Auditing Personalized Recommendation Algorithms Through Spontaneous Click-Based User Interaction

QUNFANG WU, University of North Carolina at Chapel Hill, USA
ZITONG HUANG, Syracuse University, USA
YAQI ZHANG, Syracuse University, USA
CHUNG-CHIN EUGENE LIU, Syracuse University, USA

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 users navigate personalized recommendation algorithms through daily interaction with the system. 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 found that 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 underscore the significance of click as a primary interaction between users and algorithmic systems and offer suggestions for click-based algorithm auditing. We discuss the future work and challenges in user auditing.

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

ACM Reference Format:
Qunfang Wu, Zitong Huang, Yaqi Zhang, and Chung-Chin Eugene Liu. 2018. Auditing Personalized Recommendation Algorithms Through Spontaneous Click-Based User Interaction. In . ACM, New York, NY, USA, 7 pages. https://doi.org/XXXXXXX.XXXXXXX

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 [12].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 [27].

Manuscript submitted to ACM

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, 22], resistance to algorithms [18, 26], and user-driven auditing of algorithms [1, 16]. 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 navigate personalized recommendation algorithms* and *whether can these interactions suggest any algorithm auditing methods?* We found that users were more aware of the click interaction when navigating personalized recommendation algorithms and documented the algorithm reactions under different click patterns. This position paper reports the preliminary findings and discusses the opportunities and challenges of click-based user algorithm auditing in the future.

2 RELATED WORK

2.1 Evolution of Click: From User Interface to Personalized Recommendation

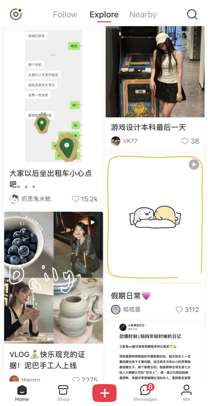
In its original definition, *click* refers to a user's action of pressing a button on a computer interface using a mouse. For instance, in a user interface, clicking on hyperlinks allows users to navigate from page to page. Although click may seem commonplace now, it was a focal point in user interface design at the time [23, 30]. The well-known Fitts's law has been utilized to assess the performance of click (and point) [29]. 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 [28, 32] 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 [19]. Because of the economic motivation, numerous studies have explored how to predict ad clicks more accurately in search engines [17, 23]. 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 [20], likes [5, 14], and bookmarks [21]. 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.

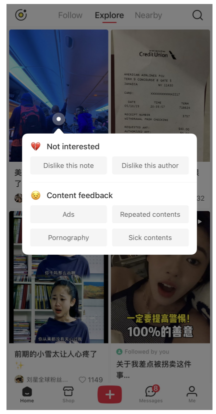
2.2 User Engagement As a Means of Algorithm Auditing

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, 10, 13, 16]. 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" [9, 24].

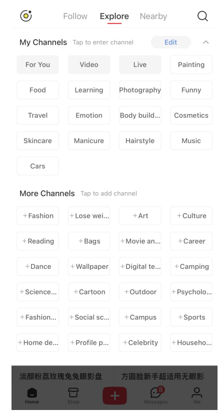
The second approach attempted to understand users' needs and usage in algorithmic systems. Through interviews, Lee and colleagues' work emphasized the importance of personalization processes accurately reflecting users' multifaceted



(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 is worth mentioning that other functions, such as search, following, and collection of savings, are also available.

and dynamic identity [22]. 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, 18, 26]. For example, users used posting and clicking to manipulate their online identities (e.g., gender, race) to circumvent harmful algorithms in TikTok [18]. Yu et al. explored the use of gamification features by food delivery platforms to optimize labor value and how riders developed resistance strategies through WeChat groups, which served as hidden transcripts of resistance [31]. The existing research illustrates the importance of understanding user behaviors when engaging in algorithms and the great potential of user engagement in algorithm auditing.

3 PRELIMINARY WORK: PILOT INTERVIEW STUDY

The preliminary work took the first step to explore how users navigate personalized recommendation algorithms through their interaction with the algorithmic system, especially through 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 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 [15]. 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 [11]. 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 navigate 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. 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. For example, P07 showed a case that the algorithmic recommendation based on a historical search resulted in irrelevant or useless information

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 DISCUSSION

4.1 Click With Awareness: Auditing Recommendation Algorithms

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. 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.

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 usability. For example, TikTok's scrolling feature eliminates both click and non-click options, which are conscious decision-making processes for users [25].

4.2 Future Work and Challenges

The findings suggest that users were more attentive to the click interaction when navigating personalized recommendation algorithms. Users adapted their clicking behaviors and documented the outcomes of various click patterns. This points toward the potential of click-based interactions serving as a means for users to audit algorithms. In the future, we plan to continue testing users' click engagement on a large scale and explore the possibility of auditing algorithms based on users' clicks. For example, we want to inquire:

- To what extent users' clicks can impact algorithms and whether these impacts are stable and predictable;
- Whether the click interaction can be recorded or collected by auditing tools and whether the platform allows for this;
- How to address unconscious and random clicks.

These questions pose challenges for future research and merit further exploration.

ACKNOWLEDGMENTS

This work was supported by Syracuse Office of Undergraduate Research and Creative Engagement Fellowship.

REFERENCES

[1] Jack Bandy and Nicholas Diakopoulos. 2021. More accounts, fewer links: How algorithmic curation impacts media exposure in Twitter timelines. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–28.

[2] Sophie Bishop. 2018. Anxiety, panic and self-optimization: Inequalities and the YouTube algorithm. *Convergence* 24, 1 (2018), 69–84.

[3] Sophie Bishop. 2019. Managing visibility on YouTube through algorithmic gossip. *New media & society* 21, 11-12 (2019), 2589–2606.

[4] Taina Bucher. 2018. Cleavage-Control: Stories of Algorithmic Culture and Power in the Case of the YouTube" Reply Girls". In *A networked self and platforms, stories, connections*. Routledge, 125–143.

[5] Millissa FY Cheung and WM To. 2022. What influences people to click 'like'on posts of branded content? *Journal of Strategic Marketing* (2022), 1–23.

[6] Kelley Cotter. 2019. Playing the visibility game: How digital influencers and algorithms negotiate influence on Instagram. *New media & society* 21, 4 (2019), 895–913.

[7] John W Creswell and Cheryl N Poth. 2016. *Qualitative inquiry and research design: Choosing among five approaches*. Sage Publications.

[8] Nicole B Ellison, Penny Triu, Sarita Schoenebeck, Robin Brewer, and Aarti Israni. 2020. Why we don't click: Interrogating the relationship between viewing and clicking in social media contexts by exploring the "non-click". *Journal of Computer-Mediated Communication* 25, 6 (2020), 402–426.

[9] Maya Indira Ganesh and Emanuel Moss. 2022. Resistance and refusal to algorithmic harms: Varieties of 'knowledge projects'. *Media International Australia* 183, 1 (2022), 90–106.

[10] Anna Gausen, Wayne Luk, and Ce Guo. 2022. Using agent-based modelling to evaluate the impact of algorithmic curation on social media. *ACM Journal of Data and Information Quality* 15, 1 (2022), 1–24.

[11] Barney G Glaser and Anselm L Strauss. 2017. *Discovery of grounded theory: Strategies for qualitative research*. Routledge.

[12] Ido Guy, Naama Zwerdling, Inbal Ronen, David Carmel, and Erel Uziel. 2010. Social media recommendation based on people and tags. In *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*. 194–201.

[13] Muhammad Haroon, Anshuman Chhabra, Xin Liu, Prasant Mohapatra, Zubair Shafiq, and Magdalena Wojcieszak. 2022. YouTube, The Great Radicalizer? Auditing and Mitigating Ideological Biases in YouTube Recommendations. *arXiv preprint arXiv:2203.10666* (2022).

[14] Xingjian Hu, Tiannan Jin, Yunjing Lu, and Shuyu Zhong. 2022. The Interest-Based Communities on Xiaohongshu Recreate the Era of "Tribalization". In *2022 6th International Seminar on Education, Management and Social Sciences (ISEMSS 2022)*. Atlantis Press, 711–720.

[15] Yanhua Huang, Weikun Wang, Lei Zhang, and Ruiwen Xu. 2021. Sliding Spectrum Decomposition for Diversified Recommendation. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. 3041–3049.

[16] Eslam Hussein, Prerna Juneja, and Tanushree Mitra. 2020. Measuring misinformation in video search platforms: An audit study on YouTube. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW1 (2020), 1–27.

[17] Jason T Jacques, Mark Perry, and Per Ola Kristensson. 2015. Differentiation of online text-based advertising and the effect on users' click behavior. *Computers in Human Behavior* 50 (2015), 535–543.

[18] Nadia Karizat, Dan Delmonaco, Motahhare Eslami, and Nazanin Andalibi. 2021. Algorithmic folk theories and identity: How TikTok users co-produce Knowledge of identity and engage in algorithmic resistance. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–44.

[19] Sungchul Kim, Tao Qin, Hwanjo Yu, and Tie-Yan Liu. 2011. Advertiser-centric approach to understand user click behavior in sponsored search. In *Proceedings of the 20th ACM international conference on Information and knowledge management*. 2121–2124.

[20] Yoojung Kim, Mihyun Kang, Sejung Marina Choi, and Yongjun Sung. 2016. To click or not to click? Investigating antecedents of advertisement clicking on Facebook. *Social Behavior and Personality: an international journal* 44, 4 (2016), 657–667.

[21] Piyanuch Klaisubun, Phichit Kajondecha, and Takashi Ishikawa. 2007. Behavior patterns of information discovery in social bookmarking service. In *IEEE/WIC/ACM International Conference on Web Intelligence (WI'07)*. IEEE, 784–787.

[22] Angela Y Lee, Hannah Mieczkowski, Nicole B Ellison, and Jeffrey T Hancock. 2022. The algorithmic crystal: Conceptualizing the self through algorithmic personalization on TikTok. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (2022), 1–22.

[23] Jiahui Liu, Peter Dolan, and Elin Rønby Pedersen. 2010. Personalized news recommendation based on click behavior. In *Proceedings of the 15th international conference on Intelligent user interfaces*. 31–40.

[24] Evgeny Morozov. 2013. *To save everything, click here: The folly of technological solutionism.* Public Affairs.

[25] Arvind Narayanan. 2022. TikTok's Secret Sauce. https://knightcolumbia.org/blog/tiktoks-secret-sauce. Accessed by May 12, 2023.

[26] Alex Rosenblat and Luke Stark. 2016. Algorithmic labor and information asymmetries: A case study of Uber's drivers. *International journal of communication* 10 (2016), 27.

[27] Virda Setyani, Yu-Qian Zhu, Achmad Nizar Hidayanto, Puspa Indahati Sandhyaduhita, and Bo Hsiao. 2019. Exploring the psychological mechanisms from personalized advertisements to urge to buy impulsively on social media. *International Journal of Information Management* 48 (2019), 96–107.

[28] Si Shen, Botao Hu, Weizhu Chen, and Qiang Yang. 2012. Personalized click model through collaborative filtering. In *Proceedings of the fifth ACM international conference on Web search and data mining*. 323–332.

[29] Mads Soegaard and Rikke Friis Dam. 2012. The encyclopedia of human-computer interaction. *The encyclopedia of human-computer interaction* (2012).

[30] Shufan Yu. [n. d.]. Investigation of Users' Experience of Social Media's Personalized Recommendation—TheCase of Xiaohongshu. ([n. d.]).

[31] Zizheng Yu, Emiliano Treré, and Tiziano Bonini. 2022. The emergence of algorithmic solidarity: unveiling mutual aid practices and resistance among Chinese delivery workers. *Media International Australia* 183, 1 (2022), 107–123.

[32] Yuchen Zhang, Weizhu Chen, Dong Wang, and Qiang Yang. 2011. User-click modeling for understanding and predicting search-behavior. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*. 1388–1396.

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

Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009