Chat with the ’For You’ Algorithm: An LLM-Enhanced Chatbot for Controlling Video Recommendation Flow

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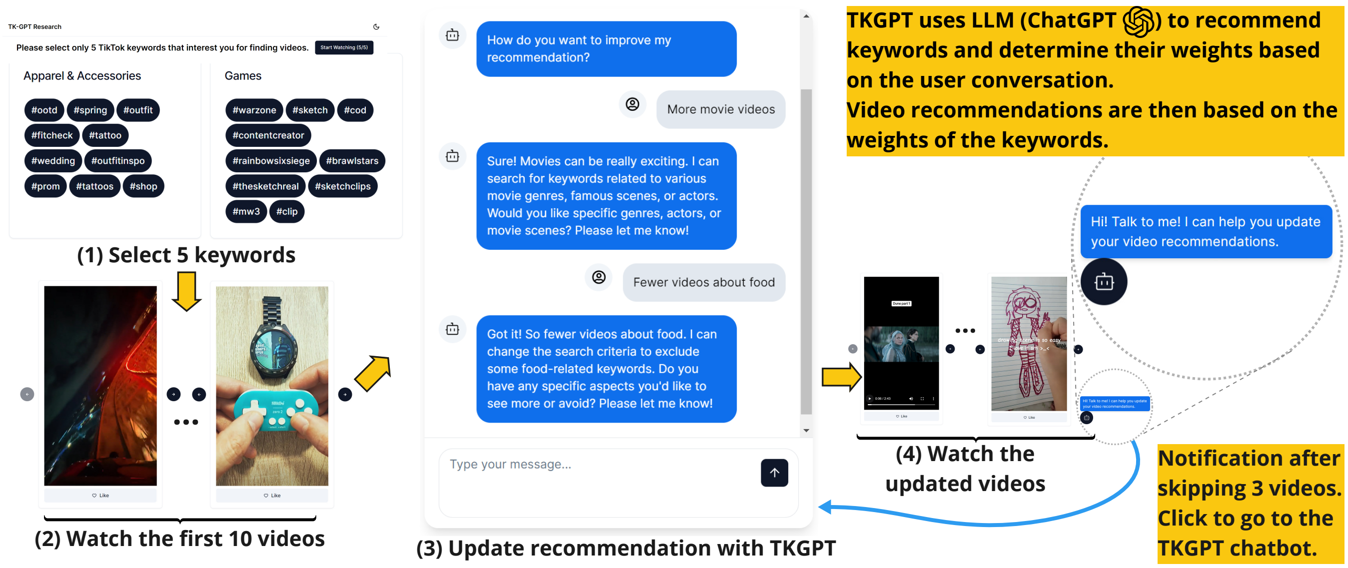

Figure 1: The interaction flow and example chats of TKGPT in the Formal Study. Users first select 5 hashtags of interest, then watch 10 TikTok videos related to those hashtags one by one as on TikTok. TKGPT invites users to update their preferences, and subsequent video recommendations are adjusted accordingly. If a user skips three videos in a row, a notification prompts them to revise their recommendations with TKGPT.

Abstract

The rise of short-form video platforms like TikTok, driven by algorithmic recommendations, fosters immersive flow experiences. While users value personalization and engagement, they also seek greater agency over their For You recommendations. This paper designs, prototypes, and evaluates TKGPT, an LLM-enhanced conversational interface that helps users articulate their interests and understand recommendations. Through qualitative interviews and a user study, we examine how the TKGPT influences algorithmic folk theories and the sense of agency. Findings show that users primarily use TKGPT to seek relevant videos, explain preferences, and exert control over the algorithm. The resulting For You videos better reflect user interests, enhance the understanding of algorithm, improve content relevance, and reduce feelings of exploitation. Notably, users’ sense of agency is significantly associated with their improved understanding of how the algorithm works. We discuss the opportunities and challenges of using conversational user interfaces to enhance user control over video recommendations.

CCS Concepts

• **Human-centered computing** → **Interaction design**; **Interaction techniques**.

Keywords

video; TikTok; Generative AI; large-language model; chatbot; recommendation algorithm; folk theory

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1 Introduction

The rise of short-form video platforms like TikTok, Facebook Reels, and YouTube Shorts, along with their algorithm-curated video recommendations [1], has significantly altered media consumption patterns, focusing on fast, engaging, and endless video content. The popularity of platforms such as TikTok is driven by algorithm-enabled personalization on the For You page, which uses interaction data, content characteristics, and engagement metrics to deliver relevant content [17, 73]. Scrolling through TikTok's videos immerses users in a *flow experience* – an immersive experience characterized by feelings of enjoyment and time distortion [12, 56]. Algorithm-created For You pages not only satisfy niche interests and engage users, but also reflect users' identities and values [37, 49]. Although users appreciate personalized AI-recommended videos, they strongly desire control over their personal data and interactions on the platform [35, 61]. However, the passive and endless scrolling may make users lose of agency over what a user can see or want to see [25, 66].

The *sense of agency* is the experience of controlling both one's actions and the external environment [25, 66]. On TikTok's For You page, users do not have a direct or explicit way to control the next-up videos. Their available actions include watching, liking or disliking, commenting, or blocking creators [8]. These behaviors represent cases of gaining agency over unintentional actions – users do not have a clear understanding of how these actions influence changes in the algorithm [36, 58]. Users' informal and intuitive understanding of how recommendations work and their attempts to influence algorithmic behavior are often referred to as *algorithmic folk theory* [13, 14, 36]. Common folk theories about TikTok include beliefs that algorithms are confining in their content recommendations, practical in prioritizing relevant content, reductive in their portrayal of user interests, intangible in their controllability, and exploitative in promoting ads and collecting user data [68]. To alter algorithmic behavior and avoid unwanted content, users often monitor and modify their video-watching habits to "train" the algorithm to deliver desired content [15, 61]. However, this process relies solely on users' understanding of algorithmic mechanisms and their mindful interactions with videos, without providing them a direct way to express control over which videos should appear or how they would like to customize their viewing experience.

The recent development of Large Language Models (LLMs), such as ChatGPT, presents new opportunities to capture user interests and suggest relevant items [32, 34, 48, 54]. Chatbots serve as an effective interaction technique for requesting user preferences and responding to personalized information requests [21, 22, 60]. However, given users' desire for a sense of agency over their For You page experiences, there is limited understanding of whether and how an LLM-enhanced chatbot can effectively gather user interests and tailor subsequent video recommendations. Additionally, there are few design guidelines for integrating LLM-enabled chatbots into For You video recommendation systems and assessing their impact on users' algorithmic folk theories.

Through a two-stage study and the lens of algorithmic folk theory [68], we designed, developed, and evaluated TKGPT (Figure 1), an LLM-based conversational video recommender that responds to users' requests to modify the video recommendation sequence on TikTok's For You page. This system pilots the concept of conversationalizing video recommendation algorithms through natural language and adjusting recommendations using keyword rating and matching. Through qualitative interviews and a formative user survey, we examined the intentional actions users take to control recommendations and how these interaction patterns influence their algorithmic folk theories. Specifically, this paper makes three key contributions:

- We design an LLM-based chatbot that enables intentional actions in controlling the For You page and enhances the sense of agency over the flow experience.
- We investigate how interacting with a chatbot that modifies the For You page influences users' algorithmic folk theories.
- We analyze how changes in folk theories impact the sense of agency and whether this sense of agency affects overall user engagement.

Through our qualitative and quantitative analysis, we found that participants primarily used TKGPT to make video recommendations more relevant by explaining their interests. They intended to configure and control the recommendation process through natural language conversations. These interactions demonstrated benefits in achieving anti-reduction, anti-opacity, relevancy, and anti-exploitation goals, with the anti-opacity use contributing to a greater judgment of agency. Based on these findings, we discuss the design patterns of intentional interest externalization and explanatory recommendation. Additionally, we highlight potential challenges, including how LLM-based chatbot control could reinforce confinement and lead to breakdowns in the flow experience.

2 Related Work

2.1 Algorith Experiences on the For You Page

Short-form video platforms such as TikTok, Facebook Reels, and YouTube Shorts have become immensely popular, attracting billions of users and generating vast numbers of daily video views [4]. In 2024, TikTok alone had 1.04 billion users worldwide, with U.S. adults spending an average of 53.8 minutes per day on the platform [3]. The success of these platforms is largely driven by algorithm-based recommendations, particularly TikTok's For You page [17, 73]. Personalization on the For You page is achieved through a combination of user interaction data, content characteristics, and engagement metrics, enabling TikTok to deliver highly relevant content [11, 46, 51, 75]. Scrolling through TikTok's For You page engages users in a *flow experience*, where users become fully immersed in the content, enjoying it and losing track of time [12, 56]. The personalization facilitated by these algorithms allows users to explore niche interests and shape individualized experiences. Over time, this process reflects their identities and values, helping them form a deeper sense of engagement [37, 49].

While some studies suggest that users accept AI taking agency in finding relevant videos [35], many still take actions to exert control over what appears in their video recommendations [47].

Users develop awareness and form "algorithm folk theories' – informal beliefs about how the algorithm works – to determine the actions needed for higher engagement and the representation of identities [13, 63]. Users experience a sense of algorithmic personalization but must also navigate fluctuations when encountering too many or highly varied recommendations at an exceedingly fast pace [61]. According to the algorithm crystal theory, TikTok users deliberately and effortfully attempt to train the algorithm to make it intentionally reflect their identities [37]. The concept of algorithmic imaginaries, or "stories about algorithms," suggests that, although users do not seek full control over the For You page, they manage their interactions with videos to avoid feeling entirely powerless in the face of algorithmic influence [58]. One strategy users employ is crafting algorithmic personas to predict AI behavior, monitor and modify searches to counter harmful content, and adjust their behaviors to influence how algorithms perceive them [15, 36, 62, 67]. Similarly, on YouTube, researchers have found that the platform's current design supports ritualized use (open-ended use for diversionary gratification) but not instrumental use (goal-directed use for informational gratification), as users felt their intentions were hijacked by autoplay and algorithmic recommendations [47]. Research suggests that the design of "algorithmic experiences" should focus on increasing user awareness of how behaviors are measured and enabling users to regain control over the algorithm [1]. However, while much research has examined how users attempt to control the TikTok algorithm through video interactions, little research has explored design options that enable users to directly control the topics that appear on their For You page – allowing them to explicitly express their interests and exert greater influence over the recommendations.

2.2 Sense of Agency on Video Sharing Platforms

The sense of agency refers to the subjective feeling of having control over one's actions and their consequences in the external world [25, 66]. Central to the sense of agency is the distinction between intentional and unintentional actions. *Intentional actions* are those undertaken with a conscious goal or purpose in mind, allowing users to assess whether the system gives them agency over their intentions. *Unintentional actions*, on the other hand, occur when activities are performed without conscious planning or decision-making, and users judge their sense of agency based on whether they feel ownership of their own activities [50]. On TikTok, passively scrolling through algorithm-arranged videos on the For You page and influencing future video recommendations is a typical unintentional action – users watch, like, and comment on videos without knowing how these actions will affect the next-up videos [8]. They can only infer the outcomes of their actions based on their own understanding of how the recommendation algorithm operates [13, 36]. While most existing research has examined how users rely on the post-hoc outcomes of algorithms to assess their agency over them [15, 36, 58, 62, 67], little work has explored the design possibilities of enabling users to *intentionally* control the For You page through natural language to direct the recommendation algorithm. In this work, we investigate how an LLM-powered conversational interface can facilitate intentional control and sense of agency over the For You algorithm.

Enabling a sense of agency over intentional actions requires consideration of two types of agency experiences. The sense of agency can be divided into *feelings of agency*, which refer to the in-the-moment perception of control, and *judgments of agency*, which involve the post-hoc, explicit attribution of an action to oneself [45, 64]. When providing a chat interface that allows users to express any request regarding the algorithm, it is crucial to understand what prospective intentions they feel agency over performing [39]. This understanding can be explored through how users take actions based on common folk theories about the algorithm [68]. Such knowledge is essential for configuring an intelligent agent that can anticipate user actions effectively. Additionally, the retrospective evaluation of action outcomes relates to the *judgment of agency* [39]. It is important to assess how users perceive their agency when they intentionally interact with the algorithm through a chatbot and later evaluate their sense of agency over the resulting recommendations. However, existing HCI research on how video interfaces affect the sense of agency on video platforms has primarily focused on how interface components influence users' judgments of agency on YouTube [47] and Netflix [57]. Little is known about how an intentional control interface could facilitate intentional actions and influence both the feeling and judgment of agency.

2.3 Conversational Recommender

An important technique for improving user control over algorithms is the use of AI-enhanced chatbots. In HCI, chatbots have been used to enhance user engagement by suggesting personalized topics [21, 60] and soliciting user preferences [22]. Conversational Recommender Systems (CRS) assist users in obtaining recommendations through multi-turn dialogues [22, 33]. Integrating LLMs into CRS enhances the social realism of conversations [69, 70]. LLMs can understand users' preferences and identify datasets relevant to their interests [20, 24, 72]. Additionally, they can provide explanations for why certain videos are recommended [41, 42, 44, 65]. Moreover, LLMs can be configured to maintain diversity in recommendations, ensuring a broader range of content in the recommended items [28].

While state-of-the-art LLMs have been explored for facilitating video recommendations, how such designs can be used to manage the flow experience on the For You page remains underexplored. Research has investigated how LLMs can interpret video data and refine recommendations. For example, ToolRec employs an LLM-driven user surrogate to autonomously trigger external tools to refine recommendation lists [72]. Similarly, LSVCR leverages LLMs for sequential recommendations based on videos and comments, yet it does not enable users to explicitly express their preferences and intentions [74]. However, these techniques operate without direct user input.

The design of conversational video recommenders primarily focuses on optimizing search and ranking accuracy, which does not reflect natural user control over For You videos. For example, MuseChat is a conversational interface that suggests one video at a time based on user requests [16]. Similarly, Chat-Rec is a movie recommender that presents multiple options in response to users' various queries to ChatGPT [24]. MACRS is a multi-agent system designed to improve the understanding of user preferences and suggest a single relevant item in the chatbot response [19]. Conversational Thompson Sampling utilizes user dialogues to understand preferences and make recommendations for users with minimal interaction history [40]. The LLM in these systems primarily offers videos through chat or ranks content based on a single criterion, rather than supporting a sense of agency over the broader behaviors that shape the TikTok experience [12].

In sum, prior approaches do not capture the dynamic and interactive nature of the For You page, where user agency is shaped by both the intention to exert control and the outcome of the LLM-arranged video flow. In this work, we design an LLM-based chatbot, TKGPT, driven by the potential of leveraging LLMs to capture user preferences and arrange videos accordingly. This paper presents the design, implementation, and evaluation of this system to examine how a conversational user interface could influence the sense of agency over the video recommendation process.

3 Constucting Sense of Agency in Algorithmic Folk Theory

As discussed above, probing users' sense of agency should involve understanding mental models for controlling the algorithm and whether the LLM-arranged videos reflect these intentions. To capture the intentional use of TKGPT, we use the algorithmic folk theory to explore users' potential interactions. *Algorithmic folk theory* is the informal, often speculative beliefs that users develop about how algorithms work and influence their experiences [13, 14, 36]. While TikTok currently does not provide explicit controls that allow users to inform their preferences, folk theories suggest potential actions users might take to address common concerns regarding the algorithm. Ytre-Arne and Moe identified five main folk theories of algorithms on social media [68]: *confinement*, *relevancy*, *reduction*, *opacity*, and *exploitation*. This framework not only describes common informal beliefs about algorithms but also suggests possible actions users may take when given control over them.

Anti-confinement. Confinement in folk theory refers to the narrowing of worldviews by recommending content that aligns solely with users' interests, rather than broadening their perspectives or challenging their beliefs [68]. The design of recommender systems must consider not only the identification of highly relevant content but also the inclusion of diverse perspectives [28]. On TikTok, users expect algorithms to reflect various aspects of their multifaceted identity, influencing their perception of content diversity in recommended videos [37, 58]. However, it remains unclear whether users would actively request a broader range of content for anti-confinement purposes or how they would perceive diverse topics when engaging with TKGPT.

Relevancy. Relevancy refers to the folk theory that algorithms sort information to prioritize what is most relevant [68]. Users actively engage with TikTok's content curation algorithms to make them more aligned with their interests [35, 58, 61]. Sufficiently relevant content can outweigh other drawbacks of algorithmic recommendations [9]. However, it remains unclear how users would request TKGPT to find relevant videos and how these recommendations would influence their sense of agency.

Anti-reduction. Users commonly believe that algorithms are reductive and offer limited portrayals of human experiences and interests [68]. TikTok users have multifaceted interests that evolve over time [37]. They perceive that the platform's algorithmic content tailoring can reinforce stereotypes and suppress content related to marginalized identities [36]. When given control, we aim to explore whether users would engage with TKGPT to articulate their interests and how this experience would influence their perception of the chatbot's role in counteracting reduction.

Anti-opacity. Opacity in folk theory suggests that algorithms are perceived as invisible, manipulative, and lacking accessible means for user control [68]. TikTok users demand greater transparency in algorithms, which influences their trust in these systems [31]. Many users believe TikTok should provide easy customization options and clearly disclose what data is used to generate recommendations [35]. However, it remains unclear whether interacting with TKGPT will enhance users' understanding of the algorithmic recommendation and whether this interaction will address their need for anti-opacity.

Anti-exploitation. Exploitation in folk theory suggests that users perceive algorithms as exploitative due to capitalist motives and consumer manipulation [68]. TikTok users believe that algorithms track their interactions to maximize time spent on the platform [58] and express concerns that liking videos results in receiving overly similar content [53]. They worry that user interaction is continuously monitored to refine video recommendations [9]. We want to understand whether interacting with TKGPT, which simulates human-like conversations, would mitigate users' concerns about algorithmic exploitation or instead reinforce their perception of being manipulated by the system.

Through these five lenses, we conducted two studies examining what are users' intentional actions in controlling the algorithm and assess whether and how the chatbot influence their judgment of agency.

4 Pilot Study: Understanding Agency and Usability Needs

Before designing the final version of TKGPT, we implemented our first prototype and conducted a pilot study to gain an initial understanding of how an LLM-based chatbot should be integrated into the For You page and how such interactions affect the sense of agency. This phase aims to identify potential design and usability challenges within TKGPT.

4.1 Initial Design

When provided with a chatbot capable of modifying the For You page, we anticipate that users will rely on folk theories to develop intentional actions toward the next-up videos. We implement a keyword-based recommendation system, as prior research suggests that hashtags and keywords are key determinants of TikTok's video recommendations [29]. TKGPT organizes the rankings of keywords, enabling users to rank topics up or down through instructions to the LLM, thereby controlling the For You page. The videos are then arranged according to the weighted topics. TKGPT plays one video at a time, and users can navigate to the next video using arrow buttons or skip any video, similar to TikTok. The TKGPT chatbot appears after every 10 videos, which uses the same screen space as a video. Chatting with TKGPT updates the next 10 videos on the For You page, allowing users to refine their recommendations dynamically.

TKGPT manages a database of 8,397 TikTok videos, each containing metadata such as the URL, description, like count, video duration, and hashtags. These videos, collected from the TikTok Creative Center[1], serve as candidates for the For You page, with trending videos gathered a week before the study to ensure freshness. We ensured that each of the 60 hashtags had at least 100 matching videos.

TKGPT uses LLM-rated keywords to rank videos based on user input (Figure 2). In the initial study, we use a finite set of keywords for TKGPT to organize. Users begin by selecting the five most relevant hashtags from a list of 60 trending hashtags. The system retrieves all videos containing these five user-selected hashtags and extracts all hashtags used in these videos. Hashtags associated with at least three videos are retained to build a keyword collection, each initially assigned a weight of 0. LLM processes this finite set of keywords and ranks them based on user instructions. For example, if a user selects #basketball from the initial 60 keywords and one video contains the hashtag #lakers, the system checks whether at least two other videos also include #lakers. If met, #lakers is added to the candidate hashtag collection for LLM to rank.

This design reflects aspects of algorithmic folk theory, as it aligns with how users could exert control over the For You page. For *anti-confinement*, since TikTok videos often include multiple hashtags, the expanded keyword collection may contain related terms unfamiliar to users. For example, users selecting #sports as a general interest may encounter videos suggested by TKGPT featuring an NBA team they do not typically watch. When users aim to enhance the *relevancy* of their video recommendations, they can explicitly inform TKGPT of their preference for a specific topic. For *anti-reduction*, users can request TKGPT to include multiple topics of their interests, increasing the diversity and comprehensiveness of video topics. For *anti-opacity*, TKGPT is instructed to generate responses in less than 20 words to inform users about which keywords are being promoted or demoted. For instance, when a user inquired about "soccer," the chatbot responded, "Got it! Soccer is a popular sport! I'll include keywords like 'soccer', 'soccerclips', and 'goalhighlights' for you." For *anti-exploitation*, users can directly express what they want TKGPT to track or what they want to see more or less, allowing the system to tailor recommendations accordingly.

After selecting the initial hashtags, the system creates a ChatGPT assistant using the OpenAI Assistant API[2]. The LLM model used in the pilot study was 'ChatGPT gpt-4-turbo.' The initial prompt given to the LLM assistant is detailed in Table 1 and subsection A.1. This prompt setup includes six key instructions that define the assistant's tasks, criteria, limitations, response style, and available resources. Upon receiving user input, TKGPT generates a new prompt by incorporating the user request and sends it, along with the candidate hashtags and their current ratings, to the LLM. This allows LLM to adjust the hashtag ratings dynamically according to users' control needs. After processing the input, TKGPT displays LLM's responses in the chat interface, providing users with real-time updates on how their preferences influence the upcoming video recommendations.

Instruction	Function
Responsibilities	Inform LLM that the task is to rank hashtags.
Criterion	Specify that the task is to rank hashtags by assigning and updating hashtag ratings, and then return the top 50 hashtags. Provide examples of how to assign ratings.
Limitations	Avoid unnecessary information generated by LLM so that the messages can be presented to the user.
Final Response	Instruct LLM on the output JSON format.
Response Format	Ask LLM to generate a summary sentence to be presented to the user.
Resources	Provide LLM with the candidate hashtag list.

Table 1: The main function sections in the LLM initialization prompt. The actual prompt can be seen in Appendix A.1.

When users leave a chat session, the system reorders the unwatched videos based on updated hashtag ratings from LLM. It calculates each video's priority by summing the ratings of its hashtags. For example, if #baseball and #basketball each have a rating of 1, a video with both hashtags will have a priority score of 2. A video with #basketball (rating 2) and #LA (rating 1) will have a priority score of 3. This approach prioritizes videos with multiple high-ranking hashtags. If videos share the same priority score, they are sorted in descending order by like count. The top 10 unwatched videos are then selected and displayed next.

4.2 Pilot Stduy

We conducted a qualitative study with 14 participants to observe the chat with TKGPT and gather feedback on how TKGPT affect users' sense of agency. The study included a demographic survey, a TKGPT user test, and a post-study interview. Participants were asked to explore trending TikTok videos using TKGPT, watch (or skip) 40 videos, and interact with the chatbot three times. The post-study interview has 7-point Likert-style questions on satisfaction, engagement, and agency, and the impact of TKGPT on the control need for anti-confinement, relevency, anti-reduction, anti-opacity, and anti-exploitation [68]. We also collect and analyze with open-ended feedback to understand how users like or dislike the control through the chatbot. The study was reviewed and approved by the IRB office of the authors.

The 14 participants were recruited from the student body at the [Authors' Institute]. Thirteen participants were between the ages of 18-24 and one between the ages of 25-34. Four participants identified as male, five as female, four as non-binary/third gender, and one self-identified as fluid gender. The racial and ethnic backgrounds were as follows: four were White, five Hispanic / Latino, three were Black / African American, one was Asian, and one identified as unlisted race or origin. All participants indicated that they use TikTok, YouTube Shorts, or Facebook Reels for at least a few hours each week.

To analyze the interview data, the researchers autotranscribed the voice recordings and segmented them into semantic blocks.

[1]https://ads.tiktok.com/business/creativecenter/pc/en
[2]https://openai.com/index/openai-api/

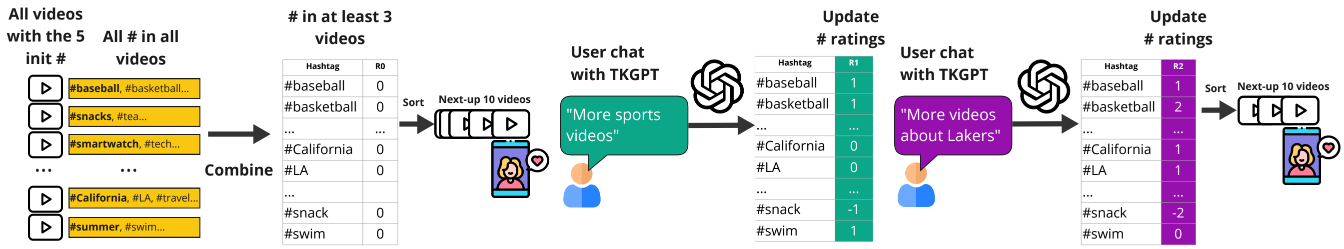


Figure 2: The workflow of TKGPT implemented in the pilot study.

Comments expressing negative feelings about the system were identified. Then, two authors followed the process of thematic analysis [7] to perform initial coding and theme development.

4.3 Results

In the post-study survey, all items utilized a 7-point Likert scale, with response options encoded as follows: `Strongly Disagree` (-3), `Disagree` (-2), `Somewhat Disagree` (-1), `Neutral` (0), `Somewhat Agree` (1), `Agree` (2), and `Strongly Agree` (3). Figure 3 illustrates the distribution. Participants were generally neutral in terms of overall satisfaction (M = -0.07, SD = 1.59). They had lower engagement with LLM-ordered videos (M = -0.43, SD = 1.34) and neutral ratings regarding whether TKGPT enhanced their sense of agency (M = 0.00, SD = 2.15). Regarding the dimensions of algorithmic folk theory, while anti-opacity and anti-exploitation received average positive scores, questions related to videos anti-confinement, relevancy, and anti-reduction received neutral or negative ratings (see Table 2). These results suggest that the design of the LLM chatbot did not effectively enhance user engagement or agency. Consequently, we analyzed interview feedback and user chat history to identify key requirements for the next design iteration.

	M	SD
Anti-confinement	-0.86	1.35
Relevancy	-0.36	1.98
Anti-reduction	-0.5	1.87
Anti-opacity	0.79	1.89
Anti-exploitation	0.21	1.58

Table 2: Means and standard deviations of the Pilot 1 interview questions.

4.3.1 Control Issue I: Users Have Their Own Definition of Relevance. The primary issue with relevancy was that the videos did not align with participants' specific and evolving interests. Despite curating 8,297 TikTok videos, 10 participants noted that the selection of hashtags was limited, and keyword searches often failed to return engaging content. For example, P3 stated, *"I was shown videos that I would not normally consume on these platforms,"* while P9 remarked, *"I like broad categories. I didn't see an anime or cartoon category."* Similarly, P6 noted, *"I asked for Valorant content but only got one that didn't interest me."* This gap was reflected in search behavior, as participants used the chat function to request content better suited to their preferences, such as *"more BIPOC, queer, or Spanish content"* or *"food videos that are more appetizing."* Some also requested video attributes that were not currently supported by TKGPT, such as *"faster-paced short-form videos"* or *"videos with trending sounds."*

This control issue stems from TKGPT's reliance on a fixed video set, which restricts its ability to cater to participants' niche interests. The limited range of hashtags further hinders LLM's ability to prioritize relevant content, leading to low engagement and a diminished sense of agency over the videos.

4.3.2 Control Issue II: Repetition of Topics on the For You Page. Seven participants found TKGPT's recommendations unengaging due to repeated videos on the same topic. For example, P8 noted, *"I asked for more fashion, and then it only gave me fashion videos. Even after requesting more variety, the tool continued to show only fashion videos for the rest of the session."* Similarly, P5 stated, *"I asked, 'Can you show me more Libra videos?' but instead of different ones, it just kept showing videos from the same person."* Participants also requested *"more variety within all the hashtags I've picked. The last 10 were all outfit videos"* and *"I would also like some more variety; it was a lot of food and not much else."*

Repetition occurs because the system prioritizes a single set of similar topics at a time, leading to repeated videos. Participants prefer more variety, but highly rated hashtags yield many videos from the same category. When a popular creator has multiple high-liked videos under the same hashtag, the system consecutively presents their content.

4.3.3 Control Issue III: Unsupported Hashtag Operation. Participants expressed a need for greater control through specific requirements, which the current TKGPT does not support. For example, some participants asked to exclude specified content, such as *"remove anti-woke content"* or *"no more tarot readings."* Others used combined hashtags like *"#libra #scorpio"* or *"#summerfun #painting #music #roomdecor."* Some participants filtered by attributes, requesting content such as *"45 seconds to 1 minute"* or *"shorter videos with captions."* TKGPT currently retrieves the most relevant videos but lacks the ability to rank different topics or merge content across multiple themes on the For You page. As a result, participants felt they had less agency in controlling their video sequences.

4.3.4 Control Issue IV: Chatbot Interruptions. The requirement for participants to interact with the chatbot every ten videos may undermine their sense of agency. Although skipping the chat was an option, four participants still found the interruptions annoying. For example, P1 suggested, *"I wouldn't want it to be a pop-up that appears every few videos; I'd prefer it to be a feature that I can initiate*

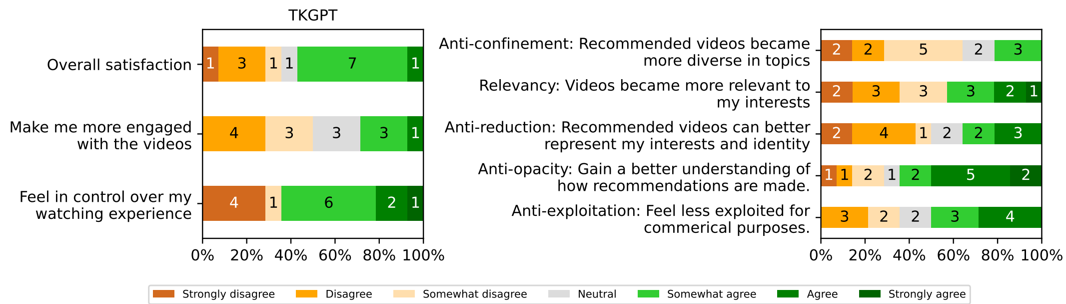


Figure 3: Ratings of overall satisfaction, engagement, agency, anti-confinement, relevance, anti-reduction, anti-opacity, and anti-exploitation during the pilot study interview.

myself.” Similarly, P10 noted, *“I didn’t like that it came up every 10 videos. I wish I had a bit more time to watch the videos.”*

5 Formal Study: Modeling Folk Theories’ Effects on Engagement and Agency

With an initial understanding of TKGPT’s capabilities, the second stage of our study focuses on improving the system design and conducting a formal user study. This study examines how TKGPT influences users’ folk theories about the algorithm and whether these effects impact their sense of agency while using the For You page.

5.1 New TKGPT Chatbot Design

To address the issues identified in the pilot study, we enhanced TKGPT’s LLM by developing two specialized assistants: one designed to help users articulate their control needs and the other dedicated to managing the For You page. Figure 4 illustrates the updated system, and Figure 1 presents the TKGPT interface. The LLM version used for this stage is ‘ChatGPT gpt-4o.’ Before the study, we reloaded the latest videos on 60 topics before the study.

5.1.1 Recommender Assistant. To help users find specific video topics (*Issue I*) and handle complex content requests (*Issue III*), we designed a Recommender Assistant using LLM. This assistant enables users to control the For You page by generating their own keywords and receiving feedback from LLM. The detailed prompt is provided in Appendix A.2, with key instructions summarized in Table 3. The chatbot interface is shown in Figure 1-(3). When a user sends a message to TKGPT, the LLM identifies keywords and generates TikTok search criteria. The Recommender Assistant then suggests relevant keywords based on the LLM’s response, allowing users to further refine their search terms through chat to better align with their interests. For example, if a user reponses that “movie” is a keyword, the Recommender Assistant suggests terms such as “movies,” “scenes,” “actors,” and “trailers” to construct a search query for TikTok. At the end of the chat session, the TKGPT API retrieves 30 new TikTok videos based on five criteria established during the interaction: Positive Keywords, which represent the content the user wants to watch; Negative Keywords, indicating content to avoid; Type, which categorizes video length as `very short`, `short`, `normal`, or `long`, with `normal` as the default; Duration, specifying the exact video length in seconds; and Final Keywords, which consist of the refined positive keywords. The retrieved videos and search keywords are then stored in the database for use by the Sorting Assistant.

Instruction	Function
Job 1&2	Define the tasks of the Recommender Assistant to identify relevant keywords and form search criteria.
Limitations	Define the response length and number.
Formatting	Define the format and tone to communicate to the user.
Example	Provide two examples of desired input and output.
Restrictions	Avoid system messages and programmatic information.

Table 3: The main function sections in the LLM initialization prompt for the Recommender Assistant. The actual prompt can be seen in Appendix A.2.

5.1.2 Sorting Assistant. The Sorting Assistant is designed to address video repetition (*Issue II*) and prioritize the most recent interests expressed in users’ messages (*Issue I*). It sends a list of system-maintained keywords, including the initial hashtags selected by the user and the Final Keywords identified by the Recommender Assistant, along with the user’s requests, to LLM. The prompt for LLM is detailed in Appendix A.3. The Sorting Assistant assigns weights to each search item: 50% for the highest priority, 25% for the second, 13% for the third, and so on. Keywords that users wish to exclude are assigned a weight of 0, allowing the system to filter out unwanted content effectively.

Once the weights are returned, the Sorting Assistant applies the criteria created by the Recommender Assistant to filter videos from new searches or those retrieved using the initial hashtags. It uses Positive Keywords to locate relevant videos and Negative Keywords to exclude unwanted content. Videos are further filtered based on Type and Duration. The system then determines the proportion of videos corresponding to each search item for the next 32 videos, the number of videos the user must watch before entering the post-study survey. For example, when the user indicates “movie” as an interest topic, the corresponding keyword set is assigned a weight of 50% in the next-up video by the Sorting Assistant, while the weights of other keywords are adjusted to collectively account for the remaining 50%. If the keyword #California has a weight of 1/4,

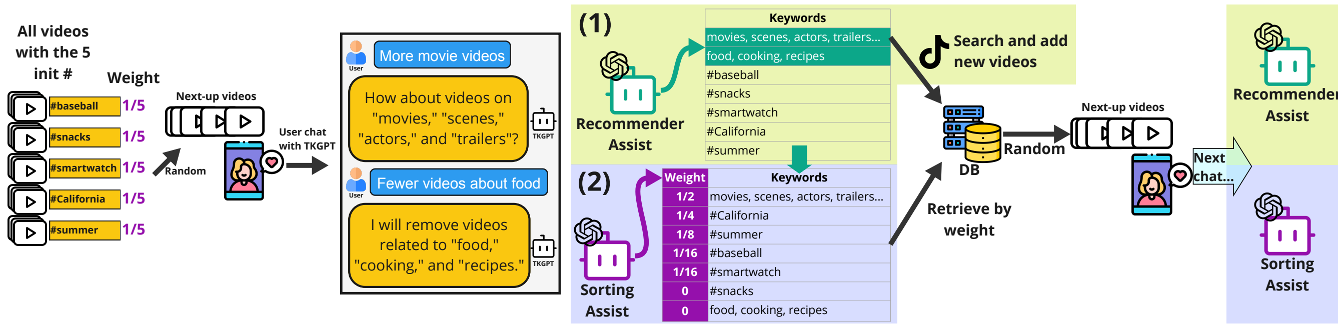


Figure 4: An illustration of how TKGPT in Study 2 organizes videos by keywords. (1) The Recommender Assistant identifies keywords based on the chat with the user and searches TikTok using the search criteria created by LLM. (2) The Sorting Assistant uses LLM to assign weights to different keywords and determines their importance. The videos are then randomized and displayed as the next-up videos.

then 8 videos (25%) of the next 32 will include #California. The fixed keyword weight distribution is designed to ensure that ChatGPT correctly interprets the sorting instructions and avoids selecting only a single topic, which could lead to a homogenized video flow (Control Issue II). A single term can occupy a maximum of 16 videos (50% of the total). Among videos tied to the same search item, those with the highest like counts are displayed first. Finally, the system shuffles the 32 videos randomly before presenting them to the user.

```
Workflow of the Video Sorting
1. Send keywords and user requests to LLM to obtain
   weights.
2. Assign the weights returned from ChatGPT to the
   searched items.
3. Filter videos using Positive Keywords, Negative
   Keywords, Type, and Duration.
4. Determine the proportion of each search item in
   the next 32 videos according to the weights.
5. Shuffle the 32 videos in random order.
```

5.1.3 Showing the Chatbot When Skipping. In addition to the two-assistant design, we also adjusted when users interact with the chatbot to prevent forcing engagement with TKGPT (*Issue IV*). The first interaction with the chatbot occurs after the 10th video. Rather than displaying the chatbot every 10 videos, the system instead triggers a pop-up notification if the user skips three consecutive videos by watching each for less than five seconds. Clicking on the notification leads to the chatbot (Figure 1-(4)), where users can interact with TKGPT and modify recommendations for the next 32 videos.

5.2 Study Design

Our formal user study has two main objectives: (1) understanding how controling For You page with TKGPT affects users' folk theories and (2) building a model to explain how these effects on folk theories influence users' sense of agency. The study recruited 50 participants online through CloudResearch [27]. The user experiment consisted of a pre-study survey collecting demographic information, a user task where participants interact with TKGPT and watched the next-up videos, and a post-study survey. The pre-study survey

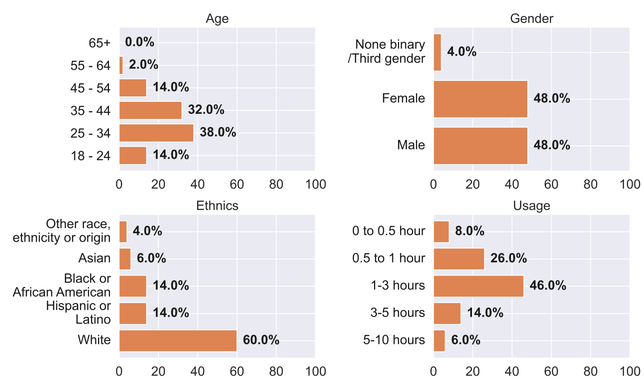


Figure 5: Demographic distribution of the 50 participants in the formal study. From left to right: age, gender, ethnicity, and frequency of using short-form video platforms.

gathered data on participants' age range, gender, ethnic group, and daily hours spent watching short-form videos. Participants were excluded if they indicated that they watch short videos "almost none" everyday or if they were under 18. The distribution of demographic responses is shown in Figure 5.

In the post-study survey, we designed multiple questions based on algorithm folk theory [68] to examine users' control during the two stages of intentional binding [45, 50]: determining *intentional actions* to modify the For You page and perceiving the *outcome* of those actions. Questions related to intentional actions ((I) Question in Figure 7) investigate the voluntary, in-the-moment use of TKGPT initiated by users, through which they experience *a feeling of agency* [64]. These questions explore actions such as reducing confinement, improving relevancy, avoiding reduction, enhancing transparency, or preventing exploitation. Outcome-related questions ((O) Question in Figure 8) assess whether TKGPT's responses and the modified For You page influence users' sense of control, reflecting their *judgment of agency* [64]. In addition to folk theory-based measurements, the assessment of outcome agency also includes a rating of users' overall sense of control.

To analyze how users' perceptions of action outcomes impact their sense of agency and whether this agency correlates with overall video engagement, we constructed a PLS-SEM model (Figure 9). PLS-SEM (partial least squares structural equation modeling) is a statistical method used to examine complex relationships between observed and latent variables [26]. This approach is particularly robust for small sample sizes and non-normal data distributions, making it well-suited for identifying interactions between measurements in our study. Specifically, we examine which outcome-related questions are most strongly associated with users' sense of agency and whether an enhanced sense of agency correlates with greater engagement with the system.

All questions followed a 7-point Likert scale, ranging from `Strongly Disagree` to `Strongly Agree`. As in the pilot study, response options ranged from `Strongly Disagree` (-3) to `Strongly Agree` (3), with `Neutral` as 0. In addition to the rating questions, we included open-ended questions inviting participants to comment on what they liked or disliked most about controlling the algorithm. To analyze user comments, two researchers coded all responses using multicategorical annotations based on the dimensions of *anti-confinement*, *relevancy*, *anti-reduction*, *anti-opacity*, and *anti-exploitation*. The researchers first independently assigned dimensions to each comment and then met to discuss and resolve any discrepancies in their annotations.

5.3 Results

Satisfaction, Engagement, Agency, and Distraction. During the study, participants accessed the chat interface an average of 1.3 times (including the initial visit after the 10th video). Ten participants (20%) returned to the chatbot more than once. As presented in Figure 6, participants rated their experience with TKGPT as generally satisfactory, with an average rating of 1.26. Users rated high on the sense of agency ($M = 1.42$). They were slightly positive about their engagement with the videos ($M = 0.66$) and found that the tool was not distracting ($M = -1.3$). For example, one participant noted, *"I liked how it asked me if I wanted to find new recommendations after I got bored of the ones I was watching."* Another participant commented, *"I like that it's available if I need it."*

5.3.1 *Intentional Actions.*

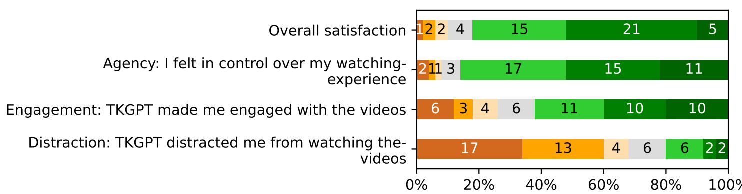
The analysis of users' intentional actions explores what actions they feel empowered to perform when using a chatbot. Participants indicated that they intended to use TKGPT to make the videos more relevant to their interests ($M_{Relevancy1} = 2.1$). However, they remained neutral about using it to avoid videos that were not relevant to their interests ($M_{Relevancy2} = 0.02$). Participants also expressed a desire to inform the algorithm about their interests ($M_{Anti-reduction} = 1.78$) and to use the chatbot to configure and control recommendations ($M_{Anti-opacity} = 1.36$). However, they were neutral about using TKGPT to avoid being tracked or becoming addicted to video watching ($M_{Anti-exploitation} = 0.16$). Additionally, participants did not actively use TKGPT to enhance recommendation diversity ($M_{Anti-confinement1} = -0.18$) and negatively rated the extent to which TKGPT encouraged them to explore videos they do not typically watch ($M_{Anti-confinement2} = -1.46$).

Twenty-eight comments addressed the relevance of videos to participants' intentions. Participants appreciated the chatbot's ability to personalize their video experience based on specific niche interests, such as country music, tattoo ideas, dog training, and other topics. For example, one participant stated, *"I asked it for longer country music videos so I could listen to the music, and I asked it for better tattoo videos so it could show me tattoo ideas. It adjusted the algorithm for me very well."* The chatbot was generally considered accurate in understanding requests and tailoring video recommendations to participants' preferences. One participant noted, *"What I liked most about the chatbot was that it was fairly accurate in following my requests. It seemed to have an accuracy of 90%."* However, some participants felt their agency was undermined when the chatbot's recommendations did not align with their requests. For example, one participant stated, *"I requested dog training tips. Some of the videos were a bit off-topic; they had dogs in them but were more general videos of dogs in training rather than specific tips or techniques."* Additionally, some participants perceived "relevancy" not only by topic but also by attributes such as emotional tone. For instance, one participant remarked, *"There were times when the chatbot's recommendations didn't fit the criteria of what I wanted to see and not see. I wanted more relaxing and chill videos but ended up getting videos that were loud and less chill."*

Ten participants' discussions related to anti-reduction. They noted that TKGPT allowed them to refine their preferences. For example, one participant commented, *"I liked that it allowed me to narrow down exactly what I wanted to see on my feed."* Another participant described chatting with TKGPT as a process *"helping me be more specific about what I want to watch."* However, participants also expressed concerns about how TKGPT hindered their intended actions and sense of agency. Some mentioned difficulties in articulating their preferences or effectively communicating their expectations to the chatbot. One participant commented, *"I felt like it was hard to communicate what I want."* When the chatbot failed to understand their expectations, another participant noted, *"It would take several tries [talking to TKGPT] to get exactly the content that I was expecting."*

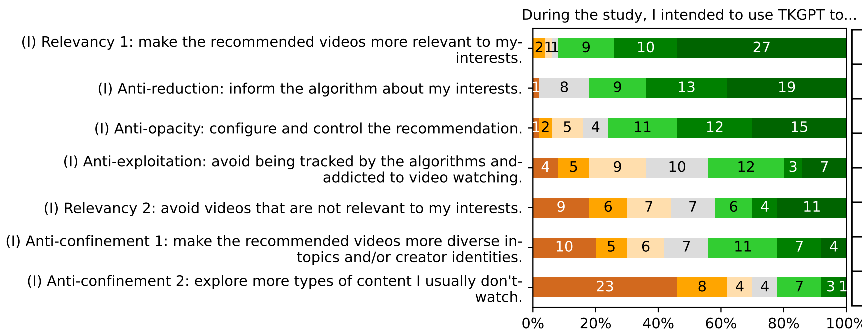
Twenty-four participants in the TKGPT group commented on the anti-opacity provided by TKGPT, noting that the tool enabled control through natural and friendly conversations. They particularly appreciated how the natural language interaction made them feel heard and allowed them to customize content according to their preferences. For example, one participant stated, *"I like the idea of being able to customize my experience using natural language, as it allows me to continually adjust the content to my demand."* Another participant noted, *"I liked that the chatbot seemed like it listened to me. It took my recommendations and engaged in a back-and-forth conversation to refine exactly what I wanted."* Participants especially valued the chatbot's friendliness and human-like interaction. As one participant expressed, *"It made the interaction feel more natural, as opposed to having a robotic communication style."* Another participant commented, *"I like how the chatbot wasn't too intrusive. Another aspect I appreciate is its ease of use, and the chatbot's way of speaking felt comforting and welcoming."*

Only two participants explicitly addressed whether the algorithms made them feel less exploited. One participant noted that interacting with the chatbot was preferable to mindless scrolling, stating, *"so that you don't sit there for hours without realizing it, as when you see the chatbot, you have to concentrate more."* Another



Measurements	M	SD
Overall satisfaction	1.26	1.31
Agency	1.42	1.42
Engagement	0.66	1.97
Distraction	-1.3	1.79

Figure 6: Distribution of ratings for the satisfaction, engagement, and distraction questions.



Measurements	M	SD
(I) Relevancy 1	2.1	1.28
(I) Anti-reduction	1.78	1.3
(I) Anti-opacity	1.36	1.59
(I) Anti-exploitation	0.16	1.75
(I) Relevancy 2	0.02	2.18
(I) Anti-confinement 1	-0.18	1.97
(I) Anti-confinement 2	-1.46	1.83

Figure 7: Distribution of ratings for intentional actions with TKGPT. Sorted in descending order of the measurement means.

participant appreciated that the chatbot tracked the conversation, suggesting a sense of continuity in the interaction.

Three participants provided feedback on the video diversity. Two appreciated being introduced to new content, while one felt that the videos were contrived and lacked diversity.

In sum, the primary intentional actions users took with TKGPT included making video recommendations more relevant, informing the algorithm about their interests, and configuring the next-up videos. Participants primarily used the TKGPT chatbot to refine video recommendations to better align with their preferences. Through natural conversations, users intended to configure and controll the For You page, thereby reducing the algorithm's opacity. However, their interests were not always accurately represented by the LLM-suggested keywords. For example, participants might have sought videos that addressed specific questions, conveyed a particular tone, or featured certain background music styles, which are preferences that keywords alone could not fully capture. Some participants attempted to explicitly communicate and clarify their preferences to prevent the algorithm from oversimplifying their interests, while others struggled to articulate their needs effectively. Notably, participants did not actively use TKGPT to increase content diversity or to reduce algorithmic tracking.

5.3.2 Sense of Control with AI Outcomes. The analysis of the outcomes of using TKGPT examines how TKGPT affect the *judgment of agency*. We assess whether participants obtain a sense of agency across the five constructs in folk theory. Our results indicate that participants felt TKGPT enhanced their sense of agency in anti-reduction, anti-opacity, relevancy, and anti-exploitation. TKGPT helped participants develop a more comprehensive understanding of their video interests ($M_{Anti-reduction} = 1.3$). They also felt that TKGPT provided better understanding into how recommendations were made ($M_{Anti-opacity} = 1.24$). While participants actively used TKGPT to improve video relevancy, they also rated the resulting For You page as more aligned with their interests ($M_{Relevancy} = 1.24$). Although participants did not explicitly use TKGPT to avoid tracking or addiction, they still reported feeling less exploited by the platform after interacting with TKGPT. The only construct that received a neutral rating was anti-confinement ($M_{Anti-confinement} = 0.36$), indicating that TKGPT-identified videos did not strongly contribute to a sense of obtaining diverse content.

We use the PLS-SEM method to examine how the feeling of agency in each folk theory construct impacts agency and whether the sense of agency influences participants' overall engagement with the videos. First, we assess whether participants' sense of agency ratings (*"I felt in control over my watching experience"*) are associated with their ratings of the *outcome* questions (O Questions in Figure 8). The model further examines whether users' sense of agency affects their overall engagement with TKGPT (*"TKGPT made me engaged with the videos"*). In the measurement model evaluation, all Variance Inflation Factor (VIF) values are 1, indicating no collinearity among participants' responses to the five folk theory constructs. In the structural model evaluation, all VIF values are below 5 (Table 4), confirming no multicollinearity. The model fit index, SRMR = 0.043, is below the acceptable threshold of 0.08, indicating a good model fit.

The results suggest that only the anti-opacity rating (i.e., *"TKGPT allowed me to gain a better understanding of how recommendations are made"*) is a significant indicator of participants' sense of agency ($\beta = 0.615$, $t = 4.688$, $p < 0.001$). This finding indicates that making users aware of the recommendation process significantly enhances their perceived post-hoc judgement of agency when interacting

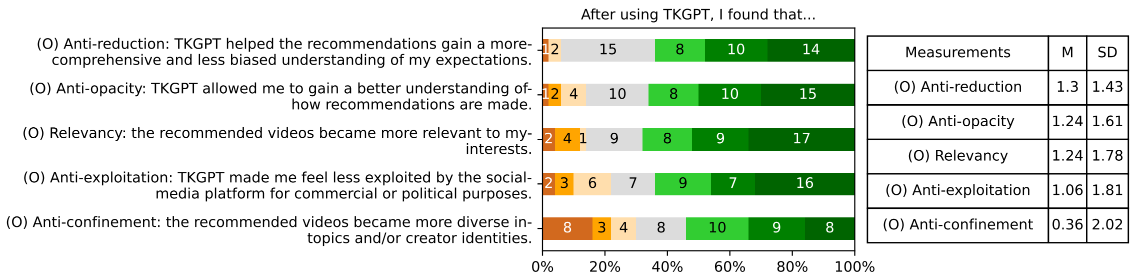


Figure 8: Distribution of ratings for the outcome questions. Sorted in descending order of the measurement means.

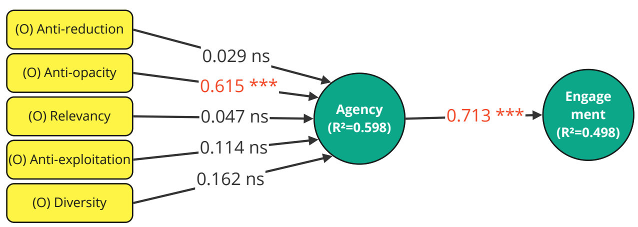


Figure 9: The PLS-SEM model examines the associations between outcome question ratings and the ratings of sense of agency and engagement. “ns” denotes no significant association. * indicates a statistically significant relationship at p<0.001.**

Path	VIF	Coef. (β)	t-value	p-value	f^2
Anti-reduction→Agency	2.494	0.029	0.207	0.836	0.001
Anti-opacity→Agency	2.282	0.615	4.688	<0.001	0.459
Relevancy→Agency	1.949	0.047	0.306	0.760	0.003
Anti-exploitation→Agency	1.421	0.114	0.963	0.335	0.025
Anti-confinement→Agency	1.185	0.162	0.117	1.566	0.061
Agency→Engagement	1	0.713	9.858	<0.001	1.032

Table 4: VIF (inner model), coefficient, t-value, p-value, and f^2 values of all paths.

with the chatbot. Furthermore, participants’ agency ratings are a significant predictor of their level of engagement ($\beta = 0.713$, $t = 9.858$, $p < 0.001$), suggesting that a stronger sense of agency positively influences user engagement with the chatbot.

In sum, participants found that they could use TKGPT to express their expectations for the For You page, and TKGPT’s responses, in turn, provided them with a better understanding of how recommendations are made. As a result, the videos became more relevant to participants’ interests, and they felt less exploited by the platform’s algorithms. Regarding which folk theory construct influences users’ judgment of agency, our model suggests that anti-opacity – helping users understand how recommendations are made – is a significant factor associated with their sense of agency. Our model also suggests that an user engagement with TKGPT is positively associated with the sense of agency.

6 Discussion

6.1 Opportunities and Challenges in Intentional Interest Externalization

The design of TKGPT offers an alternative to implicit analysis by enabling users to explicitly express their preferences. Other systems with conversational interfaces for video recommendation primarily focus on algorithmic matching of user interests and ranking criteria [16, 19, 24, 40]. These systems typically present only a single matched result or sort videos in descending order of relevance, which overlooks users’ need for continuous engagement and richer flow experience. On TikTok, users’ watching behaviors traditionally shape For You recommendations without users’ explicit awareness [8], leading to the development of folk theories [68]. Users may carefully manage their video-watching behaviors to avoid unwanted influences on future recommendations [61]. However, when these efforts fail, users may experience a loss of engagement and a diminished sense of agency [35, 61]. The design of TKGPT addresses the need for greater user control [47] by enabling users to externalize their preferences and provide explicit instructions. In our study, users expected the algorithms to develop an accurate understanding of their preferences. We argue that these conversations serve as attempts to guide the algorithms, acting as a corrective mechanism that allows users to rectify the For You recommendation algorithm when their interests and identities are misrepresented [5, 37].

However, critical design challenges arise in the process of interest externalization. Treating video recommendation as merely a task of identifying relevant items [16, 20, 24, 72] oversimplifies the complexity of users’ For You preferences. Our participants showed little interest in trending TikTok videos. Instead, they sought videos that aligned with their small, niche interests, which could be reflected in specific sensorial experiences (e.g., appetizing food visuals or relaxing content) or in achieving particular goals (e.g., learning dog-training techniques). Additionally, some participants found it difficult to articulate their interests clearly to the chatbot. This aligns with recent HCI research suggesting that engagement with social media videos – such as Mukbang [2], ASMR [52], or study-with-me [38] – is often driven more by sensation-seeking than topic relevance. However, as the Algorithm Crystal theory suggests [37], users’ preferences for For You videos are multifaceted and dynamically evolve over time. These preferences may also have to be inferred from the watching behaviors of others with similar interests. In real-world deployments of mechanisms like TKGPT, although the underlying LLM can understand general topics, significant design challenges remain in configuring it to interpret nuanced, complex user preferences such as sensations or emotions.

Our research suggests future directions for designing intentional interest externalization in the For You experience. From an intentional control perspective, future research must model diverse externalization mechanisms. A key real-world challenge is accurately identifying users' contextualized and dynamically evolving video preferences. For example, integrating cultural and community knowledge into LLMs could enable more precise interpretations. It is also crucial to distinguish between setting permanent preferences and expressing temporary, topic-specific interests. From a control outcome perspective, chatbots can enhance transparency in recommendation systems that rely on collaborative filtering [46, 73]. By enabling interest externalization and recommendation-modification loops, chatbots strengthen users' sense of control. To support this, user interests must be characterized beyond broad topics to include tone, emotion, sensory appeal, and learning value, ensuring a more accurate reflection of users' in-situ preferences.

6.2 Explanatory Recommendation to Enhance Sense of Agency

Various prior studies have emphasized the importance of transparency in algorithmic systems [59]. The anti-opacity use of TKGPT influences users' sense of agency in two key ways: first, by enhancing their understanding of how the algorithm functions through the display of keywords, and second, by providing them with control over the outcome by co-defining the keywords.

Regarding the first aspect, extensive research has highlighted the significance of algorithmic transparency [59], with one effective approach being the provision of explanations to users [55]. On TikTok, users also seek to understand the mechanisms behind the For You page [31]. TKGPT addresses this need by displaying LLM-identified keywords and prompting users to confirm their relevance, thereby reducing the perceived opacity of the algorithm. Furthermore, our result suggests that anti-opacity is the only factor positively associated with participants' judgment of agency. A higher sense of agency is further associated with greater engagement with the videos. This finding indicates that enhancing users' understanding of how recommendations are generated can meaningfully improve both their sense of agency and their engagement.

The second aspect concerns how the system offers users approaches to control recommendations. In TikTok's folk theory, users often feel powerless in exerting control over the algorithm [1, 67]. Their self-constructed explanations of how the system operates lead them to develop informal mechanisms to influence algorithmic outputs [1, 67]. In our study, participants actively used TKGPT to ensure that their requests were reflected in subsequent recommendations. They also appreciated that their preferences were acknowledged by the chatbot. The human-like, natural language-based interaction with TKGPT reduced the perceived opacity of the algorithm and enhanced users' sense of control.

The benefits of explanatory recommendations open new design possibilities for integrating LLM-based chatbots. Despite our seminal design improving users' understanding of the recommendation, the keyword-based explanation mechanism is, frankly, a highly simplified form. The actual workings of the For You algorithms are far more complex, involving larger video datasets and coordination with other features such as subscriptions and video search [8]. Therefore, we urge designers to explore diverse modalities of chatbot explanations and address both scalability and the integration of varied user interaction data. For instance, the concept of Explainable AI (XAI) [18, 41, 43] can inform the design of For You chatbots. HCI researchers should consider whether chatbots ought to explain the underlying model, its features, or the rationale behind specific recommendations [43]. Incorporating users' watch history can potentially enhance explanation effectiveness [24, 30, 72], as it informs recommendations and enables LLMs to support user reflection on their For You interactions.

6.3 The Contradiction Between Control and Confinement

Folk theories suggest that users perceive video recommendations as lacking in diversity and narrowing their perspectives [68]. However, we observed that seeking out new topics was not a primary motivation for using TKGPT. Rather, users primarily engaged with the chatbot to steer the For You page back toward their habitual viewing preferences. In the pilot study, participants did not consistently watch the videos they had explicitly requested. These usage patterns indicate that TKGPT's value lies more in enabling recommendation algorithms to develop a comprehensive understanding of users' diverse interests (anti-reduction) than in expanding exposure to entirely new topics (anti-confinement). This interpretation aligns with prior findings that For You algorithms must account for users' multifaceted and dynamic preferences [37].

These observations highlight a critical contradiction between the level of user control and the confinement imposed by the algorithm. Providing users with greater control over recommendations could, paradoxically, lead to a more restricted range of topics on the For You page. When users encounter videos that do not align with their explicit preferences, they may perceive this mismatch as a failure of the chatbot. This issue calls for careful consideration when integrating designs like TKGPT into real-world applications. Designers must be particularly mindful of how control mechanisms can enhance personalization while reinforcing filter bubbles and echo chambers [10, 23]. To mitigate such issues, new LLM conversation styles should be developed to support access to, and reflection on, information diversity [71]. Additionally, techniques such as swapping recommendations with other users have shown promise [6]; future design could incorporate such strategies into LLM-powered chatbots to help users broaden their viewing horizons [28].

6.4 Balancing the Sense of Agency and Interruption in the Flow Experience

While users generally prefer having some control over recommendations [58], this does not imply that they always desire full control over the recommendation process. Our study found that one outcome of this preference is that forcing users to interact with a chatbot can significantly disrupt their flow experience [12, 56]. In our system improvement, making the chatbot appear only when users skipped videos was well received, as it reduced distractions. Additionally, TKGPT requires multiple interaction turns for users to customize recommendations. Therefore, it is important to acknowledge that this process may be constrained by users' limited willingness and capacity to engage in extended conversations. Prior research has emphasized the importance of carefully considering *what*, *why*, *how*, and *where* AI decisions are explained [41, 42, 65]. Our results indicate that, in the context of controlling the For You page, it is equally crucial to consider *when* to offer control. The chatbot should be interacted at moments when users are dissatisfied with the current content, rather than at times that might disrupt their flow experience. Moreover, when considering the adoption of similar LLM-based chatbots on other algorithmic platforms, such as Twitter/X or Reddit, the user engagement model may differ significantly. This warrants careful examination of how the chatbot can be integrated into diverse content modalities.

Another design opportunity is to introduce the chatbot when users seek more intentional viewing experiences and wish to disengage from addictive watching. TikTok's algorithms are often perceived as exploitative, encouraging continuous video consumption [9, 58]. For example, users frequently assume that liking a video will result in similar content [53]. When such folk theory arises, inviting users to tailor their upcoming video recommendations may help mitigate their sense of being manipulated. In our study, although users did not initially intend to use TKGPT for anti-exploitation purposes, outcome analysis revealed that TKGPT alleviated the concerns about algorithmic exploitation. This suggests that a chatbot could serve as a potential solution to help users break free from passive, compulsive viewing behaviors.

7 Conclusion and Future Work

Through a two-stage study of TKGPT, this research piloted an LLM-enhanced chatbot capable of suggesting video topics based on conversations with users, identifying videos related to user requests, and managing and diversifying content within TikTok's flow experience. Our study explored the role of LLM chatbots in controlling video sequence recommendations and identified key design implications related to users' folk theories and sense of agency. This research contributes to an initial understanding of how LLMs and chatbots should be tailored and contextualized for the "For You" experience. Key considerations include designing for intentional interest externalization through LLMs, enhancing users' sense of agency through explanatory recommendations, avoiding confinement when increasing user control, and balancing agency support with minimizing interruptions to the flow experience.

Our future work will focus on three main directions. First, TKGPT currently relies on simplified video descriptions using user-provided hashtags and video durations, but videos contain multimodal data such as audio, subtitles, and emotional cues. Effectively interpreting and matching these elements with user control criteria remains a challenge. Second, additional LLM functionalities will be developed to expand the use cases of TKGPT in supporting the sense of agency. For example, exploring different prompt designs to guide LLMs in asking appropriate questions about users' needs for the flow experience is a promising direction. Integrating these controls with LLMs could potentially address biases and misconceptions users hold about recommendation algorithms. Finally, we aim to explore how chatbots can support user reflection on viewing history and video preferences. This could help users better understand their content consumption patterns and make more informed choices in shaping their For You page experience.

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A LLM Prompts

A.1 Pilot Study Instruction

Initial instructions are sent to LLM once at the beginning of the study. *Hashtag_data* is the initial five user-selected hashtags:

```
<INITIAL INSTRUCTION>:
"Follow the rating instructions strictly to respond to
   the users, your main rating instructions are {
   RESPONSE_INTSTRUCTIONS}. Please remember these are
   your main rating instructions. You will be expected
   the user interaction in couple of minutes."

RESPONSE_INTSTRUCTIONS:
"Responsibilities": "As the TKGPT's hashtag
   recommendation system, it is your job to provide
   ratings to the hashtags based on the user requests in
    accordance with criterions. Perform hashtag ratings
   by following the 'Criterion'.",
"Criterion": "Positive user requests indicate that the
   viewer like the information and would want to see
   more of a particular topics or hashtags. Negative
   user requests indicate that the person dislikes
   particular topics or hashtags. Keep track of every
   request made by the user and aggregate them all
   before rating. When rating to the hashtags, you
   should add '+1' to the hashtag for the positive user
   requests, add '-1' to the hashtags for the negative
   user requests. Let's say if user wants more content
   on sports, if we have football basketball hashtags we
    need to add 1 to football and 1 to basket ball,
   suppose if the basketball already have 1 rating then
   after applying this rating basketball rating should
   be 2. After finishing applying rating to the hashtag
   provide the top 50 related hashtags with rating
   accordance to the 'Final_Response' by applying '
   Response_Format'.",
"Limitations": "Write no more than 20 words in one
   phrase to convey your 'message' in response. Keep
   your conversation limited to your responsibilities.
   Don't talk anything else except your responsibilities
   . Only respond to user request and rate the hashtags,
    doesn't required to provide what you did.",
"Final_Response": "Your response should be in json
   format of top 5 hashtags with keys as 'hashtag_name'
   and 'rating', example response: [{'hashtag_name':'
   football', 'rating':1}, {'hashtag_name': 'basket_ball
   ', 'rating':2}]",
"Response_Format": "Mark the beginning and ending of
   the JSON string with '---start---' and '---end---'.
   In the first sentence, in less than 20 words, no more
    than a sentence. Strictly follow the format
   structures. Whatever your messages keep at before
   '---start---'",
"Resources": "Your knowledge and resources are strictly
    bound to the following hashtags : {hashtag_data}.
   Don't recommend other than above hashtags."
```

Video sorting instructions for LLM at the end of each chat:

```
<INSTRUCTION SENT TO CHATGPT AFTER EACH USER INTPUT>
"Follow the main rating instructions strictly to
   respond to the users. Follow the rating instrcutions
   and limitations strictly. Utilize the response
   instructions {RESPONSE_INTSTRUCTIONS} in providing
   your response for the user inputs. User_Inputs: {
   user_inputs}."
```

A.2 Study 2 Recommender Assistant Instruction

```
<INITIAL INSTRUCTION FOR RECOMMENDER ASSISTANT>
As TKGPT's video recommendation chatbot, by engaging
   with users, find out their desired content to find
   out the videos in our system using most relevant
   keywords. Follow the guidelines strictly when
   responding to the user:
**Job 1:** 1. Identify only relevant keywords from user
    requests and create search criteria with those
   keywords. 2. Inform users what keywords are you
   genereated from their request and get confirmation to
    procced further with some delay.
**Job 2:** 1. Generate a search criteria summary based
   on user requests. 2. Search criteria should contain '
   type': {'very_short', 'short', 'normal', 'long'},
   where 'very_short' should be of length below 20
   seconds, 'short' type of length below 60 seconds, '
   normal' type of length below 180 and above 180
   seconds are of type 'long' and by default length and
   type is 'normal'. 'duration' should be associated
   with the type. 'positive_keywords' are the keywords
   content that user might wanted to watch. '
   negative_keywords' are the keywords content that are
   less likely user want to watch or doesn't want to
   watch. 'final_keywords' are the keywords that extends
    all the user positive keywords through out the
   interaction based on user requests. 3. Aggregate
   requests into `type`, `duration`, `positive_keywords
   `, `negative_keywords`, `final_keywords`. 4. Extend
   all the keywords based on the user requests, for
   example initally user will say i want vegitable
   cutting, after some time user will say i dont want
   vegitable, so the positive_keywords should not
   include any vegitables. 5. Based on user requests
   combine all the keywords and predict the user desired
    keywords.
**Limitations:** 1. Inform users that it may be delayed
    if the keywords are too long. 2. Do not provide
   actual video data, only provide keywords that might
   be related to the user request and driectly matching
   the keywords. 3. For every user interaction maintain
   only one response. 4. Write no more than 30 words in
   the response format to convey your 'message'. Keep
   your conversation limited to your responsibilities.
   Don't be obliged to share what you did; just reply to
    the user's request like replying to a friend with
   the format below. 6. Make an interactive conversation
    with user to know what the user is looking for.
**Formatting:** 1. Begin responses with a message to
   the user (in less than 30 words). 2. Use this
   structure for the message in a single assistant reply
   : `{Appreciate their choice} {Inform what you found
   and share keywords} {Ask them what else they need? or
    ask more in details about what they are looking.} {
   Get confirmation to proceed}, aggreate all responses
   at once.
**Example:** <Two examples of user inputs and desired
   outputs>
**Restrictions:** 1. Do not disclose internal processes
    and video information. 2. Maintain a friendly tone
   and focus on the content of keywords. 3. Do not share
    video data, only keywords. 4. Follow message
   formatting so strictly and do not skip the message or
    '<data_start>' and '<data_end>' and search criterias
   . 5. Refer to the example formats for verification.
```

```
<INSTRUCTION SENT TO CHATGPT AFTER EACH USER INTPUT>
Please follow the instructions, formatting and provide
   the response to the user request below, be
   interactive with user. User request : {message}.
```

A.3 Study 2 Sorting Assistant Instruction

```
<INITIAL INSTRUCTION FOR SORTING ASSISTANT>
As the TKGPT's video recommendation system, it is your
   job to provide ratings to the keywords based on the
   user conversation with chat bot.
Follow the instructions below. 1. Rate the keywords
   with the percentage priority, the top prioritized
   keywords (or) the latest/recent requested content (by
    message time) should be with 50% (100%/2^1) and the
   second priority keywords should be of 25% (100%/2^2)
   and the third priority content should be of
   13%(100%/2^3) and the fourth priorty content should
   be focused with 7% (100%/2^4) and so on, have a
   reference of the examples provided. Adjust the
   prioritises of the content according to the user
   conversations 2. If user does not want to watch or
   does not like an certain content then make the
   percentage of those content to 0%. 3. If user ask to
   reduce or minimizing the certain content then reduce
   the content priority according to user conversation.
   4. Make sure the sum of the ratings be 100%. Response
    format of rating of keywords for the provided user
   conversation and keywords should be enclosed between
   '---start---' and '---end---' with the following
   objects in a JSON formatted string.
Example: <Two examples of user inputs and desired
   outputs>
```

```
<INSTRUCTION SENT TO CHATGPT AFTER EACH CHAT SESSION>
Follow the instruction and criteria to rate the
   keywords={keywords} based on the user conversation {
   user_conversation} and make the priority list.
```