Spontaneous and Sophisticated: Re-Evaluating Click-Based User Interaction for Personalized Recommendation in Algorithmic Systems

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Algorithms are powerful in managing people's online activities and have the potential to reshape their needs and usage patterns. Our project aims to explore how personalized recommendation algorithms shift user behavior. Focusing on Xiaohongshu, a Chinese lifestyle-sharing community with a highly effective content recommendation algorithm, we conducted semi-structured interviews with 14 users. The preliminary interview study prompts a re-evaluation of the design of human-computer interaction in algorithm-supported systems: users considered click as a continuous and adaptive way to train algorithms about their preferences, and a more precise way than other approaches, such as search; additionally, non-click was regarded as a deliberate choice made to avoid receiving unwanted content recommendations. The findings shed light on large-scale evaluation of click-based user interaction in algorithmic systems.

CCS Concepts: • **Human-centered computing → Empirical studies in interaction design**.

Additional Key Words and Phrases: click, algorithm, personal content recommendation, interview, interface design, user-centered evaluation

1 BACKGROUND

Ariela is a Chinese undergraduate student studying at the School of Architecture who regularly collects design references from other designers on social media platforms. In addition, she browses topics related to her daily life and internships. Ariela normally uses three websites, namely Pinterest, Instagram, and Xiaohongshu (a Chinese community-sharing mobile application). Ariela benefits from the personalized recommendation algorithms of these platforms, which can continuously push similar content that interests her. For Ariela, Pinterest offers rich architectural design references, Instagram is more focused on socializing and daily life, while Xiaohongshu offers both and provides more diverse inspiration for her major through its nuanced algorithmic recommendation.

Just like Ariela, we consume rich online content brought by personalized recommendations. Almost every social media platform uses algorithms to provide users with optimized recommendation services [13].The mechanism behind personalized recommendations is to record users' usage behaviors (e.g., clicks, viewing time, friend lists, likes, and favorites) to create a profile for each user, based on which content that users are interested in can be pushed to them [28].

Algorithms have penetrated into both the online and offline activities of people, potentially changing their needs and patterns of technology usage. This phenomenon has been reflected in the HCI and CSCW communities, which have increasingly highlighted the impacts of algorithms on users, as seen in recent research on users' understanding and needs of algorithms [6, 23], resistance to algorithms [19, 27], and user-driven auditing of algorithms [1, 17]. The existing literature has indicated users' potential to reshape the design of algorithm-equipped systems. To explore future shifts of interface design, our study began with two broader inquiries: *how do users adapt their interactions with personalized recommendation algorithms* and *whether can these interactions suggest any interface design change?* This position paper reports the preliminary findings—the significance of treating click as a primary interaction between users and algorithmic systems—and discusses the directions of large-scale evaluation studies in the future.

2 RELATED WORK

2.1 Evolution of Click: From User Interface to Personalized Recommendation

In its original definition, *click* refers to a user's action of pressing a button on a computer interface using a mouse. For instance, in a user interface, clicking on hyperlinks allows users to navigate from page to page. Although click may seem commonplace now, it was a focal point in user interface design at the time [24, 32]. The well-known Fitts's law has been utilized to assess the performance of click (and point) [30]. While HCI has advanced beyond the use of mice (such as taps on the screen and voice commands), click remains the term used to refer to the command on an element in a user interface.

When search engines emerged, click was endowed with more meaning related to "user intent." Scholars attempted to analyze users' click behavior under search queries [29, 33] to optimize the ranking algorithms of search engines. For commercial search engines, the number of clicks on ads has become the primary indicator of revenue [20]. Because of the economic motivation, numerous studies have explored how to predict ad clicks more accurately in search engines [18, 24]. As we entered the era of social media, the number of clicks is still an important metric to measure platform user activity and profitability. However, there was more vibrant content that could be used to predict user click behavior, such as the user's friend networks [8], posts [21], likes [5, 15], and bookmarks [22]. As TikTok and other equivalent platforms have achieved personalized recommendations to the point that users feel that the algorithms are "spying" on their thoughts, users have become aware that their clicks matter a lot to their online experiences [8]. Next, we review how users perceive and react to algorithms, particularly personalized recommendation algorithms.

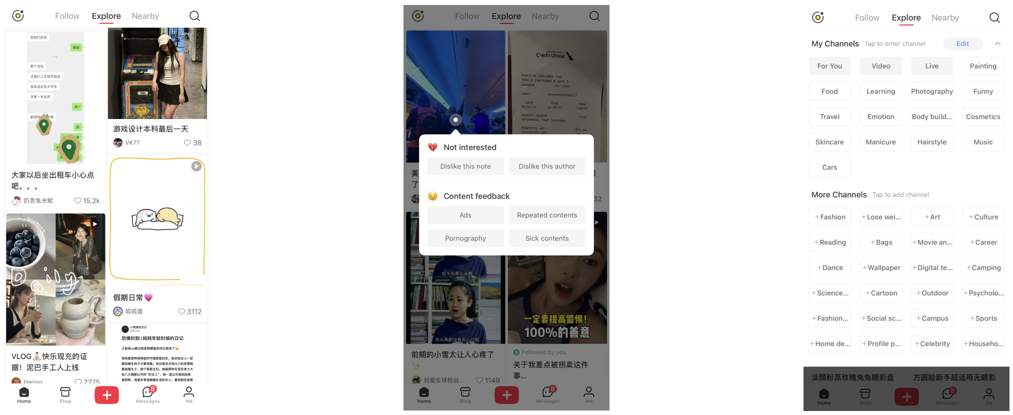
2.2 Regaining Control of User Experiences in Algorithmic Systems

Algorithmic systems refer to systems that rely on algorithms to provide services or governance, for example, recommendation systems, social media feeds, and data-driven decision support. Bishop contended that there were two main approaches in research on algorithmic systems, with one focusing on how algorithms are constructed and the other examining users' everyday interactions with algorithms [3]. The first approach applied auditing tools such as sock-puppets or browser extensions to unpack recommendation algorithms [1, 11, 14, 17]. However, this approach usually requires computational skill sets and narrows down the scope to technical aspects of algorithmic systems, thus falling into the trap of "technological solutionism" [10, 25].

The second approach attempted to understand users' needs and usage in algorithmic systems. Through interviews, Lee and colleagues' work emphasized the importance of personalization processes accurately reflecting users' multifaceted and dynamic identity [23]. Bucher conducted a case study and highlighted the impacts of YouTube's recommendation algorithm on content creators' strategies to gain visibility [4]. Overall, the works suggested that users navigated the algorithmic power and regained control of their experience as users. Additionally, some research attempted to challenge algorithmic systems to perpetuate inequalities and injustices [2, 19, 27]. For example, users used posting and clicking to manipulate their online identities (e.g., gender, race) to circumvent harmful algorithms in TikTok [19]. The existing research illustrates the importance of understanding user behaviors when they are engaging in algorithms.

3 PRELIMINARY WORK: PILOT INTERVIEW STUDY

The preliminary work took the first step to explore whether and how algorithms shift the ways users interact with personalized recommendation algorithms, especially users' click behavior. We chose Xiaohongshu (meaning "Little Red Book") as the research site. Xiaohongshu is a lifestyle-sharing community and an e-commerce platform that has



(a) The main page: “Explore”   (b) Post reporting options   (c) Customizable interest channels

Fig. 1. The Xiaohongshu mobile application interface. (a) is the main page of Xiaohongshu, which displays a selection of posts known as “notes” by the algorithm, consisting of both picture and video posts; (b) the available options for reporting a post, including “Not interested” and “Content feedback”; (c) presents the customizable channels or tags that users can create for their personalized preferences. Despite the space constraints, it’s worth mentioning that other functions, such as search, following, and collection of savings, are also available.

become increasingly popular in China. Xiaohongshu has deployed a powerful content recommendation algorithm. The algorithm can recommend diverse content to users based on the user’s browsing history, social networks, and others [16]. Figure 1 demonstrates the main features of Xiaohongshu.

We conducted semi-structured interviews with 14 Xiaohongshu users. We recruited participants based on the eligibility criteria that included anyone who has used Xiaohongshu and is 18 years or older. More demographic characteristics of the participants are presented in Appendix. Each interview lasted 40 to 60 minutes, and we utilized video conferencing tools to facilitate the interviews. Participants received a compensation of 20 Yuan RMB (approximately $2.79) for the full completion of the interview. The interview questions explored various aspects of participants’ Xiaohongshu usage, including their posting, liking, saving, and reposting behaviors, the content they are interested in, their understanding of and attitudes toward the platform’s algorithm, their resistance strategies for avoiding the negative impacts of the algorithm, and the overall suggestions to the design of the platform. The study was approved by the Institutional Review Board of Syracuse University. The data analysis was conducted by the first three researchers utilizing an inductive analysis approach derived from grounded theory [12]. The team found the “click” phenomenon prominent among the themes and further applied an axial coding method [7] to generate three primary themes around “click.”

We found that users regarded click as a continuous and adaptive way to train algorithms about their fuzzy and ever-changing needs and a more precise action than other approaches (e.g., search) as they served as a final confirmation; importantly, non-click was considered an intentional choice to avoid unwanted recommendations. We discuss how these findings indicate future work and design. Specifically, users’ needs are diverse and ever-changing, which are recognized through the continuous interaction with content recommended by algorithms. Click, as the most fundamental and common action, is a continuous and adaptive way for users to explore their needs and help the algorithm understand their needs. In addition to click, participants also reported other ways through which they could impart their preferences to the algorithm, such as search queries, interest tags, follows, likes, saves, and reports. Nevertheless, participants reflected that click represented a more *precise* and *sensitive* modality than the others.

Interestingly, non-click, the opposite act of click, is also a conscious choice made by users when engaging with algorithmic recommendations. Participants reported that they were keenly aware of what they did not click on, knowing that every click would be recorded by the algorithm and could result in changes to future recommendations. “Mis-clicks” carry a higher cost in recommendations supported by algorithms than those not. For instance, P05, P06, P08, and P11 expressed concerns about accidentally clicking on the wrong posts. P06 described that one day, he clicked on a post out of curiosity, but later the algorithm kept sending him repeated information based on that misclick, which bothered him.

4 FUTURE WORK: LARGE-SCALE SURVEY STUDIES

The interview study emphasized the importance of click-based interactions between users and algorithms for a more seamless and efficient user experience in personalized recommendations. Participants reported infrequently customizing their interest channels, suggesting their interests are ever-changing and challenging to define at any given moment. This finding suggests future designs could enable users to define their interests in a more adaptable manner through user-algorithm interactions. Furthermore, participants perceived click-based interactions to be more precise and sensitive than other actions, such as search and post reports. However, these perceptions are limited to the study’s participants, and it remains unclear how Xiaohongshu’s algorithm is affected by different user interactions.

The pilot study also highlighted the significance of non-click options as an intentional choice for participants. Neglecting non-click options can misunderstand users’ preferences and hinder the usability. For example, TikTok’s scrolling feature eliminates both click and non-click options, which are conscious decision-making processes for users [26]. Therefore, future designs could aim to incorporate non-click options into their interfaces, such as listing multiple options for users to click or not to click.

Next, we plan to conduct large-scale survey studies to investigate these directions. According to reports, over 70% of Xiaohongshu’s users were female, and the majority of them are between the ages of 18 and 35 [9, 31]. The interview sample leans toward the age range of 18 to 25. The survey study will draw a more diverse and larger user sample. The survey studies will validate the novel findings by comparing the effects of different user actions (e.g., click, search, report) on their algorithms. The insights will be used to generate design prototypes about click-based user interaction and be evaluated by Xiaohongshu users.

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A APPENDIX

Table 1. Demographic Information (i.e., age, gender, education background, and occupation) and Duration of Xiaohongshu Use Reported by Participants

No.	Age	Gender	Education	Occupation	App Usage
P01	18-25	Male	Bachelor	Salesperson	> 4 years
P02	18-25	Female	Bachelor	Student	> 4 years
P03	26-35	Female	Bachelor	Administrative staff	3 years
P04	18-25	Male	Bachelor	Student	3 years
P05	18-25	Female	Bachelor	Student	4 years
P06	18-25	Female	Bachelor	Student	> 4 years
P07	18-25	Female	Bachelor	Student	2 years
P08	18-25	Female	Bachelor	Student	4 years
P09	18-25	Female	Bachelor	Professional	< 1 year
P10	18-25	Male	Bachelor	Salesperson	3 years
P11	18-25	Female	Master	Student	1 year
P12	18-25	Female	Bachelor	Other	3 years
P13	18-25	Female	Master	Student	> 4 years
P14	18-25	Female	Bachelor	Student	2 years