Information Research - Vol. 30 No. CoLIS (2025)

Algorithmic Gossiping: sharing and non-sharing that evolve algorithmic imaginaries to folk theories

Gaohui Cao, Zhang Wen, Puyi, Liu

DOI: https://doi.org/10.47989/ir30CoLIS51922

Abstract

Introduction. This paper presents a work-in-progress diary study exploring how algorithmic gossiping contributes to the transformation of individual, momentary algorithmic imaginaries into shared and consolidated folk theories.

Method. This study utilises Douyin as the research site, employing an integrated approach that combines the critical incident technique with diary methods to capture significant moments, encompassing the formation, sharing and reception of participants' algorithmic imaginaries.

Analysis. A conventional content analysis method was utilised to analyse the 82 diary entries.

Results. Our preliminary findings suggest that algorithmic gossiping plays a pivotal role in the construction of users' algorithmic knowledge as it confirms and articulates their algorithmic imaginaries while breaking existing bias.

Conclusion. The initial findings on algorithmic gossiping highlight its role in transforming algorithmic imaginaries into folk theories and its potential to unify the current array of concepts in the field of algorithmic-related information behaviour at individual and meso levels.

Introduction

This paper is a work-in-progress diary study where we present preliminary findings from our ongoing examination of how algorithmic gossiping facilitates the transformation of individual, whim-of-the-moment algorithmic imaginaries into more shared, consolidated folk theories, thus proposing algorithmic gossiping as the pivotal behaviour in user algorithmic knowledge construction.

Background

Understanding the mechanisms behind algorithms is vital for survival in an information-rich world, as previous literature (e.g. Gao et al., 2023; Zhao, 2023; Hu and Wang, 2024; Bishop, 2019; Saragih and Morrison, 2022; Lobel, 2021) has found such understandings carry tangible consequences for personal wellbeing, social dynamics and professional success. Early research in algorithm-related information behaviour started from the notion of algorithmic awareness, emphasising whether users recognised the presence of algorithms (Eslami et al., 2015). This awareness was subsequently conceptualised as the ability to recognise and engage with online content, involving filtering out what is considered irrelevant while prioritising content deemed interesting to the users (Eg et al., 2023). The following years witnessed how algorithmic awareness became more prevalent among users in the years to come (e.g. Shin et al., 2022; Swart, 2021) compared to the findings of Eslami and her colleagues (2015). As awareness of algorithms increased, so too did academic interest in the implications of this awareness, particularly regarding how users interpret and respond to the presence of algorithms. The concepts of folk theories (Eslami et al., 2016) and algorithmic imaginaries (Bucher, 2017) emerged as the names of lay hypotheses users generated about algorithmic processes.

While some scholars (e.g., Swart, 2021; Eg et al., 2023) argue that these two concepts are essentially the same, differing only in terminology, there are important distinctions between them. Folk theory represents a more systematic interpretation of algorithms, where users understand them as the underlying mechanisms driving specific functions within information systems. Notably, algorithmic folk theories are a dynamic knowledge sometimes shared by a small group: after Eslami and her colleagues (2016) provided two alternative views of how News Feed might work, the participants revisited their four original folk theories and proposed six new ones. In that study, the number of viable folk theories diminished over time, consolidating into two dominant explanations as participants attempted to find methods to achieve their objectives or goals within the system. In contrast, algorithmic imaginaries, defined by Bucher (2017, p. 32) as '*the way in which people imagine, perceive and experience algorithms and what these imaginations make possible*,' often appear in more spontaneous, emotional forms, like '*whoa moments*', a sudden realisation that algorithms are tracking users' profiles, or '*cruel connections*', the emotional impact users suffer when recommendation algorithms bring forth a photo of a deceased loved one (Bucher, 2017).

Both algorithmic folk theories and algorithmic imaginaries have been the focus of extensive investigation since their conceptualisation. Researchers have expanded these frameworks to encompass new contexts and scenarios (e.g., Schulz, 2023; Liao and Tyson, 2021) while exploring their potential to help users mitigate or cope with the side effects of algorithm-driven information systems (e.g., Zhang and Chen, 2023; Jones, 2023). However, except for DeVito et al. (2018), who pointed out that algorithmic folk theories were the updated version of foraged information guided by self-represented goals, few studies have delved into the formation of algorithmic knowledge - whether described as folk theories or imaginaries. This gap raises two critical questions: if users' algorithmic knowledge manifests as both spontaneous, intuitive imaginaries and systematic, structured folk theories, could they represent different stages in the process of algorithmic knowledge development? In addition, what drives the transformation between those different stages?

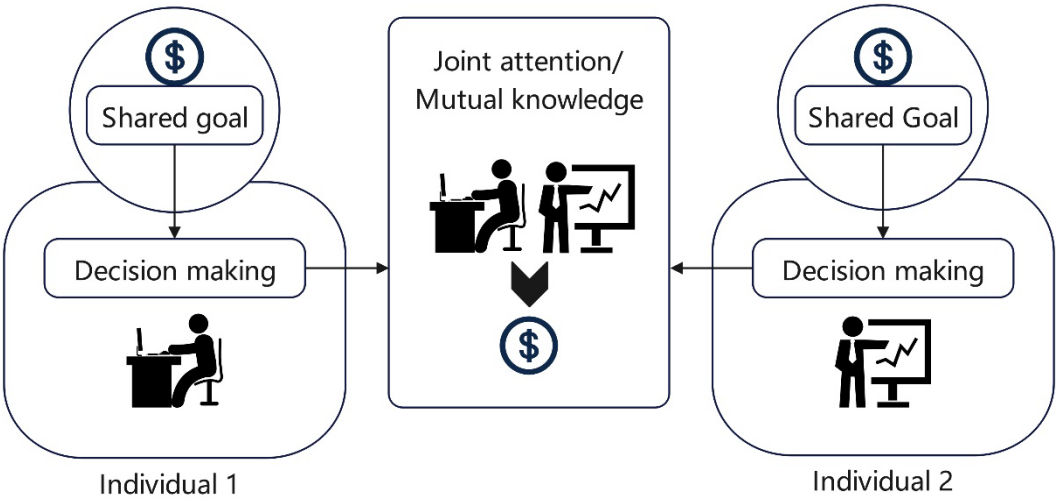

Figure 1. How individual conceptions form joint attention/mutual knowledge.

In our investigation, joint attention theory (Tomasello et al., 2005) sheds light on those questions. Tomasello and colleagues argue that when individuals work toward a shared goal, the act of information sharing facilitates the development of mutual knowledge by integrating diverse individual perspectives (see Figure 1). This suggests that individual algorithmic perspectives can converge and evolve into shared folk theories through information exchanges between actors. In addition, such knowledge sharing and creation have been identified in previous work in the field. Bishop (2019) introduced the concept of algorithmic gossip, describing it as collectively and socially constructed theories and strategies related to recommender algorithms, which are shared and applied to achieve financial stability and maintain visibility within algorithmically driven social media platforms, as exemplified in her study of beauty vloggers' efforts to strategically manage their algorithmic presence.

Extending on previous work, we adapted the notion of algorithmic gossiping, defined as the daily sharing of personal experience, tactics and projections towards algorithms among user groups. This work in progress aims to address two key questions with preliminary findings:

1. What algorithmic imaginaries do users choose to share or withhold during algorithmic gossiping?

2. How does algorithmic gossiping contribute to the transformation of algorithmic imaginaries into more systematic folk theories?

Method

This study selected Douyin, the Chinese version of TikTok and currently the largest short-video social media platform in China, as the research site. Drawing on Flanagan's (1954) principles, we integrated the critical incident technique (CIT) with diary methods to document key moments related to participants' algorithmic imaginaries, including their emergence, sharing and reception. While the application of such a combined method to the study of algorithmic imaginaries and folk theories is relatively novel, it has demonstrated efficacy in capturing dynamic and less discernible information behaviours, such as information encounters (Jiang et al., 2019).

Using a combination of convenience and snowball sampling methods, we recruited sixteen participants from Central China Normal University in Wuhan for the initial phase of the diary research conducted in November 2024. The participants were subsequently divided into three sub-groups to facilitate planned focus group interviews scheduled for December 2024. Table 1 provides an overview of the participants' demographic characteristics.

Group name	Number of participants	Number of males	Number of females	Age range	Average age	Occupations
Group 1	5	1	4	18-32	25.4	Students
Group 2	5	2	3	20-41	31.2	Full-time workers
Group 3	6	2	4	23-28	25.3	Freelance workers

Table 1: Characteristics of study participants.

Participants engaged in a seven-day diary study beginning on 25 November 2024, during which they completed two assigned tasks. From days 1 to 4, they selected a topic from a predefined list (see appendix for details) that was absent from their current Douyin homepage recommendations and actively sought to populate their homepage with videos related to that topic. From days 5 to 7, participants attempted to filter out content associated with the previously chosen topic. Throughout the study, participants recorded their experiences using diary entries submitted via a questionnaire designed based on insights from a small-scale pilot study involving six participants and a total of 82 valid diary entries were collected. The daily questionnaire consisted of two sections: self-assessment of task completion (Questions 1 and 2) and documentation of received and shared algorithmic imaginaries (Questions 3 and 4). On days 4 and 7, participants responded to two additional questions (Questions 5 and 6) designed to explore if they had developed a more structured algorithmic folk theory. The details of the questionnaire are also provided in the appendix.

A conventional content analysis approach (Hsieh and Shannon, 2005) was applied to the 82 diary entries to provide preliminary insights into the research questions. This was complemented by an inductive coding process, where codes were generated directly from the data rather than being predetermined, ensuring that the analysis was grounded in participants' experiences.

Participants were informed that their participation was entirely voluntary, that no compensation would be provided, and that they could withdraw from the study at any time without penalty. Pre-study briefings were conducted online using Tencent Meeting, during which participants were provided with detailed information about the research aims and procedures. All participants signed an informed consent form before the study commenced. To ensure confidentiality, diary entries and future interview recordings will be accessible only to research team members, with strict adherence to data anonymisation protocols.

Results

Non-sharing and sharing during gossiping (RQ1)

In those 82 diary entries, participants of the study mentioned 92 times (see Table 2) when algorithmic imaginaries emerged (55 times), or they acquired algorithmic imaginaries from other sources (47 times). We record three types of algorithmic imaginaries, namely, anecdotal occurrence manoeuvre strategy and structured theories in diary entries (see Table 2 for details). Non-sharing (N=54) is the most frequent reaction when participants acquire algorithmic imaginaries from others or form one of their own.

Type of algorithmic imaginary	Description	Frequency	Sharing or forwarding frequency	Source
Anecdotal occurrence	individual or small-scale experience that lacks empirical rigour.	44	19	Self
		3	0	Others
Manoeuvre strategy	A single deliberate effort to influence or adapt to algorithms to achieve specific outcomes, such as avoiding unwanted content or improving recommendations.	20	17	Self
		18	7	Others
Structured theory	Theories that combine various factors, such as engagement, content type and posting time, explain how content is ranked and recommended on a platform.	2	2	Self
		5	3	Others
Total		92	48	

Table 2: Types of algorithmic imaginaries and their shared frequency

Perceived effectiveness seems to be the most prevailing reason why participants decide to share or withhold algorithmic imaginaries, as they tend to share more structured information than simple speculations. This may result from their hope to maintain a reliable image in their social group:

> *I browsed through my Douyin app today and saw my e-shop purchase history. I assume that may be the reason why I cannot entirely remove those yoga videos from my homepage. I didn't share it with anyone because it may not be true. My mom likes to share everything, reliable or not. I do not quite like that.* (Group 1, Participant #3, Female, Day 6)

Participants demonstrated a tendency to share a higher proportion of their personally constructed algorithmic imaginaries compared to those acquired from external sources. This reluctance to share externally sourced imaginaries was primarily attributed to perceived conflicts between these imaginaries and participants' own experiences or preferred theories. Such behaviour suggests the presence of a self-strengthening bias in the development of users' folk theories, where individuals prioritise and reinforce their existing beliefs over conflicting information.

> *I didn't try or forward that strategy shared by a vlogger that I can use Douyin settings to manage the recommendation contents. My friend told me some time ago that won't work.* (Group 3, Participant #1, Male, Day 3)

Gossiping to articulate and confirm imaginaries while breaking biases (RQ2)

Of the sixteen participants, only six were able to give structured descriptions of how they think the recommendation/filtering algorithms work on day 4 or 7. Not surprisingly, five of the six participants were frequent sharers of algorithmic imaginaries. In their reasons for the folk theory, three of them mentioned how the sharing of algorithmic imaginaries helps to form their perceived folk theories.

Articulating their ideas is mentioned as the benefit of algorithmic gossiping towards folk theory formation. Participants mentioned how sharing their ideas required them to reflect on what they really believe and what they have already tried. Participants also become more confident about their theories after sharing and getting positive feedback. According to one participant:

> *I always knew the impact of my friends' likes on my recommendation page, but until my friend today brought up the topic of possible strategies to manage Douyin recommendations at lunch, it was like totally overlooked by me. I told that to my friend and now I am much more affirmative on that idea.* (Group 2, Participant #2, Female, Day 4)

Intriguingly, even when the shared algorithmic imaginaries were questioned or challenged by a close source, our participants still described such discussions or even debates very positively as they '*mended their wrongs*', which correlated with the idea of DeVito and colleagues (2018) that folk theories are not necessarily ironclad and can be updated with new, and potentially even contradictory, information.

Conclusion

This short paper only presents the initial findings of our ongoing investigation on algorithmic gossiping. However, these findings give a good demonstration of how algorithmic gossiping would drive, or at least contribute to the transformation from algorithmic imaginaries to folk theories, and the potential of a new theoretical framework to unify current concepts at both individual and meso levels. Following Bishop's (2019) recommendation to take gossip seriously, we argue that further looking into algorithmic gossiping could provide information researchers with unique opportunities both for theoretical implications and innovations in intervention study in the field of algorithmic-related information behaviour.

Acknowledgements

We are grateful to the information management department of CCNU for providing the resources and academic environment necessary for the completion of this study.

We would also like to acknowledge the financial support of the China Scholarship Council, which made this research possible.

About the authors

Gaohui, Cao is a professor of the Information Management College of Central China Normal University. His fields of study include information organisation, information service, information integration and big data analysis. He designed the study framework and oversaw the data acquisition and analysis while revising and editing the manuscript.

Zhang Wen is a PhD student from the Information Management College of Central China Normal University. His fields of study include information behaviour, digital stress and machine behaviour. He completed the draft of the paper. His email address is zane8953@mails.ccnu.edu.cn.

Puyi, Liu is a postgraduate student from the Information Management College of Central China Normal University. His field of study is algorithmic literacy. He coordinated the data acquisition process and participated in data analysis. His email address is puyiliu85@gmail.com.

References

Bishop, S. (2019). Managing visibility on YouTube through algorithmic gossip. *New Media & Society*, 21(11–12), 2589-2606. https://doi.org/10.1177/1461444819854731

Bucher, T. (2017). The algorithmic imaginary: exploring the ordinary affects of Facebook algorithms. *Information, Communication & Society*, 20(1), 30-44. https://doi.org/10.1080/1369118X.2016.1154086

DeVito, M. A., Birnholtz, J., Hancock, J. T., French, M., & Liu, S. (2018). How people form folk theories of social media feeds and what it means for how we study self-presentation. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pp. 1-12. https://doi.org/10.1145/3173574.3173694

Eg, R., Demirkol Tønnesen, Ö., & Tennfjord, M. K. (2023). A scoping review of personalized user experiences on social media: the interplay between algorithms and human factors. *Computers in Human Behavior Reports*, 9, pp. 100253. https://doi.org/10.1016/j.chbr.2022.100253

Eslami, M., Karahalios, K., Sandvig, C., Vaccaro, K., Rickman, A., Hamilton, K., & Kirlik, A. (2016). First I 'like' it, then I hide it: folk theories of social feeds. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pp. 2371-2382. https://doi.org/10.1145/2858036.2858494

Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., Hamilton, K., & Sandvig, C. (2015). 'I always assumed that I wasn't really that close to [her]': Reasoning about invisible algorithms in news feeds. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pp. 153-162. https://doi.org/10.1145/2702123.2702556

Flanagan, J. C. (1954). The critical incident technique. *Psychological Bulletin*, 51(4), 327.

Gao, Y., Liu, F., & Gao, L. (2023). Echo chamber effects on short video platforms. *Scientific Reports*, 13(1), 6282. https://doi.org/10.1038/s41598-023-33370-1

Hu, J., & Wang, R. (2024). Familiarity breeds trust? The relationship between dating app use and trust in dating algorithms via algorithm awareness and critical algorithm perceptions. *International Journal of Human–Computer Interaction*, 40(17), 4596-4607. https://doi.org/10.1080/10447318.2023.2217014

Jiang, T., Guo, Q., Xu, Y., & Fu, S. (2019). A diary study of information encountering triggered by visual stimuli on micro-blogging services. *Information Processing & Management*, 56(1), 29-42. https://doi.org/10.1016/j.ipm.2018.08.005

Jones, C. (2023). How to train your algorithm: the struggle for public control over private audience commodities on Tiktok. *Media, Culture & Society*, 45(6), 1192-1209. https://doi.org/10.1177/01634437231159555

Liao, T., & Tyson, O. (2021). 'Crystal Is creepy, but cool': mapping folk theories and responses to automated personality recognition algorithms. *Social Media + Society*, 7(2). https://doi.org/10.1177/20563051211010170

Lobel, I. (2021). Revenue management and the rise of the algorithmic economy. *Management Science*, 67(9), 5389-5398. https://doi.org/10.1287/mnsc.2020.3712

Saragih, M., & Morrison, B. W. (2022). The effect of past algorithmic performance and decision significance on algorithmic advice acceptance. *International Journal of Human–Computer Interaction*, 38(13), 1228-1237. https://doi.org/10.1080/10447318.2021.1990518

Schulz, C. (2023). A new algorithmic imaginary. *Media, Culture & Society*, 45(3), 646-655. https://doi.org/10.1177/01634437221136014

Shin, D., Kee, K. F., & Shin, E. Y. (2022). Algorithm awareness: why user awareness is critical for personal privacy in the adoption of algorithmic platforms? *International Journal of Information Management*, 65, 102494. https://doi.org/10.1016/j.ijinfomgt.2022.102494

Swart, J. (2021). Experiencing algorithms: how young people understand, feel about, and engage with algorithmic news selection on social media. *Social Media + Society*, 7(2). https://doi.org/10.1177/20563051211008828

Tomasello, M., Carpenter, M., Call, J., Behne, T., & Moll, H. (2005). Understanding and sharing intentions: the origins of cultural cognition. *Behavioral and Brain Sciences*, 28(5), 675-691. https://doi.org/10.1017/S0140525X05000129

Zhang, Y., & Chen, H. (2023). Can algorithm knowledge stop women from being targeted by algorithm bias? The new digital divide on Weibo. *Journal of Broadcasting & Electronic Media*, 67(3), 397-422. https://doi.org/10.1080/08838151.2023.2218955

Zhao, L. (2023). Filter bubbles? Also protector bubbles! Folk Theories of Zhihu algorithms among Chinese gay men. *Social Media + Society*, 9(2). https://doi.org/10.1177/20563051231168647

Appendix. Provided theme list and the main questionnaire of the diary study

Provided theme list

Video games	News comments	English learning
Chinese history	Food and cooking	Animals or pets
Outdoor sports	Automobile	Reality shows

Note: This theme list is refined from the themes of the hottest video ranking on Douyin on 20 November 2024

Main questionnaire of the diary study

Section A **Task Completion status**
1. Based on your self-assessment, where do you think you are currently within the 0-100% range of task completion progress?
2. Please list the actions, strategies or methods you attempted today to complete the task and evaluate the effectiveness of these strategies.
Section B **Algorithmic imaginaries acquisition and sharing**
3. Please list the algorithmic imaginaries shared with you by others today and their sources. If this information is related to the activities listed in Question 2, please specify.
4. What algorithmic imaginaries did you share with others? What were your reasons for sharing this information?
Section C **Theory development (Only on Day 4 and Day 7)**
5. What factors do you think influence filtering/recommendation algorithms? Please rank them in descending order of importance and explain the reason.
6. If your perspective on any factors influencing filtering/recommendation algorithms has changed, please specify the factors and explain the reasons for the change.

Note: The original questionnaire was in Chinese, and this version is adapted from the original questionnaire. Questions on the demographic features of participants, example answers to main questions, introduction of research and terminology explanations were removed when adapting to this version.