are needed to carry out long-term participant studies. And third, researchers recognize that the overhead of conducting human participant studies falls disproportionately on academic researchers and small business; large enterprises (such as Google, Amazon, Meta, etc.) routinely carry out massive A/B studies for their own purposes, but only rarely publish the results of those studies.

2.2 Preliminary Experience Operating Such a Research Infrastructure:

While we're still in the phase of developing the platform to carry out future experiments, we would like to share some prior studies conducted on the MovieLens platform as some preliminary data examples. MovieLens [2] (https://movielens.org/) is an academic online movie recommender website developed and maintained by GroupLens research at the University of Minnesota. We have been running our own experiments on the MovieLens infrastructure for over 25 years during which we've served over 300,000 users. These specific experiments were conducted under IRB review as a mix of non-human subject studies and exempt social and behavioral studies.

Non-human study examples:

- Sun, Ruixuan, Avinash Akella, Ruoyan Kong, Moyan Zhou, and Joseph A. Konstan. "Interactive Content Diversity and User Exploration in Online Movie Recommenders: A Field Experiment." *International Journal of Human–Computer Interaction* (2023): 1-15.
- Zhao, Q., Willemsen, M.C., Adomavicius, G., Harper, F.M. and Konstan, J.A., 2019, September. From preference into decision making: modeling user interactions in recommender systems. In *Proceedings of the 13th ACM Conference on Recommender Systems* (pp. 29-33).
- Ekstrand, M.D., Kluver, D., Harper, F.M. and Konstan, J.A., 2015, September. Letting users choose recommender algorithms: An experimental study. In *Proceedings of the 9th ACM Conference on Recommender Systems* (pp. 11-18).

Exempt examples:

- Kong, R., Milton, A., Kluver, D., Sun, R., Paterson, A.I., and Konstan, J.A., 2022, A Case Study of a Recommendation Website's Productive Flyby Users.
- Kong, R. and Konstan, J.A., 2023, The Value of Recommender Systems: Decomposing the Informational and Discovery Gains

2.3 Existing Literature:

This project was designed to address the decline in experimental research and particularly longitudinal experimental research in recommender systems and related fields. The table below summarizes the case we made in our NSF proposal (which was peer-reviewed and awarded) to justify the need for such an infrastructure.

years	offline evaluation	one-time participant evaluation	ongoing participant evaluation	works reviewed
1994 - 2000	4/15	11/15	7/15	[3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17]
2001 - 2007	8/15	6/15	1/15	[18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32]
2008 - 2013	10/15	6/15	1/15	[33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47]
2014 - 2017	10/15	3/15	1/15	[48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62]
2018 - 2021	15/15	3/15	1/15	[63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77]

Table 1: Research Method Change in U.S. Recommender System Research

Table 1 illustrates changes of U.S. RecSys research in the past 30 years. We retrieved the 15 most highly-cited papers from US authors on the topic of recommender systems (based on Google Scholar statistics) for each of the five time periods. The results are stark -- since 2014, the vast majority of research in the field has been evaluated with only offline studies against data sets. Indeed, these data understate the problem—some of these top papers with participant evaluations come from industry researchers—often the only ones with the resources to carry out these studies. (Indeed, there is extensive industry research using live studies, but most of it is never made public, and the questions asked are often narrowly focused on each company's business goals.)

3.0 Study Endpoints/Events/Outcomes

We remind the IRB that this umbrella protocol is not designed to address a specific research question, but rather to set the guidelines for an infrastructure to which we can

recruit participants, obtain their informed consent, and assign them to a variety of future studies that will each be reviewed as appropriate by their investigators' own institutions and which we propose to carry out in this infrastructure without further UMN IRB review and without separate consent from users.

Within that framework, we have a number of measures and metrics that can be used as endpoints and/or outcomes for these individual studies:

- retention of users (measured as opt-out from the experimental condition; opt-out from the platform; failure to engage after prior engagement)
- number of newsletters opened
- number of articles read (measured by click-through count)
- response to user satisfaction questionnaires
- response to research-customized survey questions
- number of forwarded article that we can detect with our platforms
- dwell session/length of reading time spent on individual articles or the newsletter

Any study could use one or more of these potential endpoints.

3.1 Primary Endpoint/Event/Outcome: N/A

3.2 Secondary Endpoint(s)/Event(s)/Outcome(s): N/A

4.0 Study Intervention(s)/Interaction(s):

We remind the IRB that this umbrella protocol is not designed to address a specific research question, but rather to set the guidelines for an infrastructure to which we can recruit participants, obtain their informed consent, and assign them to a variety of future studies that will each be reviewed as appropriate by their investigators' own institutions and which we propose to carry out in this infrastructure without further UMN IRB review and without separate consent from users.

Within that framework, we define the limits of the interventions and interactions that we will support under this protocol.

4.1 Description:

In the daily newsletter received by users, we have a wide range of allowable interventions and potential interactions. The provided examples represent the most common cases and might expand within a reasonable scope based on individual experiment designs.

Recommender System Interventions:

- selection of a different set of news items (from the set of available items in the system)
- re-ordering of news items
- introducing a set of related or alternative items for users to click on

Interface and Interaction Interventions:

- changing titles of news items
- changing brief summary of news items

  Note that all selection and change interactions are likely to be based on user profile information including prior user interactions, user expressed interests, consolidated representations of user preferences by topic, entity, etc.

- changing image or media display
- feedback options (thumbs up / down)
- displaying explanations for particular news items

Interactions:

- participants expressing explicit news preferences (geo location, topic interest)
- periodic surveys and questionnaires
  - satisfaction with recommendations
- click on embedded links in news items to see the complete articles on the source site (i.e. AP)
- customized surveys provided by researchers, including reactions to article, single-item questions, or interstitial questions, which will be approved by their own IRB.

Accordingly, we also provide a set of examples that are **not** allowed to be delivered to users:

Interventions:

- use of pornography or graphic violence in news display
- display of advertisements in the newsletter
- display of news articles not contained in the content provider database

Interactions:

- surveys collecting participants' personal or contact information
- plugins recording participants' screen content

- any use of virus or malware

5.0 Procedures Involved

5.1 Infrastructure Design:

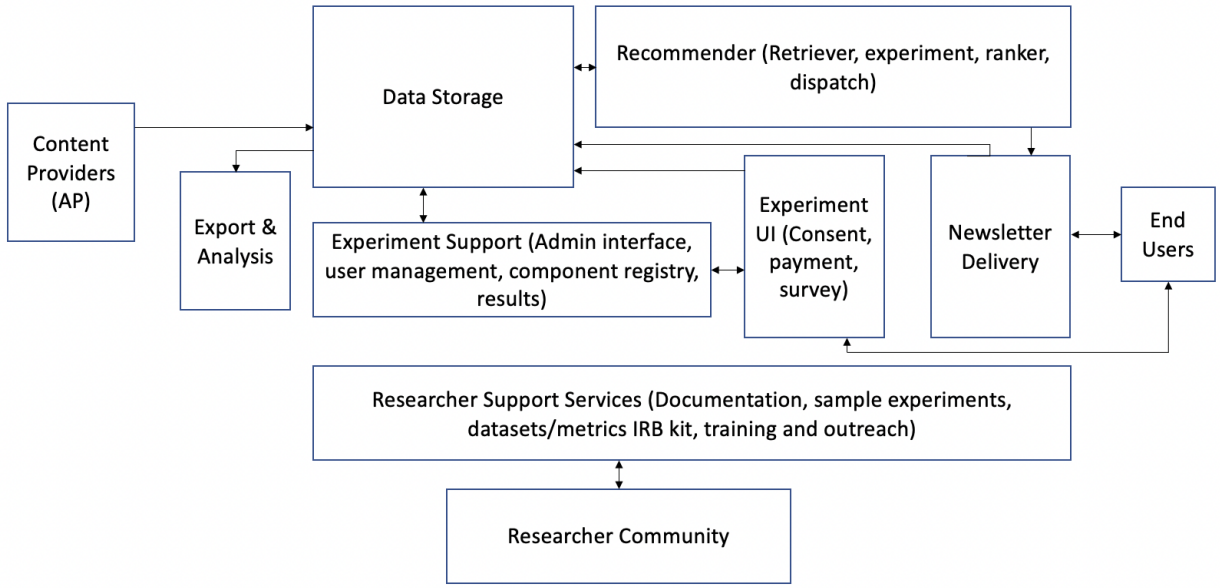

Figure 1: Design Overview of POPROX

As illustrated in Figure 1, our role of building the platform is to bring in news from content providers (i.e. Associated Press), provide basic recommender system and interface support, recruit participants, deliver a personalized newsletter to participants on a daily basis, and provide mechanisms for compensation and incentives when needed.

Support for prospective researchers is also part of the infrastructure. We aim to provide thorough documentation, sample experiments, datasets/metrics, an IRB kit, and training and outreach materials. For data export and analysis, we will provide some built-in user behavior loggings plus all extra interaction data mentioned in section 4.1. The built-in behavior logging metrics can be found in section 16.1.

5.2 Design of a Study Within the Infrastructure:

<u>Participant Experience:</u>

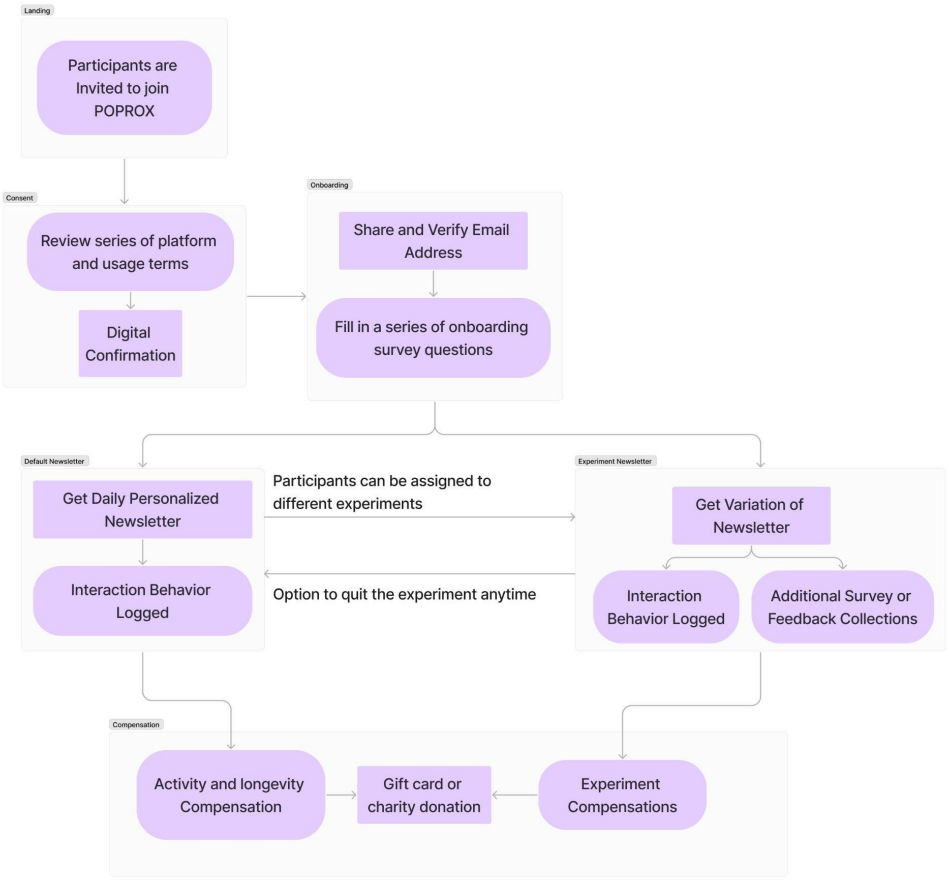

Figure 2: Participant Life Cycle in POPROX

Our plan is to recruit initially up to 200 participants, and eventually up to 3000 participants. Their life cycle is shown in Fig.2. Before getting newsletters, participants will go through an enrollment and consent process that includes: 1) Landing on the registration page; 2) Reviewing and signing the consent form (the detailed form is attached in supplementary document Article 4); 3) Filling in a series of onboarding survey questions (attached in supplementary document Article 6) . Note that all questions are optional and users have the right to quit any time in the entire process.

After participants finish filling out the onboarding questionnaire, they will start to receive daily personalized newsletters. We anticipate two different phases of use for participants' interaction within this infrastructure. The first phase is the default newsletter experience: they will continue to get daily newsletter, having their interaction behavior logged, etc. The second phase is about assignment to an experiment: they will get a variant of newsletter and potential follow-up surveys, depending on the design and research question of the specific study. Every newsletter that participants receive will provide both opt-out options from the current experiment, as well as from the whole system (details can be found in section

12). Note that for each individual participant, they can either receive the default newsletter experience, and the rest of the time they are assigned to a certain experiment.

Participants can expect to receive compensation for two types of activities: 1) reward for their activity or longevity within the platform; 2) experiment-specific compensation for substantial effort. Both types of compensation are explained in detail in Section 11.5.

Study Procedures

People who carry out experiments on POPROX can be categorized into two types: experimenters and data-use researchers. Experimenters are those who propose new user studies to be run on POPROX with participants, and data use researchers are those who only use datasets shared by the POPROX team.

Experimenter Procedures

In a normal study cycle, experimenters propose studies and prepare the newsletters of their design for participants. (From a technical perspective, they locate their experimental newsletter code in the cloud adjacent to our system and override the parts of the default experience they're experimenting with; for example they might leave the newsletter look alone but change the article selections or the headlines.) They will first be provided an agreement to understand the limit and scope of experiments that can be supported by POPROX. Then they are responsible for getting their study plan reviewed and approved by their own institution's IRB. Specifically, they need to describe research questions, experiment treatment, number of participants needed for their experiment, length of experiment, compensation plan, and other details. **An example experiment manifest can be found in the supplementary document Article 5**.

After receiving their proposal and local IRB approval documents, we will review their plan again and make sure its scope can be covered by this IRB protocol. If there are concerns about whether we should carry out an experiment, we will also seek advice from our community advisory board (CAB). In general, their design can manipulate things included in the intervention lists covered in section 4.1. We anticipate one experiment to fit under one of the three categories:

(a) If the experiment falls within this IRB-approved protocol, then if we approve it and the experimenter IRB approves it, we're good to go without our IRB's involvement.

(b) If the experiment falls outside this IRB-approved protocol, we need to determine (with CAB) whether to submit a modification to our IRB protocol so that the experiment can fit within the modified protocol. If we do so, and our IRB approves, we're back in category (a).

(c) In the very rare case where we want to support an experiment that falls outside our protocol without submitting a modification (so that others can do the same thing in the future), we would require IRB approval from our IRB (Advarra) in addition to the experimenting institution's IRB (or they could defer to Advarra for a single review). Given the effort involved, we do not expect to pursue this option except when our CAB feels that the scientific value of a one-time exception is so great as to warrant the effort.

Also, we want to note that even if the experimenter is one of the POPROX team members or their students, the same rules apply; that is, internal experiments must be reviewed by the experimenters' home IRB.

Upon internal approval, we will help researchers launch the experiment and run it in test mode to ensure it functions properly, and then launch it to deliver newsletters to participants. Then, we will provide experimenters with requested de-identified data over the course of this experiment. The complete experiment data will eventually be published on our site for future research use (including experiment proposal, manifest, and dataset).

Data Use Researcher Study Procedures

For data use researchers, the data included in the published dataset will not include any personal or contact information, and their use of the published datasets will be subject to terms and licenses preventing any attempt to re-identify participants or contact them.

5.3 Study Duration:

5.3.1 Experimenter Study Duration

For a specific study conducted on POPROX, the duration is determined by the experimenter based on the research question(s) involved, which can be as short as one single interaction, or as long as many weeks/months.

Below are two sample experimenter studies:

1) An experiment to understand the impact of recommenders on the dynamics of users choice behaviors. The experiment requests 100 participants for a period of 2 months of active experimentation and data collection for 3-months post-treatment. The participants would be randomly assigned to two conditions: (a) a condition where their recommendations are entirely based on past consumption, and (b) a condition where they are asked to specify their preferences explicitly by topic and entity and update those preferences weekly. Researchers would look at click-through data, self-reported satisfaction and diversity estimates, actual news consumption, etc.
2) A group of journalism researchers want to explore if we can adapt existing recommendation algorithms to mitigate the spread of bias in political news. They reach out to POPROX to share their study plan and hope to get 200 participants to be enrolled in reading their designed experiment newsletters for 6 weeks, followed by two rounds of surveys in the following 2 weeks to test the misinformation spreading effect. The participants would be randomly split into two conditions: (a) default baseline algorithm without any changes, and (b) a new algorithm designed with debias mechanism that would filter out news with bias over certain threshold. Researchers would look at click-through data, self-reported fake news bias awareness estimates, actual news consumption, etc.

5.3.2 Data Use Study Duration

Data use studies will only use POPROX released public datasets for offline experiments, therefore the duration of such type of study is not dependent on POPROX platform.

Below are two sample data use studies:

1) Some Machine Learning researchers propose to study a new recommender algorithm to test its effectiveness in improving hit rate and NDCG metrics of user clicks of news. They found a dataset containing news content and user interaction behavior that is released by POPROX team from poprox.ai/datasets. They decide to use the dataset to run offline evaluation on their new algorithm.
2) A group of social science PhD students want to study the level of social tension in news to readers' engagement and attention in reading such news. They plan to analyze a large dataset with sufficient datapoints to support their hypothesis. They found a recently released dataset from poprox.ai/datasets with deidentified data from over 1000 users and their interaction with 50,000 news articles. They determine to use the dataset

and run offline analysis of both news and user behaviors to answer their research questions.

5.3.3 Platform Duration

The POPROX platform is intended to operate indefinitely. The period during which we can operate it will depend on future funding (which will include plans for sustainability, including potentially charging fees to experimenters in the future). But based on our experience with MovieLens (which has been operating since 1997), we would expect the platform to last for one or more decades.

We plan to seek funding for a major upgrade to the platform that would start in 2026 – development of an on-demand news service accessible by web or on mobile devices. That upgrade would require an updated IRB protocol due to the different types of data that can be recorded.

5.4 Follow-Up:

Experiments may have a post-manipulation observation period, in which participants are still followed by their usage behaviors and/or surveys. We do not follow people who have withdrawn from the experiment or platform.

6.0 Storing Data for Future Use

6.1 Storage and Access:

We will store the data on Amazon AWS. Access will be restricted to the core POPROX members who are listed as part of the research team for this protocol (attached in attachment Article 1). Specifically, we will keep three parts of the data separated:

- The piece involved in delivering to users, such as email address and contact information for payments, will be stored separately from all experimental data (which will only be identified via identifiers that we can delete when the platform shuts down). Only the team operating the platform has access to all the identifying information.
- The platform-wide data which includes articles and metadata, user profiles, and other data used in common by all experiments; this data is made available to experimenters through defined access protocols.
- The data for an individual experiment will be de-identified and only be delivered to the research team that proposed the specific study.
    - As part of this process, each experiment has a different set of unique IDs assigned to participants in that experiment so there is no way for experimenters to unify the data between experiments to further identify users.

6.2 Data:

We will collect and store participant registration information and interaction logs with the newsletter. which will include:

Private Data

- email address
- payment contact information (might also just use email for that)

Platform-wide Data

- explicit profile information
  - geo location
  - interested news topics

Data for Individual Experiment

- implicit log information
  - open of newsletter
  - click of news articles
  - reading session length
  - click of pop-up window surveys
  - response to surveys (it can be both recommendation satisfaction survey or researcher-defined study-specific survey)

6.3 Release/Sharing:

Our data can be categorized into three parts: private data, experimental data, and data shared to the public under license.

	Private Data	**Experimental Data**	**Data Shared to Public**
Definition	- user contact information - user emails - personal information for payment	participant - one-time userId - interaction history - news topic preference - geo-location - survey responses news - title, slug, content - keywords, section, other metadata - experiment-specific user-item interaction tables	- de-identified datasets containing user-item interactions, news metadata, and user preference and/or geo-location information. - data needed to replicate certain experiments, including all de-identified experimental data and their original proposal manifest.

Who can access?	only POPROX team members	POPROX team members and researchers who proposed the specific experiment	The general public
De-identified?	No	Yes	Yes
Usage terms	N/A	Subject to all terms listed on the experimenter agreement	Subject to the license and usage agreement associated with published dataset

7.0 Sharing of Results with Participants

7.1 Sharing Results:

We do not plan to share the data with participants.

8.0 Study Population

8.1 Inclusion Criteria:

In the final study sample, we will only include participants with age of majority or older, e.g, 18 in most of the US, 21 in Mississippi or Puerto Rico, 19 in Alabama or Nebraska. The participants we recruit will be based in the United States.

8.2 Exclusion Criteria:

Employees and students of the researchers, and the researchers themselves are excluded from participation. They may establish accounts to perform quality control, but will not be enrolled in any study.

8.3 Screening:

When participants give consent, they will be enrolled to the platform (receiving daily newsletters) and entered into the pool of participants who can be assigned to future experiments.

9.0 Vulnerable Populations

9.1 Vulnerable Populations:

Population / Group	Identify whether any of the following populations will be the focus of the research (targeted), included, but not necessarily the focus or excluded from participation in the study.

Children	Excluded
Pregnant women/fetuses/neonates	included but not the focus
Prisoners	included but not the focus
Adults lacking capacity to consent and/or adults with diminished capacity to consent, including, but not limited to, those with acute medical conditions, psychiatric disorders, neurologic disorders, developmental disorders, and behavioral disorders	included but not the focus
Non-English speakers	included but not the focus
Those unable to read (illiterate)	included but not the focus
Employees of the researcher	Excluded
Students of the researcher	Excluded
Undervalued or disenfranchised social group	included but not the focus
Active members of the military (service members), DoD personnel (including civilian employees)	included but not the focus
Individual or group that is approached for participation in research during a stressful situation such as emergency room setting, childbirth (labor), etc.	N/A
Individual or group that is disadvantaged in the distribution of social goods and services such as income, housing, or healthcare.	included but not the focus
Individual or group with a serious health condition for which there are no satisfactory standard treatments.	included but not the focus

Individual or group with a fear of negative consequences for not participating in the research (e.g. institutionalization, deportation, disclosure of stigmatizing behavior).	included but not the focus
Any other circumstance/dynamic that could increase vulnerability to coercion or exploitation that might influence consent to research or decision to continue in research.	N/A

9.2 Additional Safeguards, if any, to ensure inclusion is appropriate:

9.3 If research includes potential for direct benefit to participants, provide rationale for any exclusions indicated in the table above:

10.0 Number of Participants

10.1 Number of Participants to be Consented:

Up to 10,000. During 2024, we will recruit and consent up to 200 participants. After the system has been fully functioning for several experiments, we will increase recruitment to reach up to 3000 participants. As participants withdraw, we will replace them with new participants (hence there will not be more than 3000 at one time, but may be as many as 10000 over a period of years).

11.0 Recruitment Methods

11.1 Recruitment Process:

Our recruitment will be online via news community channels and platforms. Research procedures will be performed remotely, and can be engaged with by participants in any location with internet access. Since the research is conducted online, there are no site-specific regulations or customs affecting the research, aside from standard online etiquette and respect for individual privacy.

11.2 Source of Participants:

The research team will recruit participants via various online channels, including:

1. A list of interested participants from a prior survey on the MovieLens website (https://movielens.org/, which is a UMN-maintained academic online movie recommender);
2. Participants from collegiate networks, such as alumni newsletter;
3. Recruitment posts on online news communities, such as Reddit;
4. Paid advertisements on social media platforms, such as Facebook and LinkedIn;

5. Paid or unpaid advertisement on subscriber newsletters and news-oriented platforms, such as the AP daily newsletter, Google News, or news podcasts. Our main goal is to recruit not in the recommender system community, but as close to the normal news reader population as possible.

We will involve a community advisory board with experts from both academia and industry. They will be serving advice on our platform building, experiment review, and any future modifications of terms and usage of this platform.

11.3 Identification of Potential Participants:

N/A

11.4 Recruitment Materials:

The sample advertisement example will be in the following format:

> Try POPROX News, a personalized daily newsletter!
>
> POPROX News is a research system from five universities working together to explore ways to better personalize news.
>
> Learn more about POPROX News and subscribe at <LINK>.

The template of email sent for recruitment will be in the following format:

> Hi [Name],
>
> We'd like to invite you to join POPROX News, a daily personalized newsletter bringing you the news you most want from leading sources like the Associated Press.
>
> POPROX is a collaboration of five universities to set up a research system for personalization. If you subscribe to POPROX News, you'll get to try out new innovative ways of personalizing news and your use will help scientists learn more about personalization and news summarization.
>
> We'd love to have you join – to learn more and sign up visit <link>, or if you have questions just reply to this email.
>
> All the best!
> The POPROX Team

Furthermore, we also attach an example daily newsletter interface that users can expect to receive (see attachment Article 2).

11.5 Payment:

For compensation, we try to balance the fact that we should be fair to participants when asking them to undertake time-consuming tasks, without biasing their behavior by rewarding them for things that are part of normal reading of news. We consider the service of receiving the newsletter to be adequate compensation for people's time reading it. However, we want the options to provide:

(a) Compensation for participating in experiments that require substantial participant time or effort (e.g., longer surveys) or where the experimenter and/or their institution prefers to compensate all subjects at a fair wage level. For these studies, we will restrict compensation to a level that matches prevailing wages for entry-level work. Participants will have an option of receiving an electronic gift card of their choice from among Amazon, Target, and Walmart or they may choose to direct their compensation to their choice from a set of charities.

(b) Incentive payments to reward and increase overall activity and longevity within the system. For these payments, we will have several options:

- for larger payments (>= $5):
  - Charity of their choice from a set of charities
  - Electonic gift card of their choice from among Amazon, Target, Walmart, and/or Tango.
- for smaller payments (< $5)
  - Entries into a drawing with winners paid a larger payment as indicated above
  - Designate their share to a charity of their choice from a set of charities.

We are not currently planning to conduct systematic studies of compensation strategies, but simply to adopt best practices. If we decide later to conduct such a study we will seek separate IRB approval for that study.

Total annual compensation per individual participant will be limited according to UMN's financial guidelines to ensure that we stay far below IRS reporting levels. This will allow us to avoid collecting taxpayer ID numbers, legal names, addresses, etc.

12.0 Withdrawal of Participants

12.1 Withdrawal Circumstances:

Participants may withdraw from POPROX at any time.

12.2 Withdrawal Procedures:

Participants can mainly withdraw from a specific study or the POPROX system via the unsubscribe option on every newsletter. The unsubscribe flow is described in Figure 3, with branches allowing users to withdraw from either a single study (i.e. D1234) or from the system.

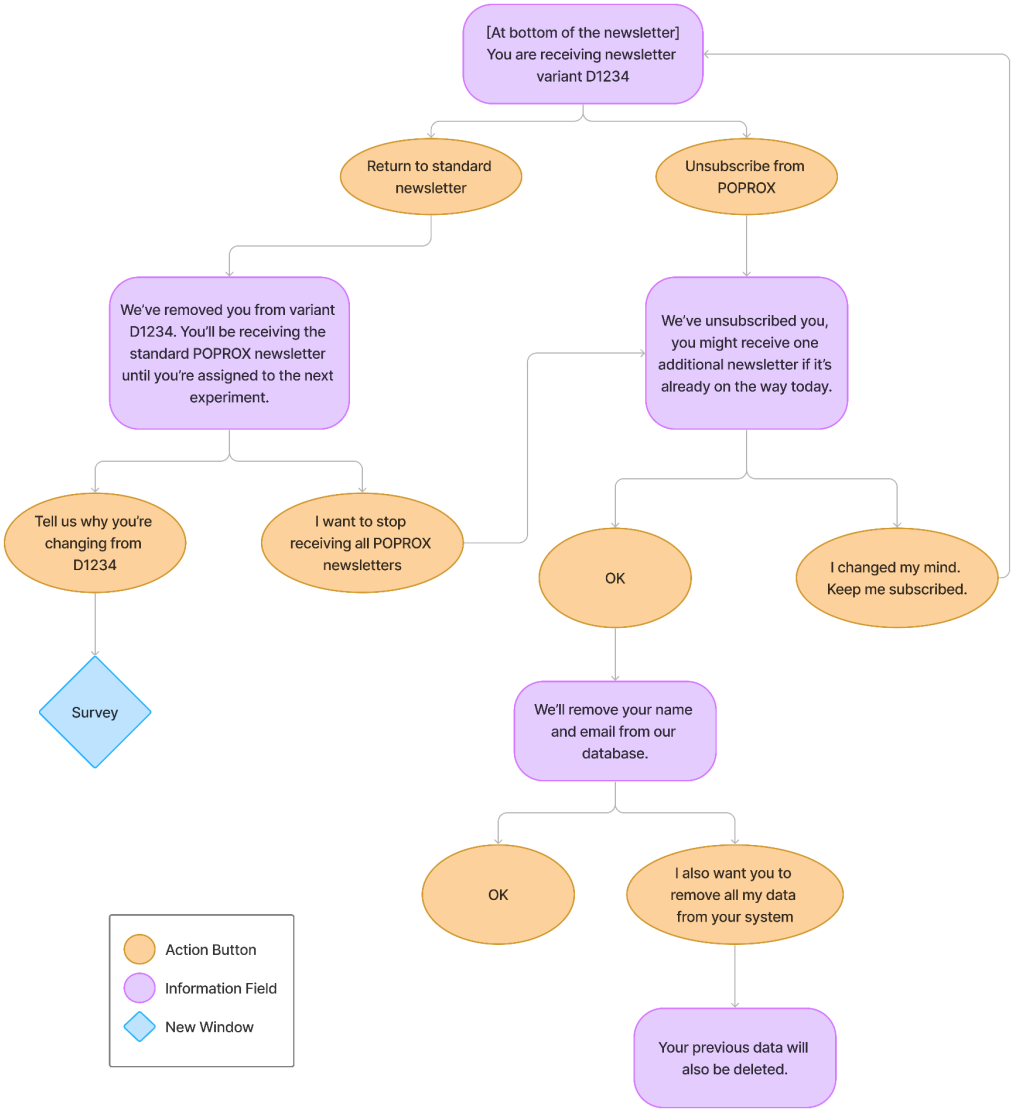

Figure 3: POPROX unsubscribe prompt

12.3 Termination Procedures:

If a participant's email address repeatedly fails to receive newsletters and we cannot reach them, we will terminate the service. Additionally, if we find that a participant is actively interfering with the system (e.g., conducting a denial of service attack using the links we provide) then we may terminate that participant from the study and

service (including potentially blocking access temporarily from the user's IP addresses). We also reserve the right to terminate and disenroll participants if they are inactive for a sustained period.

13.0 Risks to Participants

13.1 Foreseeable Risks:

The foreseeable risks involved in this study are minimal. They include possible discomfort in reading uninterested or controversial news, minimum stress in answering survey questions, or potential concerns about privacy associated with data logging. These risks can be mitigated by the fact that participants can freely choose to read whatever news they feel most interested in, their voluntary participation in surveys, and their right to quit the survey at any time. Since participant data will be fully de-identified and participants will be clearly informed about that in the consent form during their registration, the privacy concern is also addressed.

13.2 Reproduction Risks:

N/A

13.3 Risks to Others:

N/A

14.0 Incomplete Disclosure or Deception

14.1 Incomplete Disclosure or Deception: N/A

15.0 Potential Benefits to Participants

15.1 Potential Benefits:

The potential benefits participants may gain include: 1) participants can get personalized daily news recommendations and improve their news awareness; 2) participants can understand their news preferences and consumption behaviors better.

16.0 Statistical Considerations

16.1 Data Analysis Plan:

We will run regular data analysis with the POPROX interaction log to provide some standard statistics. These can be split into three categories: traditional recommender system metrics, online behavior metrics, and user experience metrics.

<u>Traditional recommender standard metrics</u>

Ranking:

- Normalized discounted cumulative gain (NDCG)
- Mean reciprocal rank (MRR)
- Other measures (ERR, RBP)

Success and conversion:

- Click-through rate (CTR)
- Hit rate (fraction of newsletter with >= click)

Online behavior metrics

Engagement:

- Implicit item-based metrics: clicks, read time, social sharing / forwarding
- System metrics: dwell time, use frequency / consistency, bounce rate

Interest:

- Explicit item-based feedback metrics, e.g. rating, thumbs up/down, like button
- Referral / newsletter forwarding

Retention:

- Time since last use

User Experience metrics:

Subjective System Aspects

- Perceived recommendation quality, perceived recommendation diversity, understandability, perceived control, perceived use effort / ease of use

User Experience

- System satisfaction, perceived system effectiveness/usefulness, choice difficulty (usage satisfaction), choice satisfaction

16.2 Power Analysis:

N/A, researchers should do their own power analysis before submitting an experiment proposal to request the number of participants.

16.3 Statistical Analysis:

N/A, researchers should do their own statistical analysis.

16.4 Data Integrity:

Procedures to ensure data integrity include regular backups and de-identification of data.

17.0 Reproducibility

17.1 Data Sharing

To benefit future research and encourage reproducibility of scientific studies, our policies include publishing experiment manifests and datasets for experiments

conducted using POPROX, after the publication of the original experiment research paper or with an extra waiting period.

18.0 Health Information and Privacy Compliance

18.1 Select which of the following is applicable to your research:

☒ My research does not require access to individual health information and therefore assert HIPAA does not apply.

☐ I am requesting that all research participants sign a HIPCO approved HIPAA Disclosure Authorization to participate in the research (either the standalone form or the combined consent and HIPAA Authorization).

☐ I am requesting the IRB to approve a Waiver or an alteration of research participant authorization to participate in the research.

Appropriate Use for Research:

☐ An external IRB (e.g. Advarra) is reviewing and we are requesting use of the authorization language embedded in the template consent form in lieu of the U of M stand-alone HIPAA Authorization. Note: External IRB must be serving as the privacy board for this option.

18.2 Identify the source of Private Health Information you will be using for your research (check all that apply):

N/A

18.3 Explain how you will ensure that only records of patients who have agreed to have their information used for research will be reviewed:

N/A

18.4 Approximate number of records required for review:

N/A

18.5 Please describe how you will communicate with research participants during the course of this research. Check all applicable boxes:

N/A

18.6 Explain how the research team has legitimate access to patients/potential participants:

N/A

19.0 Health Science Technology (HST) HIPAA Compliant Devices and Data Storage

N/A

19.1 HST Device Number:

Other non-HST managed devices:

19.2 Location(s) of storage, sharing and analysis of research data, including any links to research data (check all that apply):

N/A

19.3 Consultants. Vendors. Third Parties: N/A

19.4 Data Ownership: N/A

19.5 Links to identifiable data: N/A

19.6 Sharing of Data with Research Team Members: N/A

19.7 Storage of Documents: N/A

19.8 Disposal of Documents: N/A

20.0 Confidentiality

20.1 Data Security:

To protect data security, the research team will train and provide guidelines to all involved PIs, staff, and students on how to handle and access data. Access to the data will only be granted to authorized members. The data will be password-protected in cloud storage (AWS), and data sharing will be strictly managed as mentioned in section 6.3. The identifying information of data will only be accessible to trained core members of the research team. We do not have access to any of participant's medical, employment, or educational records.

20.2 Data Sharing:

The collected data will be deidentified before being shared with researchers and released as a public dataset. The team will perform manual checks before sharing to ensure data privacy. In addition, data will only be shared under a license that prohibits further sharing and prohibits attempts to re-identify participants through their data.

21.0 Provisions to Monitor the Data to Ensure the Safety of Participants

21.1 Data Integrity Monitoring:

We plan to have ongoing monitoring of samples of data we get.

21.2 Data Safety Monitoring:

N/A due to the minimum risk of this platform.

22.0 Provisions to Protect the Privacy Interests of Participants

22.1 Protecting Privacy:

See Section 20 for data security procedures.

22.2 Access to Participants:

Experimenters or data use researchers do not have access to participants. The core POPROX team only have limited identifying information of participants:

- We will not ask for individual personal identifiable information such as name, address, date of birth, social security number, etc.
- We will request and store their email address for delivering daily newsletter, distributing compensation, and process any requests.

- We will have access to onboarding and periodic or experimental survey responses that may include participants' socio-economic status, general geo-location, etc. Not that any individual survey question response category will not narrow to a population of fewer than 10,000 (each category of a variable must contain nationwide at least 10,000 people or households – census guideline from McKenna & Haubach 2019 [78] and Pascale et al. 2022 [79])

23.0 Compensation for Research-Related Injury

23.1 Compensation for Research-Related Injury: N/A

23.2 Contract Language: N/A

24.0 Consent Process

24.1 Consent Process (when consent will be obtained):

We will share the consent form with participants during their online registration. Participants will be given sufficient time to read and understand the chunked consent before they agree to participate. If they have any questions, they can email the POPROX team at any time for clarification. The chunked form is split into the following pieces: 1) Introduction (with eligibility, consent process, and overview); 2) Experiments; 3) POPROX Platform (with data collection, withdraw and disenroll information); 4) Compensation; 5) Final Confirmation. Detailed consent form can be found in supplementary document Article 4. We will send each participant a copy of the full form to their email at the end of the process.

The consent form draft is attached as supplementary material in Article 4 with this submission.

24.2 Waiver or Alteration of Consent Process (when consent will not be obtained):

N/A

24.3 Waiver of Written/Signed Documentation of Consent (when written/signed consent will not be obtained):

We request the waiver of written/signed documentation to allow us to accept online consent. Detailed consent form can be found in the supplementary documents. Requiring written/signed documentation would increase the amount of personally identifiable information collected (i.e., an email address would no longer suffice; we would need a legal name) and would be inconsistent with normal practices for such low-risk online studies.

24.4 Non-English Speaking Participants:

We do not expect them to enroll.

24.5 Participants Who Are Not Yet Adults (infants, children, teenagers under 18 years of age):

N/A

24.6 Cognitively Impaired Adults, or adults with fluctuating or diminished capacity to consent:

N/A

24.7 Adults Unable to Consent:

N/A

25.0 Setting

25.1 Research Sites:
Same as Section 11.

25.2 International Research:
The POPROX platform is operating within the U.S. with U.S. participants. We do not believe this is international research. However, we expect researchers outside of U.S. to conduct research on it, either via running real-user experiments or by using our published datasets.

To accommodate this, we plan to require international researchers to follow the same procedures with an IRB that has a current federal-wide assurance (FWA). Researchers will also be responsible for ensuring general data protection regulation (GDPR) compliance for studies proposed by researchers in different regions. The actual research will still take place with U.S. participants and the news source is from AP.

25.3 Community-Based Participatory Research:

N/A

26.0 Multi-Site Research

This is not a multi-site research. There is a single online-site collaborated by five institutions. See Section 11 for details.

26.1 Study-Wide Number of Participants: N/A

26.2 Study-Wide Recruitment Methods: N/A

26.3 Study-Wide Recruitment Materials: N/A

26.4 Communication Among Sites: N/A

26.5 Communication to Sites: N/A

27.0 Coordinating Center Research

27.1 Role:
N/A

27.2 Responsibilities:
N/A

27.3 Oversight:
N/A

27.4 Collection and Management of Data:
N/A

28.0 Resources Available

28.1 Resources Available:
N/A

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