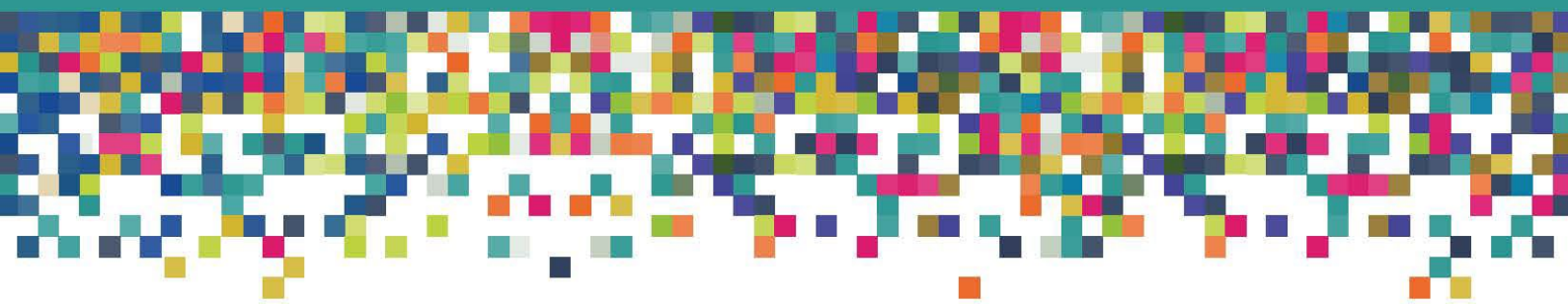




Media and
Communications

Media@LSE MSc Dissertation Series

Editors: Simidele Dosekun, Zichen Hu



The Bidirectional Domestication Game:

How Xiaohongshu Users Strategically Adapt to Algorithmic
Recommendations

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Published by Media@LSE, London School of Economics and Political Science ("LSE"), Houghton Street, London WC2A 2AE. The LSE is a School of the University of London. It is a Charity and is incorporated in England as a company limited by guarantee under the Companies Act (Reg number 70527).

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ABSTRACT

Xiaohongshu ("RedNotes"), often dubbed the "Instagram of China", is a popular social platform with over 300 million monthly users. Its proprietary recommendation algorithm curates a personalised feed, but users are not passive consumers of whatever the algorithm serves. This study investigates how users actively "train" or resist the algorithm through strategic behaviours, and what factors drive these adaptations. Drawing on domestication theory, which frames technology adoption as an active, ongoing process of "taming" new tech, we conceptualise user–algorithm interaction as a bidirectional domestication game: algorithms shape user experiences, yet users continually assert agency to shape algorithmic outputs. A quantitative survey (N=280) of Xiaohongshu users was conducted to examine whether (1) heavier platform usage, (2) greater perceived algorithmic knowledge, and (3) lower satisfaction or trust in the algorithm relate to how intensively and in what ways users adapt their behaviour to influence recommendations. Results show that more frequent users and those who feel more knowledgeable about the algorithm indeed report using more tactics to steer their feeds, especially constructive "training" behaviours like liking preferred content and using the "Not Interested" button. However, contrary to expectations, users reporting higher satisfaction with the platform were more likely to use evasive or "resistant" tactics than dissatisfied users. The results indicate that active feed curation is associated with an enhanced user experience, suggesting that strategic adaptation is not only a response to dissatisfaction but integral to engaged platform utilisation. The research enhances comprehension of how social media users domesticate algorithms daily, obscuring the distinction between user adaptability and algorithmic administration. This study discusses platform design implications and theorises algorithmic literacy and domestication in the Chinese social media context.

INTRODUCTION

Social media platforms typically have unique recommendation algorithms to filter and personalise content for users. While these algorithms offer users immersive experiences, they have also raised concerns about algorithmic manipulation, information bubbles, user autonomy, and the role users play in shaping their media consumption habits (Pariser, 2011, p.317). However, emerging research and daily user behaviours suggest that the reality is more complex and interactive: users learn to predict and respond to algorithmic filtering, effectively training the algorithms through their behaviours, or seek ways to bypass them. This article explores this interactive dynamic between users and algorithms through a case study of the Chinese social platform Xiaohongshu (RedNotes).

Xiaohongshu has become one of China's most popular social media platforms in recent years. Often referred to as "China's Instagram" (United Media Solution, 2023), the platform offers an interactive model that integrates community-driven lifestyle content sharing with e-commerce functions and has amassed a large user base in China. According to Huang and Miao (2024), Xiaohongshu has over 300 million monthly active users, 300 million daily search queries, and about 3 million new postings (Zhu, Zhang and Wang, 2024). To improve the user experience, Xiaohongshu has incorporated several interactive elements (He, 2024). In addition to marking material as favourites, liking and commenting on postings, users may also send private messages to content authors for one-on-one interactions (Qin *et al.*, 2024). Users of Xiaohongshu actively adopt ways to "tame" the algorithm to suit their tastes, as this study emphasises, rather than being passive beneficiaries of algorithmic training. This user behaviour reflects the dynamic interaction between platform control and user autonomy and is a deliberate reaction to algorithmic content screening.

This study employs the concept of the theory of domestication (Silverstone and Hirsch, 1992) to explain this dynamic interaction. The theory of domestication was proposed in the early 1990s and describes how technology is "tamed" or integrated into daily life by users. Classic domestication studies have shown that people actively negotiate the role of new media and information and communication technologies in the home and daily life, rather than passively accepting technological influence (Haddon, 2011). Against this backdrop, the process becomes complex due to the opacity

and dynamism of algorithms. On one hand, users attempt to domesticate algorithms to make them more predictable, personalised, and in line with their preferences. On the other hand, the platform's algorithms to some extent domesticate users, pushing them to adopt certain behaviours or content consumption patterns. This study conceptualises this mutual adaptation (Siles *et al.*, 2019) as a bidirectional domestication game.

Meanwhile, this study will incorporate the re-domestication mentioned by Huang and Miao (2020) to analyse the new domestication strategies of users towards social media. Suppose the personalisation of algorithms becomes overwhelming or inconsistent with their well-being. In that case, users may "escape" or pause social software, then resume using it in a new way. This use, non-use, and reuse cycle allows users to recalibrate their relationship with the platform. This study also integrates theories of algorithmic literacy, user autonomy, and platform governance structure to comprehensively analyse users' performance regarding recommendation algorithms.

Overall, this study combines domestication theory with contemporary insights into algorithm-user interaction, which helps to understand how users assert autonomy in subtle ways under algorithmic governance and the implications for platform governance and design. This study views the interaction between Xiaohongshu users and algorithms as an evolving domestication cycle, going through stages such as adaptation, resistance, and renegotiation. Users play an active and creative role in this relationship, employing various strategies to "tame" the content pushed by algorithms, thereby demonstrating algorithmic literacy and resistance capabilities. Ultimately, this study aims to show that the relationship between users and algorithms on Xiaohongshu is an active negotiation, a bidirectional domestication game, and to identify the patterns of this game.

THEORETICAL CHAPTER

This chapter consists of three parts. The literature review will elaborate in detail on the main core theories that support this research. The conceptual framework further explains the main theories

and how they lay the foundation for the research questions and hypotheses. Finally, the research questions and three hypotheses of the article will be derived.

Literature Review

Domestication Theory in the Algorithmic Era

The domestication theory offers a foundational framework for this research. This article delineates its fundamental ideas and then examines its applicability to modern algorithm-driven media. In the book "*Consuming Technology*" (Silverstone and Hirsch, 1992), domestication theory is defined as the process by which information and communication technologies are integrated into people's daily lives and given meaning at both the individual and cultural levels. Domestication research does not assume that technology has a decisive influence but instead examines how users actively utilise technology and give it specific uses and interpretations. As mentioned earlier, the classic framework delineates four overlapping stages:

Appropriation: The act of acquiring or adopting technology and claiming ownership. In this stage, users decide to bring technology into their lives. For example, installing the Xiaohongshu app and creating an account is an act of appropriation; the user is taking up the technology, often with certain expectations.

Objectification: How the technology is physically and symbolically present in the user's space. In traditional domestication studies, this referred to where a TV or PC is placed in the home and how it is discussed. Objectification might be more metaphorical in a social media context, with the phone as an extension of the self and the app icon on one's home screen. It also includes the user's initial framing of the technology's role: Is Xiaohongshu an occasional pastime or a core community for the user?

Incorporation: The integration of the technology into daily routines and social practices. The technology moves from novel to ordinary as the user develops habits around it. For Xiaohongshu,

incorporation would mean the app becomes part of one's everyday schedule and interpersonal life. Incorporation is a key part of making the technology "invisible" as an assumed part of life. Though, as we will discuss, algorithmic media often resist complete invisibility.

Conversion: The stage where the domesticated technology and associated practices are expressed outwardly or shared, thus converting personal meaning into social value. Users might display their engagement in various ways. For instance, talking about things they found on Xiaohongshu in other social circles, or using their accumulated knowledge to gain status, like becoming a micro-influencer. Conversion connects to the broader social or cultural context, showing how the now-domesticated technology reflects and contributes to the user's identity and relationships.

It is crucial to note that domestication is not a one-off linear process but cyclical and ongoing. The evolution of new social trends and individual needs may prompt users to reevaluate and adjust the role of technology in their lives (Haddon, 2006). Silverstone and Hirsch (1992) emphasise that domestication is a continuous dialectical process in which users and technology constantly shape and reshape each other's roles. A social media application may transition from a source of entertainment to a professional networking platform as a user's requirements evolve, or conversely. This viewpoint challenges the notion that adoption is a singular occurrence; rather, it is a dynamic relationship that may need renegotiation.

When applying domestication theory to algorithmic platforms, some new complexities emerge. One is the idea of domestication without an endpoint, because algorithms are constantly updating, users never fully "settle" into a stable routine without occasionally adjusting. Recent research on TikTok provides a vivid example: Simpson, Hamann, and Semaan (2022) found that many TikTok users are acutely aware of the For You algorithm and feel the need to be "constantly vigilant" in their interaction with the app. Participants described that a single accidental touch or lingering too long on an irrelevant video could "significantly alter" their information feed, requiring effort to reset or retrain the algorithm. Another complexity is that the content flowing through these platforms is diverse and

personalised, so what it means to “domesticate Xiaohongshu” can vary widely between users. Each user’s domestication process is unique because the algorithm curates a unique feed for each.

Researchers have begun explicitly exploring re-domestication in these contexts, how users adjust or renegotiate their relationship with a platform when things go awry or life contexts shift. Karlsen & Syvertsen (2020) introduced the term “reverse domestication” to describe strategies of withdrawal or media reduction, which essentially tame one’s media exposure by disconnecting or limiting use, as a counterpart to the original domestication about embracing new media. In a study of self-help guides about digital detox (Syvertsen and Enli, 2020), they argued that users actively resist media’s intrusion by creating new norms like device-free times, thus domesticating media influence by pushing it to the margins (like no phones at the dinner table). This idea resonates with social media scenarios where users feel overwhelmed by constant connectivity or algorithmic overload.

Chinese scholars have also noticed the pattern of “de-domestication” followed by “re-domestication” on social media platforms. Huang and Miao (2020) studied WeChat Moments. They found that some users would periodically abandon the function when it became too intrusive or unsatisfactory and then return in a more controlled manner. These users readjusted their way of using the app. After a suspension period, they might delete contacts who sent too much junk information or decide to check it less frequently, thereby re-domesticating the app to suit their well-being better. The cycle of “use, non-use, reuse” indicates that domestication can be a repeated process (Huang and Miao, 2020). Importantly, users are not passive victims of algorithms; they can take a step back, reassess, and then reshape their usage under more favourable conditions (Wang, 2024).

In the case of Xiaohongshu, re-domestication often takes the form of users taking deliberate actions to regain control when the recommendation feed does not feel right. Huang and Miao (2024) provide a pertinent example with their concept of the “raising accounts” metaphor. They found that if users of Xiaohongshu felt the algorithm’s recommended content was irrelevant or unsatisfactory, they would consciously input specific types of data to “correct” it (Karizat *et al.*, 2021). For instance, they

would like or comment on posts that matched their interests, actively search for specific content, and avoid interacting with popular content they disliked. By doing so, users gradually retrained the algorithm, effectively re-domesticating this platform with diverse content back into one that again met their preferences. Huang and Miao (2024) describe this as users playing an active, reflexive role: they reflect on why the algorithm might be off-track. For example, "Have I been clicking too many makeup videos such that it thinks I only like makeup?" Then, take strategic actions to steer it back. In domestication terms, this is like reaffirming the user's control and appropriation of the technology after a period where the technology's influence grew too dominant or "wild." Notably, this does not require users to abandon the platform entirely; instead, they change how they interact with it to tame the algorithm anew (Grošelj, 2021).

Domestication theory thus provides a vocabulary for describing how Xiaohongshu becomes embedded in users' lives and how periodic struggles or adjustments occur when the user–algorithm fit is misaligned. It highlights the central role of user agency in continuously shaping this relationship. Users are active subjects in the story, constantly negotiating with the application's algorithm to maintain a desirable experience. Concepts like reverse domestication help explain the more resistant behaviours observed. For example, suppose users deliberately limit or subvert the algorithm's influence. In that case, this can be seen as an attempt to de-domesticate the algorithm, so that it can later be re-integrated under more acceptable terms. In summary, domestication theory sets the stage by emphasising an ongoing, bidirectional game: algorithms shape user experiences, but users also actively shape algorithmic outputs. This perspective underpins our expectation (H1) that more intensive usage of the platform will correspond with more active "training" behaviours, since frequent users have more opportunity and motive to domesticate the algorithm's outputs to their liking. It also foreshadows the theme of resistance, suggesting that when the user's sense of control is threatened or the experience becomes unsatisfactory, users may respond with tactics to reassert their agency.

Algorithmic Literacy and Folk Theories

A key factor in how users adapt to algorithmic systems is their level of algorithmic literacy - how well they understand the algorithms that curate their online content, and the informal theories they develop to explain algorithmic behaviour. Dogruel, Masur and Joeckel (2021) define algorithmic literacy as a component of digital literacy, encompassing users' knowledge and skills to interpret and critically engage with algorithmic systems. For instance, Powers (2017) found that many young people "know very little about the behaviours and standards that shape their personalised news choices," indicating a gap between the ubiquity of algorithm-driven content and users' comprehension of how it is selected.

Without transparent knowledge, users commonly rely on folk theories to make sense of algorithmic outcomes (Eslami *et al.*, 2015). Folk theories are the informal, sometimes speculative explanations users create to explain why certain content appears (or disappears) in their feeds. Eslami *et al.* (2015) documented how Facebook users, noticing changes in their News Feed, formulated various explanations for the algorithm's logic – often inaccurate, but internally consistent narratives to rationalise their observations. Similarly, Bucher (2017) described "algorithmic imagination", noting that users imagine what algorithms might be doing and then adjust their behaviour according to these imagined rules. For example, users might think "if I get many likes in the first hour, the algorithm will show my post to more people", so they would try to collect quick likes or choose the posting time accordingly, even though this rule has not been officially confirmed.

Notably, Dogruel *et al.* (2021) suggest that users who are more knowledgeable about how algorithms rank and recommend content can adapt their behaviour in more strategic and deliberate ways. For example, by knowing which actions (likes, comments, watch time, etc.) are likely to signal preferences to the system. The correlation between knowledge and conduct is not always direct. Dogruel (2021) underscores that enhanced comprehension may also give users a misleading impression of power.

Users with advanced literacy may overrate their capacity to manipulate the algorithm, while people with little education sometimes discover successful strategies via trial and error.

Indeed, even without accurate knowledge, users often learn by trial and error. Swart (2021) observed that people learn about algorithms through direct experience, adjusting their behaviour and seeing what happens. Users tend to improvise when faced with confusing or undesired algorithmic behaviours: they test their folk theories in practice and observe the results. Over time, this experiential learning can refine their understanding of what works. DeVito (2021) even proposes that engaging in folk theorising is a path to improving algorithmic literacy; users gradually build a more informed mental model by actively guessing and testing how the system works.

Reflecting the importance of this issue, scholars have called for better measures of and education in algorithmic literacy. Gagrčin, Naab and Grub (2024) argue that users should be able to autonomously shape their experiences in daily algorithmic media environments and advocate for standardised ways to assess and enhance algorithmic literacy. The implication is that improved understanding could empower users to take greater control of their media diets rather than being at the mercy of “black box” systems.

In the context of Xiaohongshu, algorithmic literacy manifests in the folk theories and discussions users share about the platform’s recommendation system. It is common to see Xiaohongshu users exchanging tips or “myths” about getting preferable content: advising others to like at least one post per browsing session to “train” the feed, or warning that searching for too many similar items will narrow the recommendations. This study considers these insights by measuring users’ perceived understanding of the algorithm in the survey to see if higher perceived knowledge correlates with distinct adaptation tactics. By examining algorithmic literacy levels among Xiaohongshu users, we can assess to what extent strategic adaptation is an informed, conscious choice rather than an intuitive or accidental behaviour. In other words, this portion of the literature suggests a basis for H2. If users

believe they understand the algorithm well, we expect them to report using more strategies to influence their feed.

Platform Governance and Algorithmic Power

While users can learn and strategies, their agency operates within platform design and governance constraints. Platform governance refers to the rules, norms, and algorithmic systems platforms use to organise behaviour and content. It is about how platforms manage their users and content through design and policies (Zhang, Li and Tong, 2020). In algorithmic platforms, algorithms function as governance mechanisms, dictating the visibility of information and its timing. This establishes a kind of "algorithmic governance" (Katzenbach and Ulbricht, 2019) in which user experiences are influenced by obscure regulations embedded in recommendation algorithms. The influencer guide for marketing on Xiaohongshu states that the algorithm favours high-quality material that encourages engagement, and writers should use strategies like hashtags, attractive cover images, and regular posting to align with the algorithm (Song, 2022). This guideline demonstrates the impact of platform governance on user strategies. Although the platform's algorithmic criteria are not publicly disclosed, they encourage users to consciously self-regulate their content. This is a top-down form of governance: users internalise platform rules (even if informally understood) and adjust their actions to fit the algorithm's expectations.

On the other hand, the governance viewpoint brings to light concerns of power imbalance and imbalance of power. Pasquale (2015) argues that algorithms are often "black boxes," which means that regular consumers cannot completely comprehend the principles that control the material they consume. This lack of transparency might give rise to the impression that something is unfair or brutal, such as shadow bans (Are, 2021), which occur when a user's material is hidden or downgraded without the user being notified explicitly. These users engage in "invisible digital labour" to reduce the effect of the opaque algorithmic downgrading, as Kojah *et al.* (2025) reported. This is because marginalised producers perceive that the algorithmic downgrading disproportionately harms them.

These users engage in "invisible digital labour" to mitigate its impact (Simpson, Hamann and Semaan, 2022). For Xiaohongshu, Wan *et al.* (2025) provide a compelling example of user negotiation of platform governance. They found that female users creatively repurpose hashtags to control their audience on Xiaohongshu, using harmless or misleading hashtags on unrelated posts, such as those about baby food. This behaviour aims to exclude unwanted male viewers, effectively using the platform's algorithmic tagging and recommendation logic to maintain a safer community space. This case also illustrates user agency in platform governance, where users find loopholes to manage content exposure even when algorithms enforce content distribution. This represents a form of bottom-up governance or "autonomy within the algorithmic power structure" (Bucher, 2018).

Overall, the platform governance perspective reminds us of that user behaviours on Xiaohongshu do not occur on a level playing field; they are responses to an environment orchestrated by algorithmic power. Strategic user adjustments can be seen as compliance with platform incentives and resistance to algorithmic constraints. This perspective helps explain why users may need to adapt their behaviour in the first place, the platform's opaque rules and power asymmetries necessitate users' strategic navigation. It also sets the context for understanding user agency. In a highly governed space, the ways users assert control or push back (for example, the resistance behaviours hypothesised in H3) become especially significant. Building on this, we turn to literature on user agency and resistance in algorithmic environments to further illuminate how users enact their autonomy under these conditions.

User Agency and Resistance

User autonomy depends on the extent of control the platform grants them. Gillespie (2014) points out that platforms often make algorithms hard to understand, partly to maintain proprietary advantages, prevent exploitation, and avoid users manipulating the results. This opacity means that users exercise their autonomy in a semi-blind state. However, many users adapt quite well through repeated

interactions. Seaver (2017) argues that we should view algorithms as "culture", meaning they are co-created by developers and users and embedded in a cultural context. From this perspective, the interaction between Xiaohongshu users and algorithms shapes the algorithms' behaviours. Even without complete transparency, users gradually figure out the patterns over time. For instance, Xiaohongshu users have noticed that if they like too many posts in a specific category, their "Discover" page will be dominated by content from that category. This has led some users to deliberately diversify their likes to maintain the diversity of content on their page (Hu and Ou, 2025). This indicates that users have developed strategies to maintain content diversity.

Beyond these adaptive behaviours, this study introduces the concept of user resistance proposed by de Certeau (1984), which focuses on how users resist or subvert the preset usage methods or power dynamics of technology. In the context of Xiaohongshu's algorithm, the resistance theory helps to view specific strategic adjustments as acts of empowerment or protest, rather than merely practical adjustments. Wang (2024) provides an example where social media users describe attempts to "fool" the recommendation algorithm through random behaviour, such as clicking on all recommended content regardless of interest, to prevent the system from accurately profiling them. This can be seen as a privacy-protecting resistance behaviour: users sacrifice a precise information flow to reduce the feeling of being "monitored" or manipulated.

Schmidt *et al.* (2019) found that when people become aware of algorithms shaping their information flow, they tend toward one of three broad responses: (1) exit: some stop using or significantly cut down use of the platform; (2) apathy/acceptance: some acknowledge the algorithmic influence but choose not to act on it (or quickly dismiss concerns); and (3) adaptation/resistance: many continue using the platform but develop creative workarounds or personalised strategies to mitigate unwanted effects. In Xiaohongshu's user base, we likely see a similar range: a minority might abandon the app due to algorithm concerns, some trust the system and do little to intervene, but a significant portion stays while actively tweaking their behaviour to curate a better experience. This study particularly

focuses on that latter group of active adapters, examining both constructive adaptation (training the algorithm by providing feedback or engagement signals) and resistive adaptation (trying to circumvent or confound the algorithm). Understanding these forms of agency is central to addressing H3, which posits that dissatisfaction or distrust in the algorithm and awareness of phenomena like filter bubbles will correspond with more resistance-type behaviours.

Conceptual Framework

This research synthesises the studied material to provide a conceptual framework for the "bidirectional domestication game" between Xiaohongshu users and the platform's algorithm. The domestication perspective emphasises that users voluntarily incorporate the platform into their lives and consistently negotiate its use. User attributes and perceptions influence adaptation techniques in this continuing process. Intensive or regular platform use (H1) presumably indicates a profound integration of Xiaohongshu into everyday routines, equipping users with the impetus and experienced expertise to participate in lengthy feed "training" behaviours.

Then, the literature on algorithmic literacy suggests that users' understanding of the recommendation system (central to H2) will shape the complexity and variety of tactics they employ. Those who perceive themselves as knowledgeable about how Xiaohongshu's algorithm works are expected to use more nuanced strategies. Even if users' folk theories are not entirely accurate, the confidence and intent that come with higher algorithmic literacy can drive a more proactive and varied approach to influencing one's feed. Our framework thus incorporates algorithmic literacy as a key enabler of strategic adaptation: it can turn passive users into active "gamers" of the system, up to the point their knowledge allows.

Overlaying both of these user-driven factors is the recognition that the platform's governance and power structures set the context in which any adaptation occurs. Xiaohongshu's algorithm can be

considered both opponent and arena in this game. The platform governance perspective reminds us that adaptation is necessary partly because the algorithm holds significant sway over visibility and is not fully transparent. Users' feelings of (dis)satisfaction and trust in the algorithm and specific concerns like filter bubbles are often reactions to this power asymmetry. Users who are happy with and trust the algorithm might be content with mild training efforts. However, when they are dissatisfied or worried – suspecting that the feed is narrowing their perspective (a filter bubble) or not reflecting their true interests – they may resort to resistant tactics (as posited in H3).

This dissertation's conceptual framework (summarised by H1, H2, and H3) sits at the intersection of individual agency and structural constraint. It aims to explain how and why Xiaohongshu users strategically adapt their behaviour under algorithmic recommendations.

Research Question

Based on the above, the central aim of this dissertation is to investigate how Xiaohongshu users strategically adapt to and attempt to influence the platform's recommendation algorithm. The Research question is: *How do Xiaohongshu users strategically alter their interactive behaviours to affect algorithm-recommended material, and what elements are involved?*

Hypotheses:

H1 (Usage Frequency → Training Strategies): Users who use Xiaohongshu more frequently are expected to engage in more frequent and extensive training behaviours.

H2 (Algorithmic Literacy → Complexity of Training): Users who perceive themselves as understanding the algorithm (higher algorithmic literacy) are expected to employ a greater variety or complexity of training strategies.

H3 (Satisfaction/Trust & Filter Bubble Concern → Resistance): Users who are less satisfied with the algorithm's recommendations or who have lower trust in the algorithm and those who are more concerned about filter bubbles are expected to engage in more resistance behaviors.

These hypotheses reflect the expectation that user–algorithm interactions are influenced by how intensively users engage with the platform (H1), how well they understand it (H2), and how they feel about its outputs (H3). The following literature review situates these ideas in existing research, drawing on domestication theory and related concepts to build a framework for understanding strategic user adaptation on Xiaohongshu.

METHODS CHAPTER

This chapter is divided into five parts. First, it introduces the advantages of the research method of the questionnaire survey for this study and explains how the questionnaire was designed. Second, it provides an overview of the sample characteristics. Then, the main measurement methods and data analysis plans used in the questionnaire were introduced. Finally, the ethical guidelines for the implementation of the research methods were specifically described.

Research Design Overview

This research employed a quantitative survey design to examine the strategic adaptations of Xiaohongshu users in response to algorithmic recommendations. A structured questionnaire was created to assess users' characteristics, perceptions of the algorithm, and the frequency of various adaptive behaviours. Survey technique research (Ponto, 2015) indicates that self-administered online surveys are economical, easy, and effective for accessing large samples. Dillman *et al.* (2014) underscore the significance of a customised survey design, including an aesthetically pleasing layout and a coherent question sequence, to enhance response rates in online surveys. Fowler (2014) observes that a well-designed questionnaire with explicit instructions may enhance respondent engagement and completion rates. This method was chosen for its strength in gathering standardised data from a relatively large sample, enabling statistical hypothesis testing. While qualitative approaches could provide rich insight into individual experiences, the survey allowed us to capture broad patterns and test specific hypotheses about relationships between variables across many users.

This survey was conducted through an online questionnaire (see Appendix A) on the Qualtrics platform for four weeks and distributed to Xiaohongshu users via convenience and snowball sampling. Given the user base of Xiaohongshu, the survey was presented in bilingual form (Chinese and English) to enhance accessibility. However, most respondents were Chinese users, so the survey placed the Chinese version first. Before starting the questionnaire, participants were presented with an information and consent form (see Appendix C), which explained the purpose of the research (academic research on social media usage), the procedure, the voluntary nature, and the guarantee of anonymity. They had to confirm their consent (by selecting the "I agree" statement) to proceed, which adheres to research ethics standards. Only respondents aged 18 or above were eligible to participate, and this was also stated in the consent form.

The survey included a screening question to ensure respondents were actual Xiaohongshu users. Specifically, early in the survey, it asked, "Have you used the Xiaohongshu app in the past month?" Respondents who answered "No" (or who had never used it) were not allowed to continue to the main questionnaire. This helped target the relevant population – active users with current algorithm experience. In total, 394 individuals accessed the survey and answered the screening; those who did not use Xiaohongshu recently or failed to complete the survey were filtered out. We obtained 280 valid responses that met the criteria (Finished the questionnaire, passed the attention check, and confirmed recent Xiaohongshu use).

To promote quality, we embedded an attention-check question mid-way. This was a simple instructed response item: "This question tests whether one answers carefully – please choose 'Extremely dissatisfied'." It was presented as a Likert-scale item about satisfaction, but with explicit instructions. Respondents who did not select the requested answer were considered inattentive. Indeed, we found that about 19% of initial respondents failed this check (choosing other options). Those cases were excluded from the valid dataset, ensuring our analysis was based on attentive participants.

Sample Characteristics

The final sample (N=280) consists of active Xiaohongshu users, with a mix of demographics and user profiles. The sample group is mainly composed of experienced users who frequently use Xiaohongshu. They are primarily content consumers and often engage in various interactive behaviors on the platform. Generally, they like the content recommended by the algorithm, but they are concerned about the echo chamber effect and have a certain understanding of the recommendation mechanism.

Measures and Instruments

The survey questionnaire is the primary instrument, composed of closed-ended questions (Likert scales, multiple choice) and a few optional open-ended prompts. The entire questionnaire is developed from five perspectives: (1) Usage Frequency: It addresses H1 by providing an indicator of usage level to test whether heavier use is associated with more adaptation behavior; (2) Algorithmic Literacy: This measure ties to H2, which posited that users who feel they understand the algorithm better would employ more complex or varied training strategies; (3) Satisfaction and Trust in the Algorithm; (4) Filter Bubble Concern: H3 included the expectation that higher filter bubble concern would be associated with more resistance strategies; (5) Adaptation Strategy Use: The core dependent measures of the study were the various strategies users employ to influence or “tame” their feed. The 8-item adaptation scale demonstrated acceptable internal consistency ($\alpha \approx .76$). Subscales: Training (4 items; $\alpha \approx .64$) and Resistance (4 items; $\alpha \approx .63$). Items used 1–5 “never”–“very often” anchors; higher values indicate more frequent use.

Finally, the questionnaire concluded with a few additional items for context: a question asking which single strategy the participant finds most effective (for insight, though not a primary measure), a multiple-choice question on why they try to influence the algorithm (motives such as improving relevance, avoiding disliked content, privacy concerns, etc.), and an open-ended

question inviting any other comments or personal experiences with the algorithm. These provided a qualitative context and checked whether the survey captured how users adapt. However, the primary measures for hypothesis testing were the structured questions listed above.

Data Analysis Plan

After the data collection was completed, this study conducted data screening and cleaning, as mentioned above. After excluding various issues, we will analyse 280 complete and valid data sets. First, we will use descriptive statistics to explain all key variables. This included frequencies for categorical items (e.g. distribution of usage frequency: what percentage of the sample were daily users, weekly users, etc.) and means/standard deviations for scale variables (such as the average algorithmic literacy score or average strategy usage frequency). These descriptives provided a sample profile and ensured adequate variance in the variables for analysis.

Following the descriptives, preliminary correlation analysis was conducted to explore bivariate relationships among the main variables (see **Appendix B**). This step provided an initial sense of how usage frequency, literacy, satisfaction, trust, and filter bubble concern relate. However, to rigorously test the hypotheses (H1, H2, and H3) and account for potential confounding, the core of the analysis employed multiple linear regression models.

In the regression analysis, this study mainly specified two regression models. (1) Training Strategies Model: The dependent variable was the training strategy usage index. The predictor variables entered were usage frequency, algorithmic literacy, and (for comprehensiveness) satisfaction/trust and filter bubble concern. H1 and H2 predict that in this model, usage frequency and algorithmic literacy will show significant positive coefficients; (2) Resistance Strategies Model: Here, the dependent variable was the resistance strategy usage index. The key predictors of interest were satisfaction/trust and filter bubble concern, following H3. We expected lower satisfaction (or trust) and higher concern about filter bubbles to predict greater use of resistance tactics (i.e., a negative coefficient for satisfaction, a positive for concern). Usage frequency and algorithmic literacy were also entered in

this model as controls (and exploratory predictors) because heavy users or more literate users might also engage in resistance. However, H1/H2 did not explicitly hypothesise that. This regression thus examined which factors are unique drivers of resistance-type adaptations.

In summary, the data analysis plan was designed to quantitatively link user attributes to their adaptive behaviours, thereby directly answering the research question. By cleaning the data thoroughly, constructing reliable measures, and using appropriate statistical tests, we ensured that the findings would robustly reflect the patterns (or differences) hypothesised in our theoretical framework.

Ethics

This research was conducted with careful attention to ethical standards. Before data collection, the study design was reviewed and approved through the university's ethics process (including completing an ethics checklist). Informed consent was obtained from all participants at the start of the survey. On the survey welcome page, respondents encountered an information sheet and consent form (see Appendix C) explaining the purpose of the study, what their participation entailed, and their rights. They were informed that the research was for academic purposes, that participation was voluntary, and that they could withdraw at any time by simply closing the browser (since no identifying information was collected, withdrawal after submission was not applicable). It was explicitly stated that all responses would be anonymous and used only for research analysis. To proceed into the questionnaire, individuals had to actively indicate consent (by selecting "I have read and understood the above and I am 18 or over – I agree to participate"). Those who disagreed or did not meet the age criterion (18+) could not continue.

Throughout the survey, no personally identifying information such as names, emails, or IP addresses was collected. Participants could skip any question they preferred not to answer (except the necessary screening and consent items). Demographic questions were minimal and general (and none were sensitive), ensuring that individual participants could not be re-identified from their

answers. In reporting results, only summary statistics are presented, and any quotes from open-ended responses are anonymised. Participants were also debriefed at the end of the survey via a closing message, which thanked them and provided contact information for the researcher in case they had questions or wanted to know the study results later.

Self-reported data may be subject to biases or inaccuracies, so questions were phrased clearly and objectively to minimise misinterpretation and social desirability effects. The bilingual, cross-cultural context posed a risk of misunderstanding survey items; hence, the questionnaire was carefully translated and pilot tested with a small group of Xiaohongshu users to ensure clarity and cultural relevance in Chinese and English. The study mitigated these issues through careful survey design, pre-testing, and strict adherence to ethical guidelines and maintained high ethical integrity and credibility in its data collection process.

FINDINGS AND ANALYSIS

This chapter presents and interprets the survey results considering the research hypotheses and theoretical framework. The analysis is structured in four parts. First, we provide a descriptive overview of participants' strategic behaviours, including key statistics of platform use and adaptation tactics (supported by Table 1). Second, we examine how these findings confirm, challenge, or extend prior literature, discussing each hypothesis in turn – focusing on factors influencing “training” strategies (H1 and H2) supported by Table 2 and “resistance” strategies (H3) supported by Table 3. Third, we conceptualise the implications of these results for understanding algorithmic user behaviour and domestication, introducing the idea of a “co-creative literacy cycle” in user–algorithm interactions. Finally, we draw out broader implications for theory, platform design, and future research, and acknowledge the study's limitations.

Overview of Survey Data

Descriptive statistics

Table1. Descriptive statistics of key variables (N = 280)

<i>Variable</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
<i>Usage frequency (rev)*</i>	3.75	0.61	1	4
<i>Algorithmic literacy</i>	3.58	1.04	1	5
<i>Training index</i>	3.06	0.85	1	5
<i>Resistance index</i>	2.63	0.79	1	5
<i>Satisfaction</i>	3.84	0.68	1	5
<i>Trust index</i>	3.63	0.68	1	5
<i>Filter bubble concern</i>	4.04	0.97	1	5

Note. Values represent sample means, standard deviations, and observed minimum and maximum values. Higher scores indicate more frequent use, greater literacy, stronger satisfaction or trust, and greater concern.

*In this study, Usage frequency was reversed, measured on a 4-point scale (1 = Rarely, 4 = Daily), and recoded so that higher values represent more frequent use.

Participants in the sample were generally heavy Xiaohongshu users. Approximately four-fifths (79%) reported using the app daily, with 14% using it several times a week; only a tiny minority used it rarely. Half of the respondents had over three years' experience on the platform, indicating that most had well-incorporated Xiaohongshu into their daily routines. Regarding user role, the vast majority (95%) primarily consumed content (either exclusively browsing or only occasionally posting), with only about 5% identifying as regular content creators. This context helps explain their motivations and strategies: most participants are long-term, active users familiar with the app's personalised feed.

On average, respondents felt knowledgeable about the algorithm that powers their feed. On a 5-point awareness scale, the mean perceived algorithmic understanding was about 3.6 ($SD \approx 1.04$) out of 5 (where five indicates being very aware that the app uses a recommendation algorithm) (Table 1). Indeed, only ~2% of users said they were unaware of the algorithm's role, while the majority believed they understood it to some degree. This suggests a relatively high level of algorithmic literacy, or at least awareness, among the user base. In line with that, nearly half (46%) of those who tried to influence their feed said they did so because they worried the algorithm might confine them to a narrow range of content – the classic "filter bubble" concern. In other words, many users were aware of algorithmic filtering and consciously concerned about its potential limits on their content exposure.

Turning to adaptation behaviours, participants reported engaging in various strategies to shape their feeds. We differentiate between constructive "training" tactics (actively feeding the algorithm with feedback to steer recommendations) and more evasive "resistance" tactics (attempting to circumvent, confuse, or limit the algorithm). The Training Strategies Index – an aggregate measure of how frequently respondents employed training tactics – had a mean of around 3.1 on a 5-point scale ($SD \approx 0.9$), suggesting that users sometimes or often use these constructive methods. By contrast, the Resistance Strategies Index averaged around 2.7 ($SD \approx 0.8$), indicating that resistance behaviours were less frequent, used only rarely to occasionally by the typical user. This difference is intuitive: actions like 'training' the algorithm by liking content or using the "Not Interested" button were relatively common, whereas more drastic measures to evade the algorithm were less routine. Indeed, only 6% of respondents said they do not attempt to influence the algorithm, meaning 94% engage in some form of feed curation. Overall satisfaction with the feed was moderately high (mean ≈ 3.8 out of 5, $SD \approx 0.7$), with over 80% indicating they were satisfied with the content recommendations they received.

However, as we explore later, those highly satisfied users were often the same individuals actively tweaking their feeds. Most users thought they had some control over their recommendations, which is what most people thought they did. One person said, "I sometimes search for specific keywords or

browse certain tags on purpose to 'train' it," which shows that people thought they could change the algorithm's outputs by doing things on purpose. In short, Xiaohongshu users are far from passive consumers; they are generally aware of algorithmic curation, and many take concrete steps to domesticate it according to their preferences.

Correlation Matrix

Correlation coefficients were computed to examine initial relationships between the core variables (see **Appendix B**).

Regression Analyses

Drivers of Training Strategies (H1 & H2)

Table 2. Regression results for predictors of training strategies (N = 280)

<i>Predictor</i>	<i>Std. Beta (β)</i>	<i>Robust SE</i>	<i>p-value</i>
<i>Usage frequency (rev)</i>	0.29*	0.07	<.001
<i>Algorithmic literacy</i>	0.41*	0.08	<.001
<i>Satisfaction</i>	0.02	0.06	0.740
<i>Trus index</i>	0.05	0.05	0.330
<i>Filter bubble concern</i>	0.10	0.05	0.110
Model R²	0.26		

Note. Standardised coefficients (β) are reported. Two-tailed tests. Robust SE = HC3 robust standard errors. * $p < .05$; ** $p < .01$; *** $p < .001$

The first two hypotheses predicted that two user factors would positively relate to training strategies: (H1) platform usage frequency and (H2) algorithmic literacy. The regression analysis confirms both expectations. In a multiple regression predicting the Training Strategies Index, usage frequency and perceived algorithmic understanding emerged as significant, unique predictors when controlling for other variables (Table 2). Participants who use Xiaohongshu more intensively – e.g. daily, as opposed to weekly users – tend to engage in more frequent and extensive training behaviours ($\beta \approx 0.30$, $p < .001$). Likewise, those who consider themselves more knowledgeable about how the algorithm works report employing a greater variety of training tactics ($\beta \approx 0.41$, $p < .001$). These findings respectively support H1 and H2. Frequent platform use and algorithmic literacy empower users to "game" the algorithm more actively, which aligns with prior research. For example, Simpson *et al.* (2022) observed that on TikTok, heavy users remain acutely aware of the algorithm's presence and continuously adjust their behaviour to optimise their feed. Our results align with this dynamic: Xiaohongshu users who have deeply incorporated the app into their daily routines are precisely those who most often "train" the feed. This suggests that high engagement provides both the opportunity and motivation to learn the algorithm's "rules" and to apply that knowledge in practice.

The positive effect of algorithmic literacy on training strategies (H2) is consistent with the literature on folk theories and user agency. Users who perceive themselves as understanding the recommendation system tend to employ proactive tactics to influence it. Even if their understanding is imperfect, having greater confidence in how the algorithm works appears to turn previously passive scrollers into active "gamers" of the system. This finding builds on Dogruel *et al.*'s (2021) observation that higher algorithmic knowledge enables more deliberate behaviour adaptation. Our study provides quantitative evidence for that link in the Xiaohongshu context: perceived algorithmic literacy was one of the strongest predictors of feed training intensity. Notably, this remained true even when controlling for usage frequency and other factors (Table 2), implying that it is not merely that heavy users learn more, beyond usage alone, but feeling knowledgeable independently correlates with more strategic engagement. This result reinforces calls for improving users'

algorithmic literacy to empower them. Many users shared "tips" or folk theories on curating their feeds, such as liking at least one post each session or avoiding too many similar searches to prevent a narrow feed. Such practices indicate a layer of folk expertise guiding user behaviour. So, H1 and H2 are confirmed: the more invested users are in the platform, through frequent use and understanding its workings, the more actively they attempt to domesticate the algorithm's outputs to suit their tastes.

Drivers of Resistance Strategies (H3)

Table 3. Regression results for predictors of resistance strategies (N = 280)

<i>Predictor</i>	<i>Std. Beta (β)</i>	<i>Robust SE</i>	<i>p-value</i>
<i>Usage frequency (rev)</i>	0.08	0.06	0.190
<i>Algorithmic literacy</i>	0.14	0.07	0.070
<i>Satisfaction</i>	0.20*	0.08	0.015
<i>Trust index</i>	0.07	0.07	0.310
<i>Filter bubble concern</i>	0.33*	0.06	<.001
<i>Model R²</i>	0.22		

Note. Standardised coefficients (β) are reported. Two-tailed tests. Robust SE = HC3 robust standard errors. * $p < .05$; ** $p < .01$; *** $p < .001$ (n.s.= not significant)

The study now turns to the second regression model, which examined predictors of resistance strategies: behaviours aimed at circumventing or pushing back against the algorithm. H3 posited that users who are less satisfied or trusting of the algorithm, and those more concerned about filter

bubbles, would engage in more of these resistant tactics. This hypothesis was grounded in the intuitive expectation (and prior qualitative findings) that discontent with algorithmic outcomes spurs users to find workarounds or express agency against the system. However, our results only partially support H3, and even directly contradict it in one aspect. The multiple regression for the Resistance Strategies Index revealed a surprising positive association between satisfaction and resistance behaviours ($\beta \approx +0.20$, $p < .05$), opposite to the hypothesised direction. In other words, users who reported higher satisfaction with Xiaohongshu's recommendations were more likely to use various resistant strategies – the opposite of what we predicted.

Meanwhile, talk about filter bubbles, positively correlated with resistance use at a bivariate level, did emerge as a significant unique predictor in the multivariate model ($\beta \approx +0.33$, $p < .001$). In practical terms, merely worrying about algorithmic echo-chambers did not translate strongly into using avoidance or obfuscation tactics, once other factors were considered. We also included usage frequency and literacy as control variables in this model; neither had a statistically significant unique effect on resistance levels in the final analysis (Table 3). Thus, H3 was not confirmed as expected: dissatisfaction or low trust in the algorithm was not our sample's primary driver of resistance behaviours. Paradoxically, those most actively resisting the algorithm tended to be reasonably satisfied users.

This counterintuitive finding – satisfied users engage more in resistance – calls for careful interpretation. One possible explanation is a self-selection and efficacy effect: users who take the trouble to tweak or "fight" the algorithm may achieve a more satisfying feed and end up happier with the platform. In other words, causality could run in the reverse direction: instead of dissatisfaction prompting resistance, it may be that resistance (and other strategic adaptation) improves satisfaction. Indeed, our data are cross-sectional, so we must be cautious in inferring causality. The positive satisfaction–resistance correlation could mean that the most engaged and empowered users curate and enjoy their feeds more. This interpretation fits the earlier point that training strategies were

employed widely regardless of satisfaction. It suggests that active feed curation is not merely a remedy for discontent, but a habit integral to how enthusiastic users interact with the platform. Some resistance tactics can be seen as playful or empowering engagement. For example, a few users described deliberately trying to "fool" or confound the algorithm – clicking random content or talking about specific topics near their phone – not out of pure frustration, but out of curiosity and a desire to assert agency (Wang, 2024). Such behaviours blur the line between resistance and experimentation. They reflect a sense of co-creation with the algorithm, rather than simple opposition.

The lack of a direct effect of filter-bubble concern on resistance usage is noteworthy. While nearly half the users voiced concern about being trapped in an information bubble, many worried users did not necessarily take extra steps to diversify their feeds beyond the standard tactics. Awareness of a problem (algorithmic narrowing) is not always enough to spur additional action, especially if the user is already broadly satisfied. Some users possibly trust the algorithm's personalisation despite abstract concerns, echoing what Schmidt *et al.* (2019) observed: when confronted with algorithmic filtering, some users accept or tolerate it. In our sample, a subset likely fell into this "apathy/acceptance" category, acknowledging the issue but not actively countering it. Others belonged to the "adaptation/resistance" group that Schmidt *et al.* (2019) identified. They "develop creative workarounds or personalised strategies to mitigate unwanted effects". Our results indicate that these active resisters are motivated not just by fear or displeasure, but by a combination of factors, including the pleasure of curating, a desire for control, and confidence in their capacity to influence the system.

In conclusion, the expectations for H3 were not directly fulfilled. Lower satisfaction did not predict higher resistance; more satisfied users reported slightly more of these behaviours. The filter-bubble concern did not significantly boost resistance once other factors were controlled. These results challenge a simple "problem to reaction" user behaviour model. Instead, they indicate that strategic resistance is often a proactive, integrative part of engaged platform use, rather than a last resort for the disgruntled. This extends domestication theory (Silverstone & Hirsch, 1992): users' attempts to

tame the algorithm (even through resistant means) can be part of a positive, empowered engagement with the technology, not only a symptom of conflict. It also underscores the importance of user agency (Gillespie, 2014): even contented users exercise their agency to curate their experience further.

Discussion

Stepping back from individual hypotheses, the findings collectively paint a picture of the user–algorithm relationship as a co-creative, iterative cycle. We observe that heavy usage breeds algorithmic literacy; literacy leads to more strategic adaptation (training behaviours); successful adaptation can enhance user satisfaction; and a satisfied, highly engaged user tends to continue (or even increase) their adaptive behaviours. Essentially, users and the algorithm continuously shape one another's outputs in a looping cycle. This aligns closely with the idea of a "bidirectional domestication game" introduced earlier – both parties (user and algorithm) are continually learning and adjusting. Our data support this dynamic: users who learn the algorithm's rules (whether through experience or folk knowledge) then apply that learning to co-create a more pleasing feed, which further reinforces their active usage and further learning. We might term this evolving process the "co-creative literacy cycle". It is "co-creative" because both user and algorithm collaboratively generate the resulting content mix (the user provides inputs, the algorithm responds, prompting new inputs, and so on). It is driven by "literacy" in that the user's understanding of the system improves over time through experimentation and feedback (Powers, 2017).

The co-creative literacy cycle framework helps integrate our findings with domestication theory (Silverstone and Hirsch, 1992) and prior literature. Domestication theory emphasises that users incorporate technologies into their daily lives and continuously negotiate their use. Our results add a clear empirical example of that negotiation in algorithms: users do not simply adopt the platform once and for all, but repeatedly re-domesticate it as their understanding and life contexts evolve. Some participants in our study reported taking breaks or decreasing usage when the feed appeared "too intrusive," subsequently returning with new strategies, similar to the concepts of "reverse

domestication" and "re-domestication" discussed by Karlsen & Syvertsen (2020) and Huang & Miao (2020).

Furthermore, this cycle of algorithmic literacy can capture that a deeper understanding of algorithms by users can lead to more effective collaboration and smarter resistance. Our research findings indicate that literate users engage in more training. From a qualitative perspective, we also observe that literate users come up with ingenious resistance strategies (for instance, knowing that clicking on irrelevant content might confuse the algorithm's profiling of them, a strategy only attempted when understanding that the algorithm builds profiles. As Bucher (2017) pointed out, users form an "algorithmic imagination" of how the system works and then act; accordingly, our research confirms that this imagination and action feed back into how algorithms present content, effectively meaning that users and algorithms co-shape the user experience.

Implications

These findings make several contributions to media and communications theory. First, these findings empirically demonstrate that users actively domesticate algorithmic systems consistent with classic domestication stages, while highlighting new complexities such as continuous feedback loops and re-domestication. The notion of a co-creative literacy cycle extends domestication theory by illustrating how user and system agency intertwine. Our evidence suggests that user agency vis-à-vis algorithms is reactive and productive. This aligns with recent scholarship arguing that social media users are not simply "managed" by algorithms but are also managing the algorithms in return. In the Chinese context, our study adds to understanding how a platform's governance and culture shape this bidirectional game.

Our findings also detailed the concept of algorithmic literacy. Prior work often frames literacy as empowering users to resist unwanted algorithmic outcomes. Literate users in our study were proactive and generally satisfied; they engaged with it as knowledgeable actors. This suggests that algorithmic literacy can foster a sense of mastery or "playing the game" rather than outright

opposition. It would be simplistic to cast all user tactics as compliance or resistance; many of our participants blurred these categories, fluidly using both training and resistant moves. We find resonance with Foucault-inspired notions of power: users exercise a form of power within the constraints of algorithmic power, rather than entirely external to it.

For social media platforms and designers of algorithmic systems, our study highlights the value of user agency and transparency. Platforms might note that empowering users to shape algorithmic recommendations can enhance user satisfaction and engagement. For example, introducing more granular preference settings, offering explanations for why content is shown (and how to change it), or providing easier ways to reset or diversify one's feed might not only address user concerns (like filter bubbles or monotony) but also encourage the kind of deep engagement that makes users stickier. Our data suggest that users who feel in control of their feed are among the most satisfied and loyal. Thus, designing for co-creation could be a win-win strategy. At the same time, platforms should acknowledge the prevalence of folk theories and misconceptions. Many users in our sample were guessing how the algorithm works. Providing more explicit guidance or debunking false folk theories (perhaps via official help pages or community education) could improve the efficacy of user strategies and build users' loyalty. In the Chinese context, where transparency around algorithms is often low, even small steps toward openness could foster user goodwill and more rational adaptation behaviours.

Future research direction: This study opens several avenues for further inquiry. One clear need is for longitudinal research to observe the co-creative literacy cycle over time. A longitudinal or experimental design could disentangle the causal relationships we discussed: does greater algorithmic literacy lead to more strategic behaviour, or do those who experiment more gain literacy? These questions of directionality can be better answered by tracking users and their feed changes over time, or by interventions that educate some users about the algorithm and seeing if their behaviour shifts. Another fruitful area is qualitative research, which complements our survey.

Interviews or digital ethnography could deepen understanding of how users develop their folk theories, interpret the success or failure of their tactics, and emotionally experience the domestication game. Additionally, cross-platform comparisons could be enlightening: Do we see similar strategic adaptations on platforms like TikTok or Weibo, and are the predictors similar? If, say, algorithmic literacy predicts adaptation on Xiaohongshu but not on a different platform with a different user base or content style, that would refine how generalisable our conclusions are.

Limitations

First, the data are self-reported and cross-sectional. Self-report behaviour measures may be prone to biases: some users might overestimate their savvy, while others under-report less socially desirable tactics. We attempted to mitigate this with clear, concrete questions and anonymity, but biases cannot be eliminated. We also relied on perceptual measures for key constructs (like "algorithmic literacy", which was essentially measured by self-assessed awareness). Future work could include objective knowledge quizzes or behavioural data to validate these self-perceptions. Another limitation is the sampling: our survey, like many online surveys, likely attracted more active and interested users. Indeed, a large portion were daily users and moderately young and educated. This means our findings apply to engaged Xiaohongshu users; we know less about truly casual users or those who might have quit the platform altogether. The experiences of users who became disenchanted and left are not captured here, yet they are part of the broader domestication story. Thus, our conclusions should reflect the behaviour of continuing users, not all possible users. Similarly, the cultural context – Chinese social media usage – may condition these behaviours. Norms on Chinese platforms (such as accepting algorithmic feeds as the primary content source, or the prevalence of social commerce) might differ from elsewhere. While we believe many user–algorithm adaptation principles are universal, specific patterns could vary internationally.

CONCLUSION

This study examined how Xiaohongshu users adapt their behaviour to the platform's recommendation algorithm and what user characteristics drive those adaptations. The survey results show that frequent platform use and greater algorithm understanding correspond to more intensive "training" tactics, confirming that heavy, knowledgeable users actively shape their feeds. However, the expectation that dissatisfied users would engage in more "resistance" tactics was not supported. Participants reporting higher satisfaction and trust in the algorithm employed slightly more resistance behaviours than less satisfied users, and concern about filter bubbles had no significant influence. These findings indicate that active feed curation is not simply a response by unhappy users, but a normal aspect of engaged platform use – even contented users continually assert agency over their algorithmic experience.

These results depict user–algorithm interaction as an iterative, co-creative cycle, confirming the bidirectional domestication game in practice. Users and algorithms continuously influence one another: heavy use tends to foster higher algorithmic literacy, and in turn, literate users employ more sophisticated feed-tuning tactics that further enhance their experience. Notably, even satisfied users engaged in some resistance tactics, indicating that user agency here is not merely a response to dissatisfaction but part of routine personalisation.

This ongoing feedback loop extends domestication theory into the algorithmic era, and domestication becomes a continuous, mutual process rather than a one-time adoption. Users of Xiaohongshu actively modify the recommendation system to align with their preferences, while simultaneously adapting their behaviour in response to the algorithm's signals. This study empirically demonstrates the domestication of social media algorithms through continuous user intervention, effectively obscuring the distinction between compliance and resistance.

The findings have important implications for algorithm design and platform governance. Users will be more satisfied and engaged for longer if they have more control over their feeds. Features that enable this two-way "taming" process can be beneficial for platforms like Xiaohongshu. Further enabling constructive user-algorithm engagement might be educating consumers about the algorithm's inner workings. Platforms may achieve their engagement objectives while providing a healthier and more enjoyable user experience by designing with user agency and algorithmic literacy in mind.

Finally, future research needs to explore this user–algorithm dynamic further. Longitudinal studies could track users to see how algorithmic literacy and adaptive behaviours co-evolve, clarifying whether greater knowledge drives more adaptation or vice versa. In-depth qualitative approaches would complement our survey by examining how users form folk theories about the algorithm and how they experience their attempts to tame the feed. Comparative studies across different social platforms or cultural contexts would also be valuable. Identifying similar adaptation patterns on other services would suggest our findings are generalisable, whereas contrasting results might highlight the influence of platform-specific designs or norms. Such studies would deepen our understanding of the complex interplay between user agency and algorithmic governance across diverse settings.

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APPENDIX



THE LONDON SCHOOL
OF ECONOMICS AND
POLITICAL SCIENCE ■

Default Question Block

感谢您参加关于‘双向驯化博弈：小红书用户对推荐算法的策略适应’的问卷调查。“双向驯化博弈” (Bidirectional Domestication Game) 是指用户与平台算法之间的互动适应过程。本研究是关于小红书用户如何通过他们的行为（如重复点击、屏蔽内容）影响算法内容推荐。

我的参与是什么？

如果您同意参加，您将被要求完成一份关于您使用小红书推荐算法的体验的在线调查。调查大约需要10-15分钟的时间。

参与是自愿的。你不需要回答任何你不想回答的问题，如果你愿意，你可以在任何时候停止完成调查。由于数据收集是匿名的，一旦您完成并提交调查，您所提供的信息将无法撤回。

参加本研究将没有任何金钱补偿。

我的信息会被用来做什么？

你的回答将用于我未来的研究。

您的个人信息将被妥善保管，并在研究结束时销毁。

本次调查不会收集您的IP地址。

您的参与将是匿名的，您的名字将不会出现在本次研究的任何报告或出版物中。伦敦政治经济学院研究隐私政策可以在网上找到。

Title of your study: Bidirectional Domestication Game: Strategic Adaptation of Xiaohongshu Users to Recommendation Algorithms

Degree programme: MSc in Media and Communications (Media and Communication Governance)

Department: Media and Communications London School of Economics and Political Science

Thank you for your interest in this study. The study is about how users of Xiaohongshu influence algorithmic content recommendations through their behaviours (e.g., repeated clicks, blocking content).

What will my involvement be?

If you agree to take part, you will be asked to complete an online survey about your experiences with Xiaohongshu's recommendation algorithm. The survey should take approximately 10-15 minutes of your time."

Participation is voluntary. You do not need to answer any questions you don't want to, and you can stop completing the survey at any point if you wish to. Since the data collection is anonymous, it will not be possible to withdraw the information you have provided once you have completed and submitted the survey. There will be no monetary compensation for participating in this study.

What will my information be used for?

Your responses will be used in my future research.

Your personal information will be kept securely and destroyed at the end of the study.

Your IP address will not be collected during this survey.

Your participation will be anonymous - your name will not be used in any reports or publications resulting from the study. The LSE Research Privacy Policy can be found online.

如果你同意以下陈述，请开始作答问卷

Please read and select the following statements if you agree with them:

- 我已阅读并理解以上的解释且我年满18岁 / I have read and understood the explanations above and I am 18 or over

您是否在过去一个月内使用过“小红书”？ Have you used the "Xiaohongshu" App in the past month?

- Yes
 No

1. 你使用小红书的频率是？

How often do you use Xiaohongshu?

- 每天 / Daily
 每周几次 / A few times a week
 每月几次 / A few times a month
 很少 / Rarely

2. 你使用小红书多久了？

How long have you been using Xiaohongshu?

- 少于6个月 / Less than 6 months
 6-12个月 / 6-12 months
 1-3年 / 1-3 years
 3年以上 / 3+ years

3. 以下哪项最能描述你使用小红书时的身份?

Which of the following **best** describes you when you use Xiaohongshu?

- 主要是内容浏览者 (很少/从不发布) / Mainly content viewer (rarely/never posts)
- 偶尔的内容创作者 (有时会发布) / Occasional content creator (sometimes post)
- 经常的内容创建者 (经常发布) / Regular content creator (often post)

4. 在今天之前的认知, 您是否知道小红书使用推荐算法来个性化您的内容?

Before today, were you aware that Xiaohongshu uses a recommendation algorithm to personalise your feed?

“推荐算法”是指小红书根据你平时的浏览、点赞、收藏、评论、搜索等行为, 自动判断你可能感兴趣的内容, 并将相关笔记优先推荐到“发现页”或首页的机制。这个系统并不是人工编辑的, 而是通过你过往的使用习惯, 自动为你“定制”内容推荐。

- 完全不了解 / Not well at all
- 了解甚微 / Slightly well
- 适度理解 / Moderately well
- 非常了解 / Very well
- 完全了解 / Extremely well

5. (多选) 你认为以下哪些因素会影响小红书的推荐算法?
(Multiple choices) Which of the following factors do you think influence Xiaohongshu's recommendation algorithm?

- 你过去与笔记的点赞, 收藏, 评论 / Your past likes, collections and comments
- 笔记的受欢迎程度 (点赞、评论、分享的数量) / The popularity of the post (number of likes, comments, shares)
- 你浏览笔记或与笔记互动所花费的时间 / How long you spend viewing or interacting with a post
- 你是否关注内容创建者 / Whether you follow the content creator
- 你经常搜索或主动浏览的主题或关键字 / Topics or keywords you frequently search or actively browse
- 随机推荐 / Random chance
- 不知道/不确定 Don't know / Not sure
- 其他 / Other

6. 请根据以下每一项陈述对您的同意进行评分。
Please rate your agreement with each of the following statements.

非常不同意 不同意 中立 同意 非常同意
Strongly disagree disagree Neutral agree Strongly agree

我觉得我可以控制小红书推荐给我的内容 / I feel I can control the types of content I see on Xiaohongshu.

	非常不同意 Strongly disagree	不同意 disagree	中立 Neutral	同意 agree	非常同意 Strongly agree
推荐算法通常会向我提供我喜欢或认为有用的内容 / The recommendation algorithm usually shows me content I enjoy or find useful.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
我担心算法会限制我看到的内容的多样性 (信息茧房) / I worry that the algorithm creates an 'information bubble' or biases what I see.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
我清楚地明白为什么小红书会向我推荐每个帖子 / I clearly understand why Xiaohongshu recommends each post to me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

7. 本题检测是否认真作答 This question tests whether one answers carefully !

请选择 非常不满意/ **Please choose Extremely dissatisfied**

- 非常不满意 / Extremely dissatisfied
- 不满意 / dissatisfied
- 中立 / Neutral
- 满意 / satisfied
- 非常满意 / Extremely satisfied

8. 你多久进行一次以下活动来影响或管理您的小红书的推荐内容? How frequently do you do the following activities to influence or manage your Xiaohongshu feed recommendations?

	从不 Never	很少 Rarely	有时 Sometimes	经常 Often	总是 Always
故意为某些笔记点赞、评论或收藏, 以查看更多相似内容 / Deliberately like, comment, or collect certain posts to see more similar content.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
避免与你你不喜欢的笔记互动 (没有点赞/评论), 以减少看到类似的内容 / Avoid interacting (no likes/comments) with posts you dislike to reduce seeing similar content.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
使用搜索栏或直接访问关注用户的页面, 而不是依赖推荐的笔记 / Use the search bar or visit followed users' pages directly instead of relying on the recommended feed.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

	从不 Never	很少 Rarely	有时 Sometimes	经常 Often	总是 Always
<p>有意识地关注或订阅某些主题标签/主题，以多样化或更改推荐笔记 / Intentionally follow or subscribe to certain hashtags/topics to diversify or change your feed.</p>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
<p>暂时停止使用或卸载小红书以重置或影响你的推荐笔记 / Temporarily stop using or uninstall Xiaohongshu to reset or influence your recommendations.</p>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
<p>使用多个小红书账号来区分兴趣并控制推荐内容 / Use multiple Xiaohongshu accounts to separate interests and control feed content.</p>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
<p>随机与各种不相关的帖子互动，以混淆算法对你的兴趣分析 / Randomly interact with various unrelated posts to confuse the algorithm's profiling of your interests.</p>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
<p>使用'不感兴趣'或'内容反馈'的按钮以避免某些内容 / Using the 'Not Interested' or 'Content Feedback' button to avoid certain content.</p>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

9. 在上述策略中，你认为哪种策略最能有效地影响你的小红书推荐内容？

Among the above strategies, which single strategy do you find **most** effective for influencing your Xiaohongshu recommendations?

- 故意为某些笔记点赞、评论或收藏，以查看更多相似内容 / Deliberately like, comment, or collect certain posts to see more similar content.
- 避免与你你不喜欢的笔记互动（没有点赞/评论），以减少看到类似的内容 / Avoid interacting (no likes/comments) with posts you dislike to reduce seeing similar content.
- 使用搜索栏或直接访问关注用户的页面，而不是依赖推荐的笔记 / Use the search bar or visit followed users' pages directly instead of relying on the recommended feed.
- 有意识地关注或订阅某些主题标签/主题，以多样化或更改推荐笔记 / Intentionally follow or subscribe to certain hashtags/topics to diversify or change your feed.
- 暂时停止使用或卸载小红书以重置或影响你的推荐笔记 / Temporarily stop using or uninstall Xiaohongshu to reset or influence your recommendations.
- 使用多个小红书账号来区分兴趣并控制推荐内容 / Use multiple Xiaohongshu accounts to separate interests and control feed content.
- 随机与各种不相关的帖子互动，以混淆算法对你的兴趣分析 / Randomly interact with various unrelated posts to confuse the algorithm's profiling of your interests.
- 使用'不感兴趣'或'内容反馈'的按钮以避免某些内容 / Using the button for 'Not Interested' or 'Content Feedback' to avoid certain content.
- 无 / None
- 其他 / Other

10. (多选) 你试图影响小红书推荐算法的原因有哪些?
(Multiple choices) What are the reasons you try to influence the recommendation algorithm on Xiaohongshu?

- 使内容推荐更符合我的兴趣和偏好 / To make content recommendations better match my interests and preferences
- 为了避免看到不喜欢或不感兴趣的内容 / To avoid seeing content I dislike or have no interest in
- 因为担心算法过度限制我看到的 content 类型 (避免信息茧房) / Because I worry the algorithm overly restricts the types of content I see (avoid filter bubble)
- 出于隐私原因, 不希望算法过多了解我 / For privacy reasons, I don't want the algorithm to know too much about me
- 出于好奇, 尝试看看自己的行为如何影响推荐结果 / Out of curiosity; to see how my actions affect recommendations
- 我不试图影响它 / I do not try to influence it
- 其他原因 (请简要说明) / Other reasons

11. 你觉得你的行为对小红书推荐的内容有显著影响吗?
Do you feel your actions significantly influence the content recommended by Xiaohongshu?

完全没有 / Not at all 轻微 / Slightly 适度 / Moderately 非常 / Very much 完全 / Completely

12. 总的来说, 你对小红书上收到的内容推荐满意吗?
Overall, how satisfied are you with the content recommendations you

receive on Xiaohongshu?

非常不满意
Extremely
dissatisfied

不满意
dissatisfied

中立 Neutral

满意 satisfied

非常满意
Extremely
satisfied

13. 如果你有其他策略来影响小红书的推荐，或者你对算法有具体的体验或想法（正面/负面），请简要描述一下：

If you have other strategies you use to influence Xiaohongshu's recommendations, or if you have specific experiences or thoughts (positive/negative) about the algorithm, please describe them briefly

Block 3

你的性别是什么？ What is your gender?

- 男性 / Male
- 女性 / Female
- 非二元性别 / Non-binary
- 无可奉告 / Prefer not to say

请选择你的年龄段。 Please select your age group.

- 18岁以下/under 18 years old
- 18-24
- 25-29
- 30-34
- 35-39
- 40岁以上/over 40 years old
- 无可奉告 / Prefer not to say

你的最高学历是?

- 高中生以下 / High school or below
- 学士学位 / Bachelor's degree
- 硕士及以上学历 / Master's degree or above
- 无可奉告 / prefer not to say

Powered by Qualtrics

A. descriptives (frequencies of responses) of the variables in the questionnaire

Correlation Matrix: Table presents the correlation coefficients among the key variables: usage frequency, perceived algorithm understanding, satisfaction, filter bubble concern. This matrix provides a snapshot of how these factors interrelate in our sample.

Table. correlation matrix and descriptive statistics for key variables (N=280).

<i>Variable</i>	<i>1. Usage freq</i>	<i>2. Alg. understanding</i>	<i>3. Satisfaction</i>	<i>4. Bubble concern</i>
<i>1. Usage frequency (1=Daily,...4=Low)</i>	1.00	-0.12	-0.18*	-0.16*
<i>2. Perceived alg. understanding</i>	-0.12	1.00	+0.22**	+0.07
<i>3. Satisfaction with recommendations</i>	-0.18*	+0.22**	1.00	+0.04
<i>4. Filter bubble concern</i>	-0.16*	+0.07	+0.04	1.00

Note: * $p < .05$, ** $p < .01$ (two-tailed). Usage frequency coded 1 = “multiple times a day”, 4 = “rarely”. Alg. understanding, satisfaction, and concern are each on 1–5 scales (higher = more understanding, more satisfied, more concerned).