석 사 학 위 논 문
Master's Thesis

소셜 미디어 사용자들이 "관심 없음"을 누르는 이유: 동기, 기대 효과, 그리고 결과 해석

Why Social Media Users Press "Not Interested": Motivations, Anticipated Effects, and Result Interpretation

2025

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The study was conducted in accordance with Code of Research Ethics[1].

[1] Declaration of Ethical Conduct in Research: I, as a graduate student of Korea Advanced Institute of Science and Technology, hereby declare that I have not committed any act that may damage the credibility of my research. This includes, but is not limited to, falsification, thesis written by someone else, distortion of research findings, and plagiarism. I confirm that my thesis contains honest conclusions based on my own careful research under the guidance of my advisor.

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초 록

소셜 미디어 사용자는 개인화된 피드에서 원치 않는 콘텐츠를 피하기 위해 다양한 방법을 사용한다. 특히 인스타그램이나 유투브와 같은 플랫폼은 특정 콘텐츠나 유사한 유형의 콘텐츠를 덜 보고 싶다는 선호를 표시할 수 있도록 돕는 “관심 없음” 기능을 제공한다. 이 버튼의 사용 방식을 이해하는 것은 사용자가 추천 콘텐츠와 개인화 추천 알고리즘을 어떻게 평가하는지, 그리고 콘텐츠 회피를 지원하는 기능이 어떻게 설계되어야 하는지를 파악하는 데 중요하다. 본 연구는 사용자가 1) 이 기능을 사용할 때 콘텐츠를 평가하는 방식, 2) “관심 없음” 기능을 다른 리액션 기능과의 관계 속에서 정의하는 방식, 3) 이 기능의 작동 원리를 해석하는 방식을 탐구한다. 우리는 지난 1년 동안 인스타그램의 “관심 없음” 기능을 12회 이상 사용한 경험이 있는 28명의 사용자를 대상으로 인터뷰를 진행하였다. 사용자들은 문제성 있는 콘텐츠를 회피하거나 추천 알고리즘을 미세 조정하기 위해, 도덕적 판단, 평판, 감정과 같은 개인적 가치를 고려하여 “관심 없음” 기능을 사용했다. 사용자들은 일반적으로 “관심 없음” 피드백이 다른 사용자를 해치지 않고 자신의 피드에만 영향을 미치는 점을 특징으로 여겼고, 이 점을 활용하고자 했다. 그러나 때로는 더 큰 영향력을 행사하고자 하는 의도에 적합한 리액션 기능이 없을 때, 대안으로 “관심 없음”을 사용하기도 했다. 사용자들은 때때로 “관심 없음” 피드백을 제출하고 피드의 변화를 관찰한 후, 각 피드백이 알고리즘에 어떻게 반영되었는지에 대해 확신하지 못했다. 우리는 소셜 미디어 플랫폼이 고려해야 할 사용자 특성으로, 콘텐츠 기피와 관련된 다양한 사용자 동기, 다양한 범위의 콘텐츠 큐레이션에 영향을 미치려는 요구, 그리고 개인화 알고리즘의 세밀한 통제와 깊은 이해에 대한 요구를 논의한다.

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Abstract

Social media users employ a variety of methods to avoid unwanted content in personalized feeds. Platforms like Instagram and YouTube offer the “Not Interested” feature, allowing users to signal their preference to see less of certain content or similar types. Understanding the usage of this button is crucial for understanding how people evaluate the suggested content and personalized recommendation algorithm and how the feature for content avoidance should be designed. This study explores users’ 1) evaluation of content when utilizing the “Not Interested” feature, 2) definition of “Not Interested” feature in relation to other reactions, and 3) perceptions of how this interaction works. We conducted semi-structured interviews with 28 Instagram users who had used the “Not Interested” button more than 12 times over the past year, focusing on their experiences with this feature. Users used the “Not Interested” feature to avoid problematic content or to fine-tune the recommendation algorithm, in consideration of different personal values such as moral judgment, reputation, and emotion. Users generally hoped that their “Not Interested” feedback is unique in that it would only affect their own feeds without harming other users. However, they sometimes utilized it as an alternative when other features did not support their desire for a broader impact. After submitting the feedback and observing the changes in the personalized feed, they were often uncertain of how each of their interactions was reflected in the algorithm. We discuss user characteristics that social media platforms need to consider, including diverse motivations related to content avoidance, users' demands to influence a broad range of content curation, and the need for granular control and deeper understanding of personalized algorithms.

Keywords social media, interactive recommender, personalized recommendation, user feedback

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Chapter 1. Introduction

Modern social media platforms use personalized algorithms to curate content from an overwhelming amount of user-generated material, tailoring recommendations to individual preferences [Zhang et al.(2024), Chen(2023)]. Through this personalized content, users can easily access topics that align with their diverse interests and connect with others who share similar values [Lee et al.(2022)]. However, this personalized recommendation can sometimes lead to unintended consequences, such as trapping users in a filter bubble where they are overly exposed to content aligned with their interests and preferences, limiting their exposure to diverse perspectives [Pariser(2011)]. It can also lead to user dissatisfaction when users encounter either too little of the content they want or too much of the content they wish to avoid [Lee and Wei(2021)].

To improve user satisfaction with recommended content, platforms aim to capture signs of dissatisfaction through user feedback and use it to adjust future recommendations. The most natural form of feedback comes from users' implicit actions [Ellison et al.(2020)], such as choosing not to click, not liking certain content, or quickly skipping past it. Recently, platforms have introduced more explicit feedback channels, such as "Not Interested" or "See Less Like This," allowing users to directly signal their disinterest and shape future recommendations [1]. In this study, we refer to a set of features that allow people to label content they do not wish to see as the "Not Interested" feature. Such explicit feedback mechanisms give users greater agency and control over their personalized feeds [Eslami et al.(2016)]. Moreover, such features offer a lightweight interaction for users to provide negative feedback to the recommended content. However, despite its popularity, there is limited research on how social media users use the "Not interested" feature.

In this paper, we explore how social media users engage with the "Not interested" feature. Specifically, we aim to gain a deeper understanding of its usage by addressing three research questions.

- RQ1. Why do users select "Not Interested" on certain content recommendations?
- RQ2. How do social media users conceptualize "Not Interested" compared to other reactions?
- RQ3. How do users interpret the result of the "Not Interested" feature?

In RQ1, we explore the cases and motivations behind users' use of the "Not Interested" feature. Previous studies have highlighted that users seek to avoid content in personalized feeds on social media for various reasons such as escaping filter bubbles [Plettenberg et al.(2020)], protecting their mental well-being [Milton et al.(2023)], or avoiding content they perceive as morally wrong [Stephenson et al.(2024)]. Some have found that users have various emotions, opinions, and rationales, even when using a single interaction feature [Tanaka et al.(2014), Sumner et al.(2018), Meier et al.(2014)]. Expanding on these findings, our study aims to identify what types of content users choose to mark as "Not interested" and why they do so.

In RQ2, we expand our understanding of how users use the "Not interested" feature by investigating users' conceptualization of "Not interested" compared to other reaction features. When presented with a variety of interaction tools, users tend to select the option they find most suitable for a given context. Previous studies have demonstrated that people use different social media reactions such as Share and

[1] Screenshots of "Not interested" interactions can be found in Appendix A.

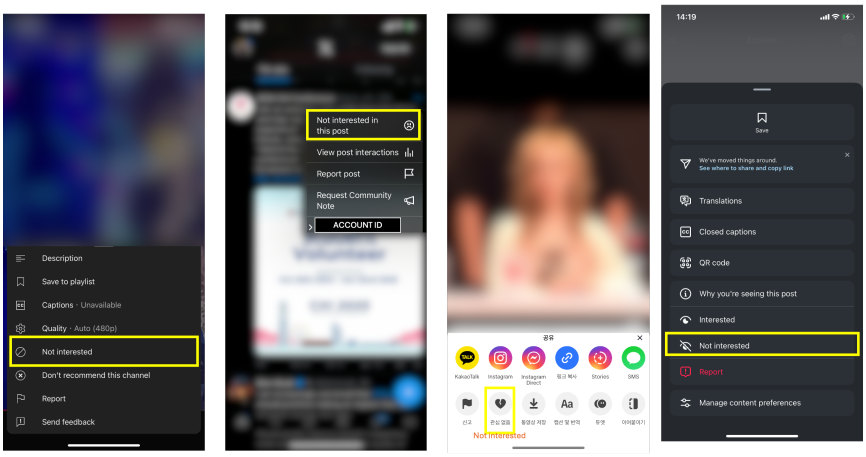

Figure 1.1: The "Not interested" feedback on social media platforms: YouTube, X, TikTok, and Instagram

Like for different purposes [Kim and Yang(2017)]. In the case of encountering undesirable content, users may employ different reactions for the same reason or combine options like Report, Blocking, or "Not interested" [Zhang et al.(2023)]. Existing research suggests that "Not interested" is often applied to personally discomforting content, whereas Report is typically used to safeguard the broader community [Park et al.(2024)]. However, there has been little exploration into how "Not interested" and other negative reactions differ in terms of the outcomes users expect to achieve. Thus, RQ2 aims to investigate why users choose "Not interested" over other negative reactions when dealing with undesirable content, with a particular focus on their expectations for its impact.

In RQ3, we explore users' interpretations and assumptions about how content avoidance functions through the "Not interested" feature. Previous studies have reported user frustration and a sense of diminished control when unwanted content continues to appear despite using these feedback tools [Landesman et al.(2024), Milton et al.(2023), Harris et al.(2023)]. Personalized algorithms are highly complex, involving various elements such as feature extraction, ranking, flagging, and other user preference signals. Moreover, platforms that hold the authority to determine how algorithms operate intentionally and strategically conceal or disclose information about these algorithms, creating a power dynamic [Pasquale(2015), Cotter(2023)]. As a result, it is challenging for the average user to understand which factors influence their feed and how they do so [Smith et al.(2022)]. Instead, social media users develop their own folk theories about how the systems work and adjust their behavior accordingly, such as intentionally modulating their tracked actions on the platform to signal their preferences [Ellison et al.(2020)]. Understanding users' interpretations of how content avoidance functions through the "Not Interested" is crucial for designing interactions and algorithms that minimize user frustration stemming from misunderstandings or uncertainty about how the system works.

To explore these questions, we conducted semi-structured interviews with 28 participants who had clicked "Not interested" on Instagram more than 12 times in the past 12 months, averaging at least once per month. Participants shared their experiences with the feature, including the reasons behind their choices and the changes they hoped for. We also compared their use of the "Not Interested" feature with other negative reactions, such as Dislike and Report, to clarify how it fits within the broader landscape of content-sanctioning methods. Participants also shared their experiences of observing changes in their personalized feed after using the "Not interested" button, reflecting on whether the outcomes were

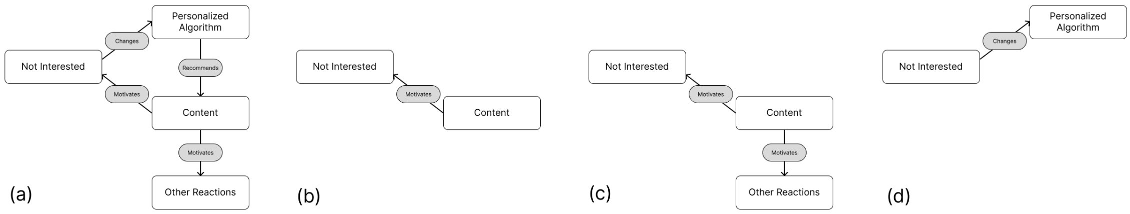

Figure 1.2: Construction of Research Questions for understanding how people use "Not interested" feature. (a) depicts the basic mechanism around "Not interested". (b) depicts the content that leads to "Not interested" choice. In RQ1, we aim to identify why users select "Not interested" on certain recommended content. (c) depicts "Not interested" and other reactions available for the content. In RQ2, we aim to identify how users define "Not interested" in relation to other possible reactions. (d) depicts the changes that "Not interested" makes on the personalized algorithm. In RQ3, we aim to identify how users understand the result of the "Not interested" feature on the algorithm.

satisfactory and offering their own analyses of the reasons behind these results.

The interviews revealed that social media users employed the "Not Interested" feature to avoid content that violated personal values to varying degrees, such as subjective assessments of problematic content, concerns about reputation, and alignment with their own opinions and emotions. Participants also recognized that certain content and values might be particularly negative or sensitive to them individually. While they appreciated the "Not Interested" feature's ability to modify their algorithmic feed without affecting the content's visibility to others, some wished they could influence content availability for other users without resorting to other moderation tools. Participants were often uncertain about how—or if—their feedback was reflected in the algorithm, leading to speculation about how the feedback system impacted their feeds.

Based on the interview results, we discuss how social media platforms should acknowledge the diverse motivations behind the use of the "Not interested" button. Additionally, we explore how this feature enables users to curate their feeds independently—without impacting others on the platform or choosing to remain passive—and highlight the importance of enhancing the transparency and controllability of content avoidance mechanisms.

Chapter 2. Research Background

Our investigation of social media users' experience of removing content from personalized feeds builds on two bodies of previous studies. First, we discuss how the content avoidance behaviors of social media users are accomplished with different affordances. Second, we discuss how social media users understand the personalized feed and interact with them.

2.1 Content Avoidance in Social Media

Avoiding content that viewers do not want to see has been a key phenomenon in media consumption even before the days of social media, manifesting in behaviors like changing the television broadcast channel [Fahr and Böcking(2009)] or moving away from the screen [Newhagen(1998)]. Media selection is typically influenced by the content itself rather than the initial motivation of utilizing media, which makes users avoid content that provokes negative sentiments such as feeling inauthentic, bored, and disgusted [Fahr and Böcking(2009)].

Avoiding social media content can result from different reasons even for the same type of content. Political news and opinions, for example, could be avoided due to accumulated experience on the platform (e.g., repetitive and excessive exposure to news) [Villi et al.(2022), Park(2019)], or pre-existing perception of the content type (e.g., whether they think news is biased) [Toff and Kalogeropoulos(2020), Aharoni et al.(2021)]. Characteristics of individual posts such as being out-party or from different opinions [Mukerjee and Yang(2021), Zhu et al.(2017)] may also result in avoidance of the particular post.

While social media users can simply ignore the unwanted content by scrolling down [Mcdonald et al.(2024), Chen(2023)], or signal their preference by intentionally liking some posts or not clicking certain posts [Karizat et al.(2021), Rong et al.(2022)], they can also use various avoidance affordances [Table 2.1].

Affected Audience. Jhaver et al. [Jhaver et al.(2023)] distinguish between personal and public content moderation, depending on whether the moderation impacts only an individual user's feed or the broader platform. Building on this distinction, we further classify content avoidance affordances into *personal* and *public*, defined by the scope of the affected audience. From this view, the "Report" feature, which flags harmful content for platform review [Zhang et al.(2023)], serves as a mechanism for protecting the entire user base by facilitating its removal.

Category of Avoided Content. Certain avoidance affordances predefine the types and scope of content to which they can be applied. For instance, many platforms specify the categories of content considered problematic and subject to reporting, thereby communicating the platform's own judgment of what constitutes inappropriate material and imposing these standards on individual users [Crawford and Gillespie(2016)]. Some personal avoidance affordances also come with predefined categories. For example, Instagram provides tools that allow users to limit exposure to 1) sensitive or 2) political content [1]. Similarly, Gobo [Bhargava et al.(2019)], a tool designed to give users more control over their social media feed, offers preset categories for more granular filtering, such as seriousness, rudeness, and gender.

[1] Checked in the Instagram app in October 2024

Table 2.1: Content Avoidance Affordances in Social Media Platforms and Previous Work

Avoidance Affordance	Affected Audience	Category of Content	Interaction Method	Algorithmic Interpretation
Not interested	Personal	Up to user	Bottom-up	Required
Natural Language Feedback	Personal	Up to user	Top-down	Required
Slider / Toggle	Personal	Pre-defined	Top-down	Required
Block / Hide	Personal	Up to user	Bottom-up	Not required
Word filter	Personal	Up to user	Top-down	Not required
Report	Public	Pre-defined	Bottom-up	Not required

On the other hand, certain avoidance affordances allow users to apply them freely to any type of content they wish, without predefined restrictions on content type or category. For instance, "Not Interested" or "Dislike" buttons are not limited to exclusive categories, allowing users to use them on diverse types of content they do not wish to see or find unpleasant. Although platforms may occasionally ask for a reason (e.g., YouTube asking if "Not interested" is due to boredom, being overly sexual, violent, etc. [2]), these affordances are not restricted to specific reasons for use.

Interaction Method. Social media users' expression of preferences can be classified into two distinct approaches: a *top-down* method, where overarching rules are established to apply broadly across all content, and *bottom-up* approach, where rules are incrementally built through reactions to individual pieces of content. The top-down method encompasses interactions such as word filters, where posts containing user-defined terms are automatically excluded [Choi et al.(2024)]; toggles that block entire categories of content; and natural language feedback [Feng et al.(2024)] mechanisms that allow users to express their preferences in a broader, more comprehensive manner. The top-down method is more straightforward when the unwanted content shares clear, easily describable characteristics. In contrast, the bottom-up method is known to impose a relatively lower cognitive load and is well-suited when users have an intuitive sense of their preferences [Wang et al.(2024)].

Algorithmic Interpretation. Rule-based affordances such as word filters, account-based affordances like "Block", and content-specific affordances like "Report", do not rely on algorithmic interpretation. In contrast, affordances like "Not interested" necessitate algorithmic processing to classify and filter content that aligns with the user's preferences.

Our research focuses specifically on the use of "Not interested" as a content avoidance tool, which allows users to provide negative feedback and refine their algorithmically personalized feeds. While prior studies have examined various aspects of this tool, such as its inaccessibility within the interface [Ibrahim et al.(2024), Liu et al.(2024)], its role as a stopping point for infinite scroll [Ruiz et al.(2024)], its utility for advanced users [Gaur and Liu(2020)], and its effectiveness in either meeting or failing to meet user needs [Wang et al.(2023), Landesman et al.(2024), Milton et al.(2023), Harris et al.(2023)], there has been little research on interpreting the goals and outcomes of those who use the tool. Our study addresses this gap by exploring the diverse purposes for which "Not interested" is employed and investigating users' perceptions of how the tool operates.

2.2 Users Understanding and Interacting with the Personalized Feed

Algorithmically curated, personalized feeds became common across various social media platforms, where algorithms serve as the bridge connecting users to the vast content and users on the platform [Zhang

[2] Checked in the YouTube app in October 2024

et al.(2024)]. These algorithms offer an efficient and enjoyable way to quickly access content that aligns with personal interests [Schellewald(2023)].

Users are often aware that their past interactions influence the content that appears in their feed, leading them to feel that the platform is not a detached, impersonal system but one that provides something specifically tailored for "me" [Siles et al.(2022)]. The feed reflects their multifaceted, diverse interests and adjusts dynamically based on changing factors such as changing location [Lee et al.(2022)]. This dynamic personalization can even prompt users to reflect more deeply on their identity, as they contemplate whether the algorithm knows them better than they know themselves [Alper et al.(2023)].

In some cases, users feel validated or "seen" when the algorithm recommends content from people with similar characteristics or interests. Conversely, when they do not see enough content from similar people, feelings of exclusion or marginalization may arise, and there can be frustration when the algorithm surfaces content from individuals who challenge or invalidate their identity [Simpson and Semaan(2021), Zhao(2023)].

With the massive number of user-generated content distributed via personalized algorithms, studies report a wide range of content users wish to avoid such as violations of public figures' privacy [Kritika and Ringland(2023)], or content that overexposes children [Stephenson et al.(2024)]. Content avoidance in the algorithmic feed poses the new challenge of altering the algorithm and the rules around the feed to prevent the future appearance of potentially unwanted content. The platform-level moderation takes initial measures to regulate unsafe posts, but individual users hold subjective judgments of what constitutes content with low integrity and quality [Garcia-Pueyo et al.(2023)] or invoke low interest [Park et al.(2024)]. To influence the feed, users may attempt to boost the visibility of desired content by engaging directly with it [Simpson and Semaan(2021)].

Our research investigates how social media users employ content avoidance affordances, focusing on how they express disinterest in content recommended by personalized algorithms. In this process, we explore how individuals subjectively assess the appropriateness and relevance of content, as well as how they determine whether "Not interested" is an appropriate or inappropriate affordance for addressing their concerns.

Chapter 3. Method

We conducted semi-structured interviews to understand participants' perceptions and usage of the "Not Interested" feature. In this section, we describe the protocol of the interview, the inclusion/exclusion criteria and recruitment of the participants, and the analysis procedure.

3.1 Interview Procedure

The interviews followed the outline provided below.

- Introduction: We began by explaining the purpose of the study and informed participants that they were not required to disclose or discuss anything they felt uncomfortable sharing with the researchers. This was to prevent any emotional discomfort, especially when revisiting content they had previously classified as problematic (e.g., clicking "Not interested"). We also sought their consent to record the interview.
- Review of "Not Interested" History: Participants reviewed their history of using the "Not Interested" feature, explaining why they chose to click it, how they felt about the content, and how they would categorize the unwanted content represented by each instance. To minimize bias, they were asked to answer only about Instagram posts that were marked as "Not Interested" before the interview recruitment announcement.
- Reflection on the "Not Interested" Feature: We asked about participants' expectations when using the "Not Interested" feature and whether those expectations were met.
- Comparison with Other Negative Reactions: Participants were asked about their experiences using other negative reactions, such as "Block," "Report," customized word filters, and any others they were familiar with. We asked how these options differed from the "Not Interested" feature.

The interviews were conducted either remotely via Zoom or in person in a lab, depending on the participants' preferences. Each interview was conducted in Korean or English, according to the participant's language preference. This study was approved by the Institutional Review Board (IRB) of our institution.

3.2 Participants

It was important for participants to review actual records of their "Not Interested" usage rather than rely solely on memory, as it allowed them to view the specific content they had marked and describe their thoughts and feelings about it in detail. Since Instagram allows users to access their "Not Interested" history, we conducted the study with Instagram users.

For recruitment, we uploaded the recruitment post on several university communities in Korea and the researcher's social media accounts. The recruitment post stated the purpose of the study, the compensation, the expected duration, and the inclusion/exclusion criteria: Participants must have an Instagram account, and must have experience using the "Not interested" feature on Instagram more than twelve times within the year leading up to the day before the recruitment notice was posted. It informed that participants would be asked to share examples of the content they clicked “not interested”, “Block” and “Report” on as well as associated experiences.

We recruited 28 participants. Each participant was compensated with 25,000 KRW (approximately 18 USD). Each session lasted for around 50 minutes to 75 minutes, depending on a participant’s response and how many cases of “Not interested” they have. We intentionally refrained from asking for personal information such as gender, age, or nationality, as disclosing such details could potentially cause discomfort and influence participants’ willingness to share their personal experiences during the interview. We asked the participants for a self-report of their Instagram usage that may be relevant to their usage of the “Not interested” feature, including how long they’ve used the platform, their daily usage, and the number of “Not Interested” clicks over the year. For participants with a high number of reports of using “Not interested” or who have used Instagram for a long time, they were asked to provide rough estimates. Twenty-six out of 28 participants (except P9 and P22) reported using Instagram for over two years. Every participant used more than one social media including Instagram, with YouTube also being used by every participant. On average, participants reported a daily Instagram usage of 1.6 hours.

3.3 Analysis

We analyzed the transcription based on the thematic analysis approach [Braun and Clarke(2012)] to identify recurring themes. We first transcribed the recording using Clova Note[1]. Two authors read through every transcript individually and used atlas.ti[2] to come up with primary codes with a focus on but not limited to: the types of “not interested” use cases, expected results, and their distinction from other negative reactions to resolve the research questions. The authors then gathered together to share the codes they each generated, while merging similar ones and coming up with initial categories. Then, the authors exported the codes to MIRO[3], where they grouped related codes together to identify higher-level themes. The quotes in Korean were translated into English by the authors to report the results in the paper. The authors sometimes used ChatGPT to translate the quotes, and then checked the result for any potential errors.

[1] https://clovanote.naver.com
[2] https://atlasti.com/
[3] https://miro.com

Chapter 4. RQ1. Why do users select "Not Interested" on certain content recommendations?

We present our findings for each research question (RQ) in Sections 4 through 6. In this section, we answer the first research question on the reason behind users' use of the "Not Interested" feature. In the interview, participants shared various instances where they used "Not interested" for a range of motivations. Participants used "Not interested" for content that they found problematic or personally discomforting. In contrast, participants also used "Not interested" for content they did not see as problematic or discomforting but felt was either a waste of time or did not meet their standards for meaningful engagement.

4.1 Avoiding Emotionally Disturbing Content

Participants used "Not interested" to express their negative judgments toward content they found problematic or personally discomforting. However, the reasons and intensity of these negative evaluations varied. Participants used "Not interested" to avoid problematic content or to prevent the discomfort of others seeing such content on their feed. Also, they used "Not interested" to avoid content that, while not inherently problematic, they personally disagreed with or brought up unpleasant memories or feelings.

Avoiding Socially Inappropriate Content

Participants used "Not interested" for the content they found **inappropriate, such as those involving sexuality, violence, or discrimination - areas typically considered harmful to society and covered by reporting features.** For instance, the content that the participant considered sexual and used "Not interested" on included people wearing revealing clothes (P27), suggestive dances (P23), and personal anecdotes on sexual topics (P22).

The problematic components of the content were sometimes relatively clearer, such as using certain keywords.

> "The content uses the word *Im-ming out* (combination of *Imshin* which is pregnancy in Korean, and *Coming out*, and I have heard that this term is discriminatory (P15)."

Sometimes, the problematic aspect of the content was not tied to specific expressions or objects but rather arose from the interpretation of its overall message. For instance, P27 described using "Not interested" on several posts featuring interviews critical of the queer community, viewing them as politically incorrect and discriminatory.

Social media users often sought to avoid problematic comments written by other users, especially on posts about controversial topics. In such cases, avoiding the content entirely was more practical than blocking every offending commenter.

> "I usually read comments, but when it comes to posts that depict revealing bodies, the comments often contain sexual harassment, which makes me feel very uncomfortable." (P24)
> "Sometimes the post itself is interesting enough to read, but then I open the comment section

> and see comments that provoke conflict or are filled with hate speech targeting specific groups. In those cases, I end up blocking all the users who wrote such comments and then use "Not interested" to avoid similar posts in the future." (P25)

Avoiding Content that Damages Personal Reputation

Some participants were more concerned that personalized algorithms may misinterpret them as someone who enjoys problematic content. Since social media users thought the recommendation was mainly influenced by their interests and previous activities on the platform, they thought that the recommended content hinted at their interests. P27 noted they do not like that *"the platform (Instagram) has categorized them as that kind of person"*.

These concerns were extended to **fear of being perceived by others as someone who enjoys such content.**

> "When someone glances at my YouTube or Instagram For You page, it is like they are seeing a collection of things I am interested in, the reflection of what I like. So I think I end up hitting "Not interested" more often to create a recommendation feed that would not feel embarrassing or awkward for others to see." (P7)

This was particularly the case with the content that could be considered sexual. The imagined viewers of their screen ranged from strangers (P17, P22, P25) to their friends (P9, P11, P17) to significant other (P19). They described the content to be *"inappropriate for public spaces"* (P25), *"can make people misunderstand me"* (P11), and *"can lead to social exclusion"* (P17).

Avoiding Personally Discomforting Content

"Not interested" was also used on content that **each participant found personally discomforting.** Unlike in previous cases, participants recognized that their negative reaction was **highly personal and that the content itself was not morally or ethically problematic.**

There were cases where people clicked "Not interested" to contents that posit a perspective or ideology that they do not agree with. In such cases, participants wanted to avoid such content while acknowledging differing views. P12, P21, and P27 used "Not interested" on posts promoting religions they did not believe in.

> "The content says "the description of the amazing creativity of [religious figure]". To be honest I really hate this religion. I am from [country] and a lot of people practice this religion. I see a lot of stupid posts like this that do not bring any value." (P21)

P21 identified themselves as a "student who studies science" and is "against religion". They also shared their attempts to understand religious perspectives but ultimately abandoned the effort.

> "I feel like I am trying to understand what they say but always I have some cornerstones that I find it inevitable that oh, I should not open this book, I should not waste my time again trying to disprove because it is like always dealing with the same debate topics." (P21)

Some participants also reported using "Not interested" on the content that advocates political opinions that they do not agree with, such as one supporting a particular political movement (P4), an online community with a certain political ideology (P27), and a political figure (P21).

"Not interested" was also used on content that triggered negative emotions, often by recalling past experiences participants preferred to avoid. For instance, P11, P14, and P24 used "Not interested" to remove content related to college entrance exams and high school life after graduation because they had *"never thought of going back to high school, and do not have any good memories related to high school"* (P24), and the college entrance exam was *"traumatic"* (P11). Similarly, P2 used "Not interested" to avoid content offering advice on a particular scholarship program because they had been rejected twice, which brought out *"personal issues"* (P2) for them. Another example was content that reminded participants of previous romantic relationships. Not only posts dealing with romance like dating tips, but posts that were particularly about the previous partners were also discomforting.

> "My ex-girlfriend's MBTI is ISTP, and I have noticed that a lot of the posts I marked as "Not interested" are related to ISTP traits and personality. (P7)"

In cases where the content was not inherently problematic but simply did not align with their personal preferences or experiences, participants found "Not interested" helpful as this action only affected their own algorithm without impacting others. They compared this with the 'Dislike' feature, explaining that while "Dislike" feels like a negative judgment on the content itself, "Not interested" simply prevents the content from appearing in their own feed without *"criticizing the effort put into creating it"* (P19).

4.2 Avoiding Unproductive and Indifferent Content

Participants used "Not interested" not just for content that was problematic or discomforting. Sometimes they used the feature even when their evaluation of the content is not negative. In these cases, participants aimed to optimize their social media experience by reducing recommendations for content did not provide high value. They used "Not interested" to limit content that appears too frequently, fell short of their standards, or could cause dissatisfaction over the long term.

Avoiding Repetition

There were also cases where participants used "Not interested" simply because they felt certain content **appeared too frequently in their feed**. Being overly exposed to the same or similar content, even ones they initially enjoyed, led to fatigue and prompted them to actively seek ways to reduce its visibility. In this case, the content has nothing wrong in its content or with their preferences or prior experiences. Even for content that they were genuinely interested in, participants used "Not interested" to reduce the frequency of exposure when it became excessive. This was especially common with trending 'challenge' content on social media.

> "There were so many dance challenges going viral on Reels—everywhere I looked, it was challenge after challenge. I do not dislike dancing, but there was just too much. At first, it looked fun, but after a while, I started thinking, "Why is this popping up again?" Eventually, I got tired of it, and if it kept going, I would even start disliking the background music." (P3)

Even for contents that are neither good nor bad to participants, they said that the repetition itself became the trigger for using "Not interested" to those contents. P10 explained that even if a post was not particularly interesting or aligned with their preferences, they didn't feel the need to immediately press "Not interested" when it appeared once or twice.

> "At first, I do not think I need to press "Not interested"—it is just one post, and it is not worth the effort. But when the same content keeps popping up, it becomes disruptive, and that is when I feel like I have to take action to fix the algorithm, even if it is a bit inconvenient to do so." (P10)

In these cases, using "Not interested" for repetitive content was less about providing negative feedback on the content itself and more about providing direct feedback to the algorithm for recommending it too often. Unlike the earlier cases where users wanted to avoid the content altogether, here participants primarily wanted to reduce the frequency of its appearance.

Avoiding Mediocre Content: "Not bad nor good, but there is better content"

Participants also used "Not interested" for content that they **did not essentially consider to be negative, but not worth the time and space on the platform**, which could be better spent on more valuable content. Therefore, the "Not interested" feature was often used on content that did not accomplish its goal, such as being uninteresting, unhelpful, or unfunny – content considered to be a "waste of time" (P2). From this perspective, they used "Not interested" as a tool to optimize their experience.

> "My evaluation of the content is neither positive nor negative, but I pressed "Not interested" because I feel there are better things I could be seeing." (P28)
>
> "There is a limit to the number of posts that can appear on the "For You" page at once. As the proportion of content I am "not interested" in increases, the amount of (interesting) content I can process at a glance decreases. That is why I chose to remove content I am not interested in." (P6)

Some participants applied particularly high standards to content in order to fine-tune their feed. They used "Not interested" to avoid content that addressed their interests but failed to meet their personal expectations. For example, P11, who enjoys dance, explained why they used the feature on a post by a dancer:

> 'This dancer's style was a bit different from what I prefer. I like waacking, but this dancer's moves felt too powerful, and honestly, to me, it came across as just freestyling. So, I did not want to see more of their content and used "Not interested".' (P11)

Avoiding Content That Leads to Short-Term Pleasure and Long-Term Regret

Participants' efforts to optimize their experience often took long-term satisfaction into account, and **to stop themselves from watching content then regretting later**. Even for content that was temporarily entertaining or addictive, they would use "Not interested" preemptively if they later felt the time spent on it was unproductive or unsatisfying. This allowed them to reduce the exposure to such content and better manage their overall platform experience.

> "Whenever a craft video appears, I end up watching it almost as if I am mesmerized, thinking it is fascinating. But then I feel like it is a waste of time, so when a lot of similar content showed up, I decided to remove it." (P10)

Chapter 5. RQ2. How do social media users conceptualize "Not Interested" compared to other reactions?

In this section, we address the second research question on how users differentiate "Not interested" with other reactions, resulting in using "Not interested" for particular cases. In our interviews, participants valued "Not interested" as a tool to adjust their own feeds without affecting others' experience. However, in some cases, they also wanted their action to impact the content recommended to others.

5.1 Personalizing One's Own Feed Without Harming Others

Compared to other reactions such as "Dislike" and "Report", participants valued the ability to remove content from their feeds without impacting the content creator or other users' recommendations.

For instance, P15 appreciated that "Not interested" *"feels like a less assertive action, one that only applies to my feed, allowing me to freely use it for content I'm not interested in."* They emphasized that "Not interested" is less direct than options like "Dislike" or "Report", which could be perceived as punitive. P11 expressed concern that a "Dislike" might hurt the creator, whereas "Not interested" offers a more private, indirect way to avoid content. P15 echoed this, worrying that if "Not interested" reduced the content's overall visibility, it might undermine the creator's work, underscoring that "Not interested" should impact only their personal feed. The consideration of the creator of content was also reflected in how social media users press "Not interested" for problematic content (Section 4.1). Participants explained that they use "Not interested" when they consider the content problematic but are not sure if other users would find it problematic as well. Even for the problematic content, different users may have varying standards and thresholds for what is acceptable (e.g., *"people from different countries may have different standards regarding the sexuality of the content"* (P26)). Participants hesitated to report content unless it posed clear harm to the public, such as scams or universally inappropriate material, fearing unfair consequences for the creator.

> "Reporting means that the person who posted this content should face direct sanctions. Their activity on Instagram needs to be restricted, and they should be removed from the public space." (P27)

Additionally, participants appreciated "Not interested"'s lack of influence on other users' feeds. Participants acknowledged that some content they found problematic might actually be something that some people enjoy. Participants mentioned that reporting the content and making it removed or deprioritizing the content in the personalized feed of others might not be an appropriate action for this case.

> "I clicked "Not interested" on disturbing content, not "Report" because I realized some people actually like that kind of thing. There was a feature where I could see "why this content was shown to me," and it turned out that one of my friends had reacted to it. That is why it appeared in my feed. So I thought, "Oh, they must like it," and just clicked "Not interested" without reporting it." (P8)

P25 and P28 noted that their choice to mark content as "Not interested" was subjective, and they preferred that it not affect other users. They saw the presence of certain content in their recommendations as indicative of demand by others, so it should remain visible to those who want it. Often, the existence of the content and its appearance on the recommended feed was interpreted as a response to the demand from other users, therefore the content should still appear to them.

> "The content that I pressed "Not interested" on was supplied because there is demand for it." (P17)

P17 provided an example of using "Not interested" on posts that incited gender conflict, often from communities exaggerating or fabricating content to provoke tension on topics like marriage. They felt this content negatively impacted the public, possibly contributing to declining marriage and birth rates. Yet, acknowledging that some people want to view such content, P17 concluded that while it might not be feasible to remove it from the platform entirely, they were satisfied as long as it no longer appeared in their feed.

5.2 When Changing One's Own Feed is Not Enough

In contrast to cases where users only wanted to modify their own personalized feed, sometimes participants commented that the content they used "Not interested" is harmful to other users as well. Social media users could report such content to the platform and ask for removal when they want to protect others [Zhang et al.(2023)], but often users resort to using "Not interested" instead of using existing moderation features.

One example is when users felt that although certain posts might negatively affect others, the result of platform-level moderation seemed too severe. For instance, P21 shared their experience of pressing "Not interested" on content featuring celebrities with exceptional appearances and unrealistic body images. They believed that such content could lead to feelings of depression and decreased self-confidence in one's own appearance. While they primarily used "Not interested" to avoid seeing such content themselves, they also hoped that their feedback would influence the algorithm and reduce the overall exposure of similar content to others on the platform to prevent harm. However, they perceived "Report" as a tool meant for more serious consequences, like having the post completely removed or restricting the uploader's activity.

Secondly, some users replaced "Report" with "Not interested" because they felt that reporting would be ineffective. For example, P27 shared that while they would prefer harmful political content not to appear for anyone, they also assumed the platform would not act on their report, rendering it pointless, thus using "Not interested" instead. In other cases, users chose "Not interested" over "Report" because the volume of harmful content was overwhelming. P1 explained that for problematic gossip content, even if they reported it, similar posts would continue to be generated, making "Not interested" a more practical choice with a broader impact.

Some users found the reporting process too cumbersome. P7, for instance, initially reported graphic or explicit content with the hope that it would be removed from others' feeds as well. However, they eventually switched to using "Not interested" because the process of navigating menus, selecting categories, and pressing additional buttons felt too tedious.

Lastly, some users chose "Not interested" over "Report" when they believed the harmful content was problematic for a limited audience. P17 shared that while certain content they marked as "Not interested" should ideally be restricted from minors or come with an age limit, they did not mind if adults viewed it. In these cases, they were satisfied with simply preventing such content from appearing in their own feed.

Chapter 6. RQ3. How do users interpret the result of the "Not Interested" feature?

In this section, we answer our third research question on how participants understand content avoidance through "Not interested". Many participants said they do not think their "Not interested" works or that the effectiveness differs from time to time. In such cases, participants shared a variety of folk theories regarding how their "Not interested" interacts with the algorithm, believing that its effect depends on factors like their positive interaction with other content, the frequency and number of "Not interested" they leave, and platform-level constraints or intentions.

6.1 Positive Feedback and "Not interested" Balances Each Other Out

As previous studies have reported [Eslami et al.(2016)], participants were aware that implicit positive feedback such as pressing on a post or watching a post for a long time may indicate to the algorithm that they enjoy the content. Some participants believed that the accidental or intentional implicit positive feedback may have balanced out "Not interested". For instance, P28 compared their experience of expressing "Not interested" on Instagram posts comprised of pictures with noticeable ones at the front, with Instagram reels, which are videos.

> "I can press "Not interested" right away on gossip content with the front image having a fixed style of having only texts with colored backgrounds. However, in the case of reels, I watch until the end and press "Not interested", so that may have affected the algorithm. Eventually, the duration time on such reels is long because I have to watch them until the end to identify (whether I need to use "Not interested"), so it felt like it became less effective." (P28)

Therefore, after hypothesizing positive feedback interfered with their negative feedback, some participants (P15, P26) strategically tried to avoid giving positive feedback to contents they disliked. Instagram users can press "Not interested" either without or after pressing on the post on the 'For You' Page. Those who were concerned about giving a wrong signal to the algorithm chose the former interaction to avoid appearing as if they wanted to view the content.

6.2 Effectiveness Varies by Feedback Volume and Type

Since "Not interested" is an example-based interaction where users have to "teach" [Feng et al.(2024)] the algorithm of their preference, users had various understandings based on their experiences regarding how examples are reflected to the algorithm, specifically regarding the amount and similarities of examples. Many participants believed that frequently using "Not interested" and giving more examples of their discomfort increases the accuracy.

> "Maybe they (Instagram) have some algorithm that if you press "Not interested" five times they certainly shouldn't show that content again." (P19)

Participants would also press “Not interested” multiple times in one sitting to signal their strong desire to avoid content.

> “Sometimes I got so frustrated thinking “I want to beat the algorithm”. On those days, I would scroll through the feed, hitting “Not interested” on every post I did not like, and actively seeking out more posts to do the same.” (P3)

P25 compared the different effectiveness of using “Not interested” on different types of content, saying the fitness profile pictures that P25 used “Not interested” the most are considerably less appearing on the feed, but college-related content is appearing a bit more since P25 did not use “Not interested” on such content as much as the fitness pictures.

The high similarity within the posts that “Not interested” was used on as well as their distinction from the content they enjoy was also considered important. For instance, P26 pointed out that the college acceptance certificates were successfully removed using “Not interested” because they share similar visual characteristics. In contrast, users attributed the failure of content removal to related content they enjoy, such as continuously being exposed to revealing photoshoots because of interest in fitness tips (P22), or to baseball game cheerleaders due to their interest in baseball (P19).

6.3 The Platform Cannot or Does Not Hide the Content

Participants also often attributed the ineffectiveness of “Not interested” to factors other than the algorithmic ability - a plethora of relevant posts or the platform’s neglect. Participants (P3, P4, P7, P8, P10, P18, P24) often attributed the failure to remove content to the continuous influx of similar content generated by other users that win over the algorithmic curation. For instance, P10 speculated that reels of a certain Instagram challenge kept appearing because there were too many of them. P8 noted that widespread posts would inevitably reach them despite their use of “Not interested”.

A small count of participants speculated that the platform simply does not care about the user’s feedback. For instance, P15 said *“It feels like, from Instagram’s perspective, as long as posts keep coming up and attracting people’s attention, it does not really matter whether I am interested or not. It makes me wonder if they’re just not filtering anything at all.”*

Chapter 7. Discussion

We explored how social media users 1) make versatile usage of "Not interested", 2) wish to limit the impact of their decisions on other users, and 3) draw assumptions about how the feature works based on their experiences. In this section, we discuss the necessity for platforms to meet varied user motives, consider users' desires to influence individual feed or platform-level content exposure, and provide granular control and deeper knowledge of tailored algorithms.

7.1 Nuanced Content Evaluation behind "Not interested" Usage

Our study finds that when users select "Not interested" on recommended content, they consider a variety of personal factors, such as subjective assessments of problematic content, concerns about reputation, and alignment with their own opinions and emotions. Prior research has suggested designing the "Not Interested" interaction to allow users to communicate more precisely why they wish to avoid certain content [Harris et al.(2023), Park et al.(2024)]. This approach is believed to create personalized feeds that better reflect users' subjective evaluations of content, potentially even reducing incidents where unwanted exposure to content incites anger or leads to hateful or prejudiced remarks directed at other creators [Harris et al.(2023)]. Additionally, since there may be various reasons to avoid the same content, allowing users to specify these reasons could support more precise curation. Some social media platforms already ask for specific reasons when users submit "Not Interested" feedback. Based on the reasons identified in our research, platforms could further refine and diversify these reason categories.

However, asking users to specify their reasons for avoiding content with "Not interested" also brings potential drawbacks. First, the interaction could become more complex and lengthy, resulting in reduced usability. Users noted that even the current "Not Interested" option, without requiring reasons, feels more cumbersome than simply skipping content without feedback. Since part of the motivation behind pressing "Not Interested" is to avoid certain content as quickly as possible, heavy and lengthy interactions can lead to discomfort. Therefore, platforms may explore interaction methods that blend in the fast-paced usage of short-form content while allowing more expression of nuance. For instance, pressing "Not interested" multiple times could signal stronger discomfort, or users could indicate where in the multimedia was particularly discomforting by pressing the part. Second, users might feel uneasy explicitly selecting reasons to avoid content, as it requires them to face their preferences. When reasons are not required, users can freely use "Not Interested" without self-censorship. However, confronting the fact that they dislike certain content could feel embarrassing or raise personal discomfort.

7.2 "Not interested" as a Social Action

When users use "Not interested", they often consider not only their own interests and tastes but also the potential impact of their actions on content creators and other consumers in social media. Many users see "Not interested" as a way to curate their own feeds without harming the creator through actions like "Report", which could lead to account suspension or content removal. Additionally, they perceive demoting the content they are not interested in as a potential damage for creators who want to reach a broader audience, as well as for other users who might enjoy the content they personally wish to avoid (Section 5.1).

Some types of content (e.g., profanity, sexuality) inherently evoke diverse opinions about what should or should not be visible [Aroyo et al.(2019)], with users and creators often feeling conflicted when such content is removed or deprioritized across the platform [Are and Paasonen(2021)]. Research shows that people who support freedom of speech tend to prefer personalized moderation, allowing individual users to set content preferences rather than imposing centralized restrictions [Jhaver and Zhang(2023)]. The option to use "Not interested" to avoid specific content aligns with the right to post content. This right to selectively avoid content through "Not interested" mirrors the balance between personal autonomy and community dynamics, allowing users to tailor their experiences without impeding others' freedoms or contributions.

At the same time, certain uses of "Not interested" could raise issues in platform-wide social dynamics. First, avoiding content with opposing views (Section 4.1) could contribute to filter bubbles, limiting exposure to diverse perspectives. This calls for future discussion on how and to which extent the user agency to deliberately put themselves in a filter bubble should be supported. Second, users sometimes resort to "Not interested" when they desire platform-level moderation but find existing moderation too harsh, ineffective, or cumbersome (Section 5.2). Currently, existing affordances allow users limited solutions to unwanted content provided by personalized recommendations. They could either remove unwanted content only from their own feeds using "Not interested" or "Report" it, which requires final confirmation from the platform, often resulting in various decisions such as content removal from others' feeds or content owner penalties. However, there is a need to explore intermediate actions that users want to take, such as restricting content visibility to specific audiences or applying only selective outcomes from reporting actions.

7.3 Strategies and Adaptations around Algorithmic Ambiguity of "Not interested"

When users found that their attempts to avoid unwanted content through "Not interested" were ineffective, they developed folk theories — based on their experiences and perceptions of the platform — about when each feedback might succeed or fail. These findings align with known challenges in interactive recommenders, such as the difficulty users face in interpreting results due to an overwhelming number of parameters [He et al.(2016)], or the ambiguity around how specific feedback changes the algorithm [Wang et al.(2024)].

Sometimes, users adjusted their behaviors to match these theories, such as consciously refraining from positive engagement with disliked content while pressing "Not interested", or increasing feedback frequency to reinforce its intended impact. Particularly in social media, actions that were previously light and spontaneous, like clicking on posts, became more deliberate; some users even went so far as to refresh their feeds frequently, consistently pressing "Not interested" in an attempt to shape the algorithm — a process that often felt labor-intensive.

However, simply removing the algorithm's opacity could inadvertently restrict users' ability to employ "Not interested" flexibly. For instance, if "Not interested" feedback were to override all positive feedback, and prevent the recommendation of related content, users who might later wish to revisit certain topics would be hindered. The current flexibility allows users to re-engage with content naturally, without resetting any previous feedback or toggling settings, offering a unique advantage for adapting interests over time.

Instead, platforms might explore options for enhancing user control and transparency without sacrificing flexibility. For example, providing adjustable settings for "Not interested" feedback strength could allow users to indicate how strongly they wish to avoid certain content types. Additionally, platforms could clarify how content that was submitted "Not interested" feedback is processed. This explanation could go further than simply stating the considered elements of posts like images, hashtags, or creators - such as stating how parts of images and different timestamps of video are evaluated to identify users' preferences.

7.4 Generalizability of the Findings to Different Platforms

Our study focused on the use of the "Not interested" feature on a single social media platform, Instagram. This decision was made because Instagram is the only major platform that keeps a record of users' "Not interested" interactions, allowing us to address two potential data collection challenges. First, we aimed to prevent participants from relying solely on memory and reflect on actual instances of using "Not interested", which could lead to less detailed responses. Second, we aimed to avoid potential impact on the authenticity of the data that may happen if we had developed a custom tool to track "Not interested" use, due to participants interacting with it differently than they usually would. In this section, we discuss the factors that need to be considered for our findings to generalize to other platforms.

How personalized recommender algorithms work

Each platform's personalized recommender system may vary in how it interprets users' preferences and suggests content accordingly. For example, prior studies have noted user anecdotes that TikTok, compared to Instagram, offers a wider selection of diverse content, styles, and trends, while also being more responsive to users' shifting interests [Lee et al.(2022)]. In this context, users on TikTok might encounter a broader range of content types, potentially leading to a wider variety of reasons for pressing "Not interested". On the other hand, TikTok's adaptability to changing interests might lead to users finding fewer reasons to use "Not interested" as their feed aligns more closely with their current preferences. Nevertheless, we believe the types of content identified in our study that prompt the use of "Not interested"—such as problematic content, content that provokes personal discomfort, or content that feels time-consuming or tempting—are common across platforms, suggesting that our findings may apply more broadly.

Perceived Effectiveness of "Not interested"

The effectiveness of "Not interested" may influence its usage frequency, the types of content it is applied to, and users' interpretations of the interaction. For instance, if the content category marked as "Not interested" stops appearing after only a few feedbacks, users would not have to use "Not interested" for similar content. Moreover, if "Not interested" is so sensitive that it drastically changes the feed, users could be careful when they use it. Conversely, if users perceive that "Not interested" is ineffective, they might be reluctant to use it even for content they wish to avoid. Prior research on platforms such as Instagram [Landesman et al.(2024)], Douyin [Rong et al.(2022)], and TikTok [Harris et al.(2023)]

has highlighted cases where users, despite marking content as "Not interested" continued to encounter undesirable posts. This indicates a common limitation across platforms, revealing that the feature often fails to meet user expectations, although the degree and nature of this failure may vary. Furthermore, while the insights from RQ3 regarding the functionality of "Not interested" may depend on perceived effectiveness, we argue that the interaction of labeling unwanted content has broader applicability across various platforms.

Interaction Design of "Not interested"

How users can access the "Not interested" feature and which steps they have to take to use the feature may affect the user behavior, such as the threshold of the intent to avoid certain content that results in the usage of the feature. Although platforms have some differences regarding the interaction design of "Not interested" (e.g., how the 'menu' button that leads to "Not interested" option looks like and where it is located on each content), every platform we observed requires users to first press a menu button and find the "Not interested" feature. Therefore, the usage of the "Not interested" that we studied on Instagram can be generalized to other platforms in terms of interaction.

Chapter 8. Limitations and Future Work

Our current study focused on understanding how users use "Not interested", and what they expect as the result of the feedback on Instagram. It presents several limitations and leaves promising opportunities for future work to broaden the investigation across different platforms, examine long-term interaction, and consider diverse stakeholders in platforms.

8.1 Understanding the use of "Not interested" across diverse demography

In this study, we intentionally refrained from collecting demographic information to ensure that participants could respond as comfortably as possible. However, user experiences with "Not interested" may vary depending on individual identities such as nationality, gender, or political stance. For instance, the type of content users are exposed to can differ—users from countries with shared languages and cultural proximity may see more posts from neighboring nations. Additionally, the way users evaluate recommended content might also differ. For example, sensitivity to and perception of posts that threaten one's identity could influence the degree to which users wish to avoid such content. Future studies could further explore how the use of "Not interested" varies across specific user identities, providing a more nuanced understanding of its application.

8.2 Understanding the use of "Not interested" across diverse platforms and user characteristics

As discussed in Section 7.4, we only interviewed participants about their experiences on Instagram.

Future research can extend our work by exploring how people use "Not interested" in other social media platforms with different content pools, platform cultures, and platform design.

Additionally, in our study, we observed that even among users of the same platform, Instagram, participants had diverse expectations and media consumption habits. Future studies could benefit from identifying different user types and analyzing how each group of users utilizes negative feedback features. By connecting user characteristics with their behavior, researchers could gain a deeper understanding of how "Not interested", or negative feedback, is perceived and utilized by each type of user.

8.3 Consequence of "Not interested" malfunctioning

While our research focused primarily on the purposes for which users engage with "Not interested" and how they interpret the outcomes, future studies could further examine how users react to the perceived malfunction of "Not interested". Our interviews provided glimpses of users reducing the time spent viewing recommended content or decreasing their platform usage when they felt the button did not work as intended. Prior research has reported negative outcomes like hostile comments directed at creators when "Not interested" fails to meet expectations [Rong et al.(2022)]. Future work could explore how user attitudes toward not only the platform but also content and specific creators shift when their content avoidance attempt fails. Moreover, as previous research reported that users often use multiple content avoidance affordances together [Zhang et al.(2023)], further studies could observe whether the failure of “Not interested” results in the usage of different affordances.

8.4 “Not interested” from the view of different stakeholders

Our study only observed how social media users as consumers use and perceive “Not interested”. However, it is worth considering the impact on content creators when users opt to avoid content rather than provide direct feedback. Some participants even mentioned that if pressing the “Not interested” was communicated to creators, it could help them improve their content. Currently, estimating how many “Not interested” clicks a piece of content receives is quite difficult, with creators sometimes only finding out through comments where users explicitly mention pressing the button [Rong et al.(2022)]. Future studies could explore ways to support users’ content avoidance preferences while also making the “Not Interested” feedback more useful for content creators.

Chapter 9. Conclusion

To understand how social media users attempt to avoid certain types of content on personalized feeds with “Not interested”, we explored how each content leads to avoidance, how users interpret the avoidance mechanism, and how they restrict the impact of their feedback to other users. We showed that users used the “Not Interested” feature to avoid certain content or adjust the algorithm, driven by personal values. Users generally hoped their feedback would only affect their own feeds without affecting others, though sometimes they sought a broader impact. However, they were often unsure how their “Not interested” interactions were interpreted.

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Chapter A. Appendix

Screenshots were taken in October, 2024

A.1 "Not interested" interaction interface of social media platforms

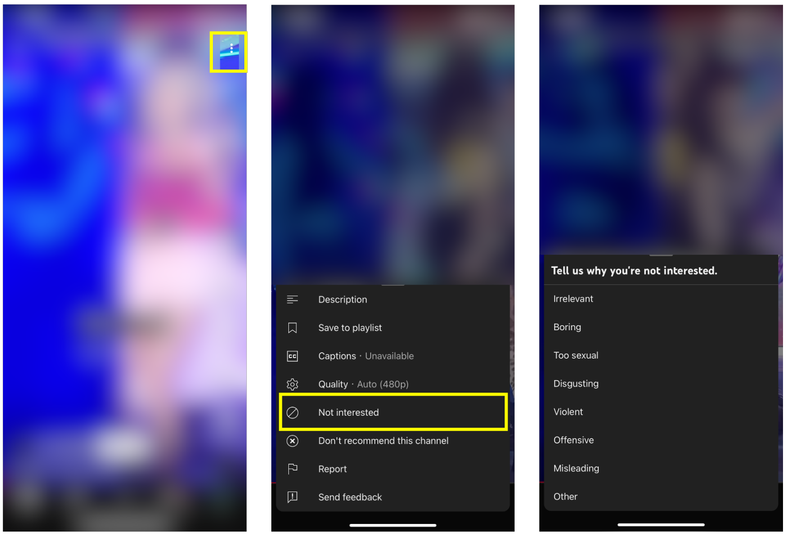

Figure A.1: "Not interested" interaction on YouTube Reels

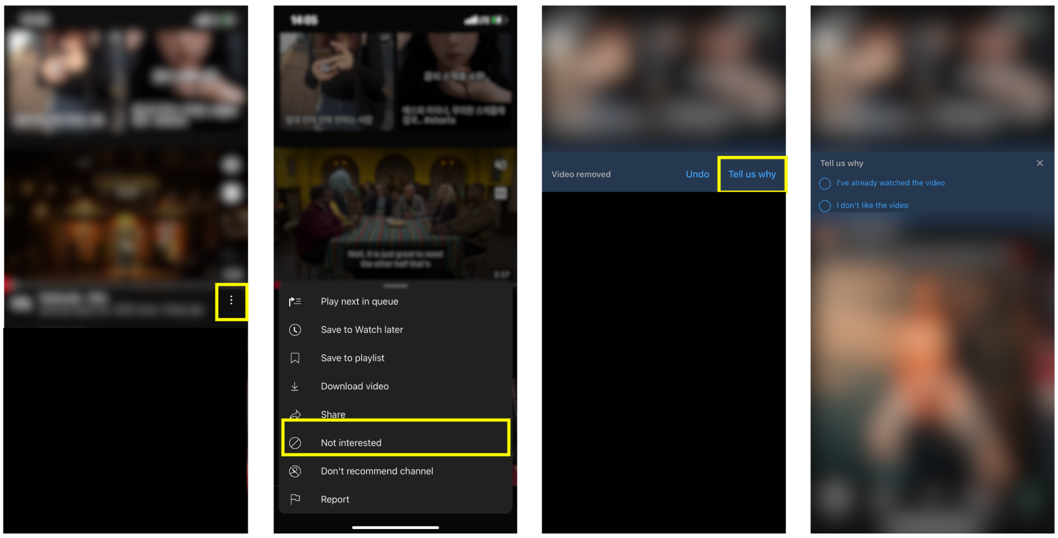

Figure A.2: "Not interested" interaction on YouTube Video

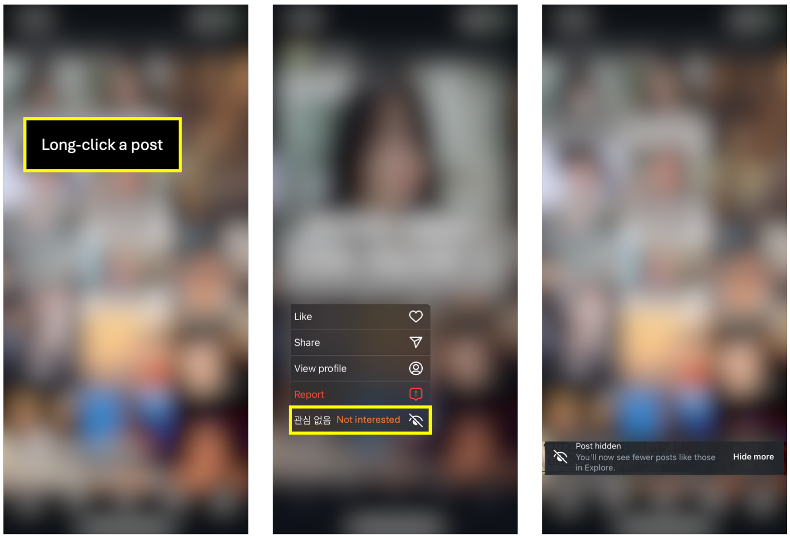

Figure A.3: “Not interested” interaction on Instagram Explore Page

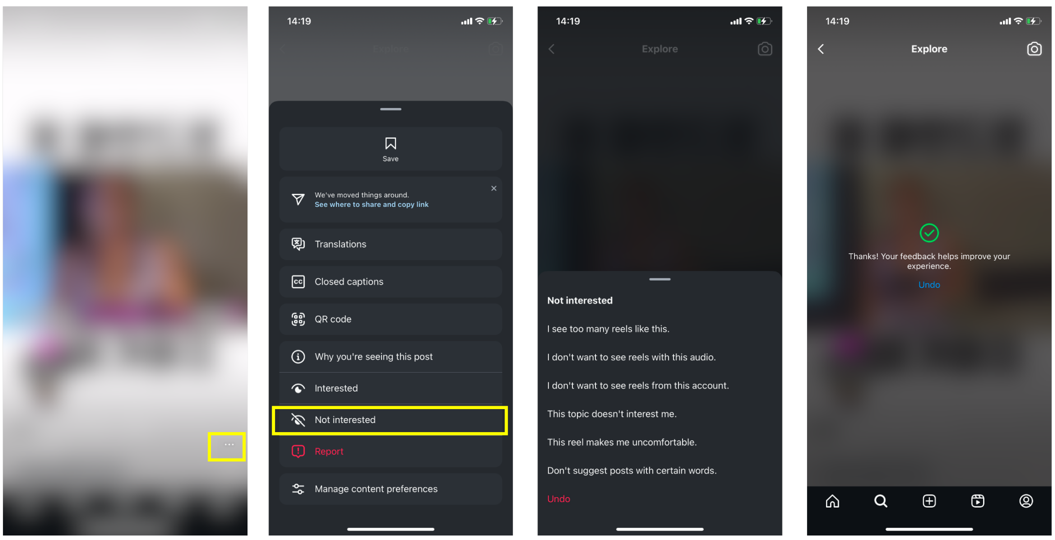

Figure A.4: “Not interested” interaction on Instagram Reels

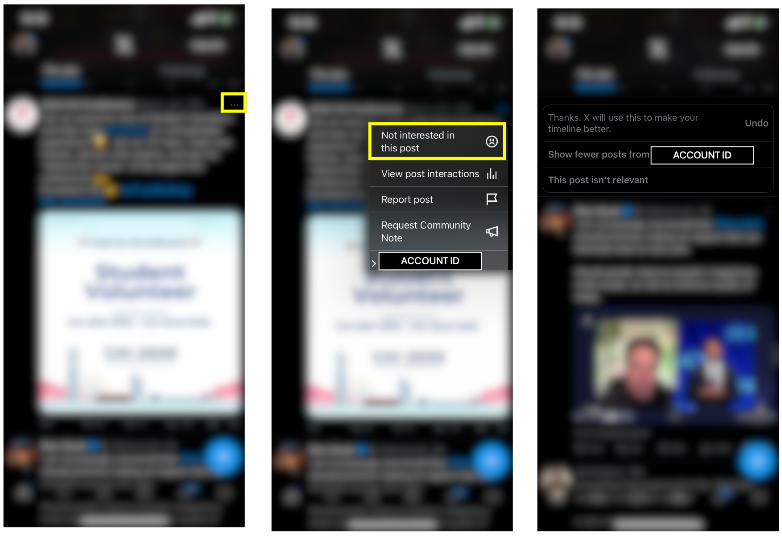

Figure A.5: “Not interested” interaction on X(Twitter)

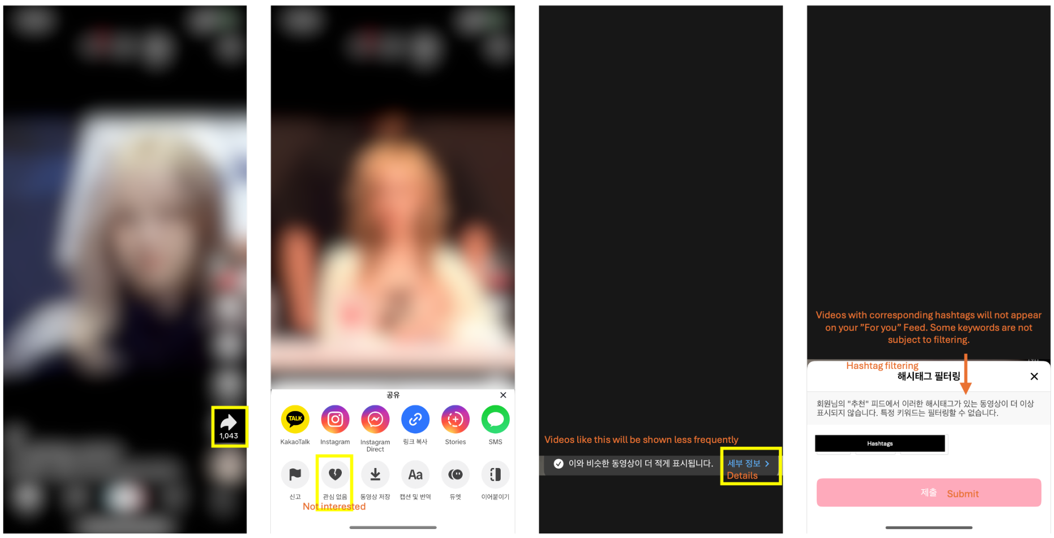

Figure A.6: “Not interested” interaction on TikTok

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