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An Empirical Study of User Playback Interactions and Engagement in Mobile Video Viewing

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ABSTRACT Mobile video viewing on popular platforms such as YouTube and Netflix is widespread, yet the role of specific viewing interactions in shaping user engagement remains underexamined. This study investigates how skipping behaviors (including their types and directions) and playback speed adjustments relate to user engagement, with a focus on video abandonment and user satisfaction. We developed a custom mobile web application for video viewing and collected viewing logs and self-reports from 25 participants during two 10-day field studies. Our findings reveal that different skip types and directions are associated with distinct engagement outcomes. For example, scrubbing often correlates with higher abandonment, whereas backward skips may indicate greater engagement. Playback speed adjustments can signify deeper involvement, allowing users to tailor their viewing speeds without missing key content. Notably, video abandonment did not always equate with dissatisfaction; some users left after meeting their immediate viewing goals. These insights suggest that users' playback interactions may serve as indicators of user engagement and can be incorporated into video recommendation systems to enhance user satisfaction. We conclude by discussing the design implications of enhancing user satisfaction.

INDEX TERMS Engagement, experience sampling, HCI, interaction, mobile, motivation, skip, speed, video

I. INTRODUCTION

With the widespread adoption of smartphones [1], mobile video viewing has become increasingly popular. As Internet infrastructure and wireless technologies continue to advance, online video streaming services—such as YouTube and Netflix—have also surged in popularity, providing fast and convenient access to information and entertainment.

Recently, human-computer interaction (HCI) researchers have begun examining mobile viewing interactions in online streaming services as these platforms expand. For example, users may skip certain segments or watch at faster playback speeds (e.g., 1.5× or 2.0×), reflecting their level of involvement or specific intention such as seeking wanted information from a video. They can also adjust screen size or resolution manually. Such features are closely tied to the viewing experience and can serve as key indicators of user engagement—for example, how long users watch a video or whether they abandon it [2]–[6]. If users skip, it may reflect changes in involvement or satisfaction that could lead them to leave a video. Consequently, understanding these behavioral patterns is crucial for streaming services in order to enhance the viewing experience and maintain user engagement.

Prior studies have investigated user engagement from various perspectives. For example, quality of service (QoS) factors—such as buffering, low bitrate, or high latency—can negatively affect quality of experience (QoE) [7]–[10]. In general, strong QoE leads to increased engagement, whereas poor QoE often prompts users to abandon streams or switch platforms. Engagement is usually measured through surveys, interviews, or behavioral analyses [8]–[11]. Other factors, such as video metadata (category, title, view count, likes, thumbnails), also affect user engagement [12]–[14], as users often select a video based on motives or preferences shaped by this information.

Nevertheless, although many studies have examined how users select videos under certain conditions (e.g., QoS or video metadata) and how this relates to user engagement, relatively few have investigated how specific, intentional interactions that occur during playback, such as skipping or adjusting the playback speed, are associated with engagement and satisfaction. For instance, video abandonment is often viewed as a negative indicator, yet user intentions and goals can influence whether an early departure genuinely reflects dissatisfaction. In this study, we aim to deepen our understanding of how these deliberate viewing interactions inform both engagement and satisfaction.

To achieve this, we pose the following research questions:

- RQ1: Why do people skip content, and how does skipping relate to user engagement?
- RQ2: Why do people adjust playback speed and how does this behavior relate to user engagement?
- RQ3: Why do people leave a video before it ends and how is this decision related to their satisfaction level?

We focus on skipping and playback speed adjustments as primary viewing interactions, and on video abandonment and level of satisfaction as key indicators of user engagement. To study these behaviors, we developed a mobile web application for online video viewing that captures users' viewing logs and self-reports, and We conducted two 10-day field studies, involving 16 participants in the first and 9 participants in the second. We also conducted post-study interviews to gain deeper insight into users' viewing habits and rationales.

Our findings show that user interactions are closely linked to engagement outcomes, such as video abandonment and satisfaction. In particular, different skip types (e.g., double tapping vs. scrubbing) and skip directions (e.g., forward vs. backward) appear to be associated with level of engagement. Moreover, playback speed adjustments may indicate positive engagement among users who habitually utilize this feature. Finally, our results indicate that video abandonment does not always signify low satisfaction; users may leave a video once their immediate goals have been met.

The key contributions of our study are as follows:

- We designed and implemented a mobile web application for video watching in a field study setting (rather than an in-lab environment), enabling the collection of real-world viewing data.
- We employed mixed-methods analysis (quantitative and qualitative) to explore how and why users engage in specific viewing interactions that occur during playback.
- We offer empirical findings and design implications that may help enhance the mobile viewing experience and support user engagement in online video streaming services.

II. RELATED WORK

A. USER'S INTERACTIVE BEHAVIORS IN ONLINE MEDIA

User behavior is fundamental to understanding how people consume content on online media services. On audio streaming platforms (e.g., Spotify and YouTube Music), users typically listen to music or podcasts, and their main interactions include skipping backward or forward, pausing, and switching tracks [15]–[18]. In contrast, video streaming services such as YouTube and Netflix offer a wider range of user interactions. Since viewers must keep their eyes on the screen while watching longer-form video content, they tend to be more actively involved. Consequently, in addition to standard playback controls, features such as playback speed adjustments and scrubbing are used more frequently and intensively on video platforms than on audio-only services.

Prior studies have investigated various user behavioral patterns in online video streaming services. One prominent context is Massive Open Online Courses (MOOCs), where user interactions are strongly linked to educational factors such as engagement levels and course completion rates [3], [5], [19], [20], and video difficulty [21]. On other video streaming platforms, including YouTube and over-the-top (OTT) services (e.g., Netflix), researchers have examined user interactions during video playback to better understand behavioral patterns and identify user-centered design opportunities [6], [22]–[24].

However, much of this prior work has focused on quantitative behavioral analyses [6], [23]–[25] or relied on in-lab studies to explore user behavior in video consumption [9], [22], [26]. As a result, the motivations for different playback interactions, along with users' satisfaction regarding their viewing experiences, remain relatively underexplored. In this study, we address this gap by conducting a field study with a customized mobile online video streaming application and employing a mobile experience sampling method to capture in-situ user insights.

B. MEASURING USER ENGAGEMENT IN ONLINE VIDEO SERVICES

User engagement is crucial for online video streaming platforms because understanding how users interact with content helps deliver more personalized and satisfying experiences. Prior research has measured user engagement using a variety of metrics, with Quality of Service (QoS) and Quality of Experience (QoE) being the most prominent.

QoS is commonly quantified through monitoring tools that track data rates, latency, error rates, and other network-related metrics, reflecting the technical performance of the service. Poor QoS metrics—such as low bandwidth [7], high latency [7]–[9], and frequent buffering [7]–[10]—lead to more playback interruptions, which negatively affect QoE and the user's subjective impression of the service [2].

QoE, in turn, is typically assessed through user surveys, interviews, or behavioral indicators (e.g., stream abandonment rates and satisfaction ratings) [8]–[11]. Generally, higher QoE correlates with increased engagement (e.g., watching longer), whereas lower QoE often drives users to abandon streams or switch platforms. Consequently, maintaining robust QoS is essential for preserving high QoE and supporting user engagement.

Even as information technology and communication infrastructures advance—reducing the extent to which QoS impacts QoE—many users still abandon videos before completing them [27]. Additionally, high QoE does not necessarily imply that users have fully achieved their viewing goals.

In this study, we specifically investigated why users may abandon videos even when QoS is adequate. We conducted our field study in South Korea, which is recognized for its well-developed internet infrastructure—including fast and stable mobile (5G) and Wi-Fi networks [28], [29]. As a result, QoS-related issues were largely mitigated. In fact, South Korea ranked highest in Asia for its 5G video experience in 2024, suggesting that users could generally stream 1080p or higher videos with fast loading times and minimal stalling [30]. Through our field study and an experience sampling method, we collected detailed data on why users chose to leave videos, even when they initially intended to watch them. In particular, we examined the relationship between reasons for abandonment and various playback interactions—such as 10-second skips forward or backward, scrubbing the progress bar, and adjusting playback speed. We then quantitatively analyzed how these behaviors relate to video abandonment, illustrating how each interaction is closely associated with overall user engagement.

C. EXAMINING VIDEO SELECTION, PLAYBACK BEHAVIORS, AND THEIR ROLE IN ACHIEVING GRATIFICATIONS

Extensive research has examined users' various motivations for watching online videos—such as entertainment or information seeking [31]–[36]. Regardless of these broader motivations, viewers must still select videos that align with their immediate goals. To accomplish this, they often explore recommended videos or actively search for specific content [37], relying on visible metadata (e.g., category, thumbnails, titles, view counts, and likes) before ultimately deciding which video to watch [12]–[14]. Once they settle on a video, they proceed to access it.

In the process of video selection, metadata can influence which content is chosen, while Quality of Service (QoS) factors—such as buffering or latency—may affect user engagement during playback. Poor QoS negatively impacts the viewing experience and can lead users to abandon a video. Conversely, with sufficient QoS, users are free to focus on the video and may interact through skipping or adjusting playback speed to better achieve their goals [4], [38]–[40]. For instance, if viewers seek information, they might skip ahead to locate the relevant segment more quickly; if they encounter an interesting scene, they might rewind to watch it again. These actions represent active, intentional user behaviors aimed at fulfilling their needs and maximizing their viewing gratifications. In some cases, viewers may depart early because they have already met their goal—even if satisfied—whereas others might watch a video to the end yet remain dissatisfied. After viewing, users reflect on their satisfaction levels, which can guide subsequent video choices.

In our study, rather than focusing on the pre-activity stage of video selection based on video content, we emphasize users' active interactions during the dur-activity stage. Because these interactions are deliberate user behaviors, they can serve as useful indicators of user engagement [41], [42]. To capture these interactions and better understand real-time motivations and reasons for abandonment, we developed a mobile YouTube wrapper application that logs user interactions during video playback. We also incorporated a mobile experience sampling method (mESM) [11] to gather immediate, context-rich data on users' motivations and abandonment rationales. Conducted as a field study, this approach offers deeper insights into how users progress from video selection to engagement outcomes, such as abandonment, while seeking their desired gratifications.

III. METHODOLOGY

A. YOUTUBE MOBILE WEB WRAPPER APP DEVELOPMENT

In this study, we chose YouTube as the primary platform for analyzing the video-viewing patterns of online users. In December 2024, YouTube ranked first in downloads on both the Google Play Store and the Apple App Store, reflecting its widespread adoption. Although the YouTube API provides access to certain user data (e.g., recently watched videos), it does not capture more granular behaviors such as playback speed adjustments or skipping. To facilitate a detailed examination of user interactions on the online video platform, we developed a mobile web wrapper for YouTube, enabling the collection of comprehensive viewing logs.

As shown in Fig. 1, we created a cross-platform mobile application to view YouTube videos using the Flutter framework. By leveraging the WebView[1] library to render YouTube's mobile website, the application allows users to watch YouTube videos on their smartphones in the same manner as a standard mobile web browser does.

When users finish watching a video and navigate away from the page, the device ID, timestamp, video metadata, and viewing behavior data are stored in the Google Firebase database. The collected video metadata included the video URL, title, and duration. Meanwhile, the user behavior data captures actions such as skipping and playback speed adjustments.

- *Skipping* can occur in two ways: (1) via *double tapping* on the left or right side of the video screen to move the video 10 seconds backward or forward (e.g., double-tap left for backward, double-tap right for forward), and (2) by *scrubbing* the playback progress bar at the bottom of the screen to jump to a specific point in the video. Each time a skip occurs, both the start and end time points are logged.
- *Playback speed adjustments* refer to changes made through YouTube playback speed control options. YouTube supports speeds of $0.25\times$, $0.5\times$, $0.75\times$, $1.0\times$, $1.25\times$, $1.5\times$, $1.75\times$, and $2.0\times$. Each time a user changes the playback speed, the exact point in the video and the selected speed are logged.

In addition, dwell time (i.e., the actual time a user spent watching a video), the exact point at which a user left the video, and the URL visited immediately before accessing the video were also recorded. In cases where a user skips or adjusts the playback speed, the video running time may differ from the actual time spent viewing. By analyzing the dwell

[1] https://pub.dev/packages/flutter_inappwebview

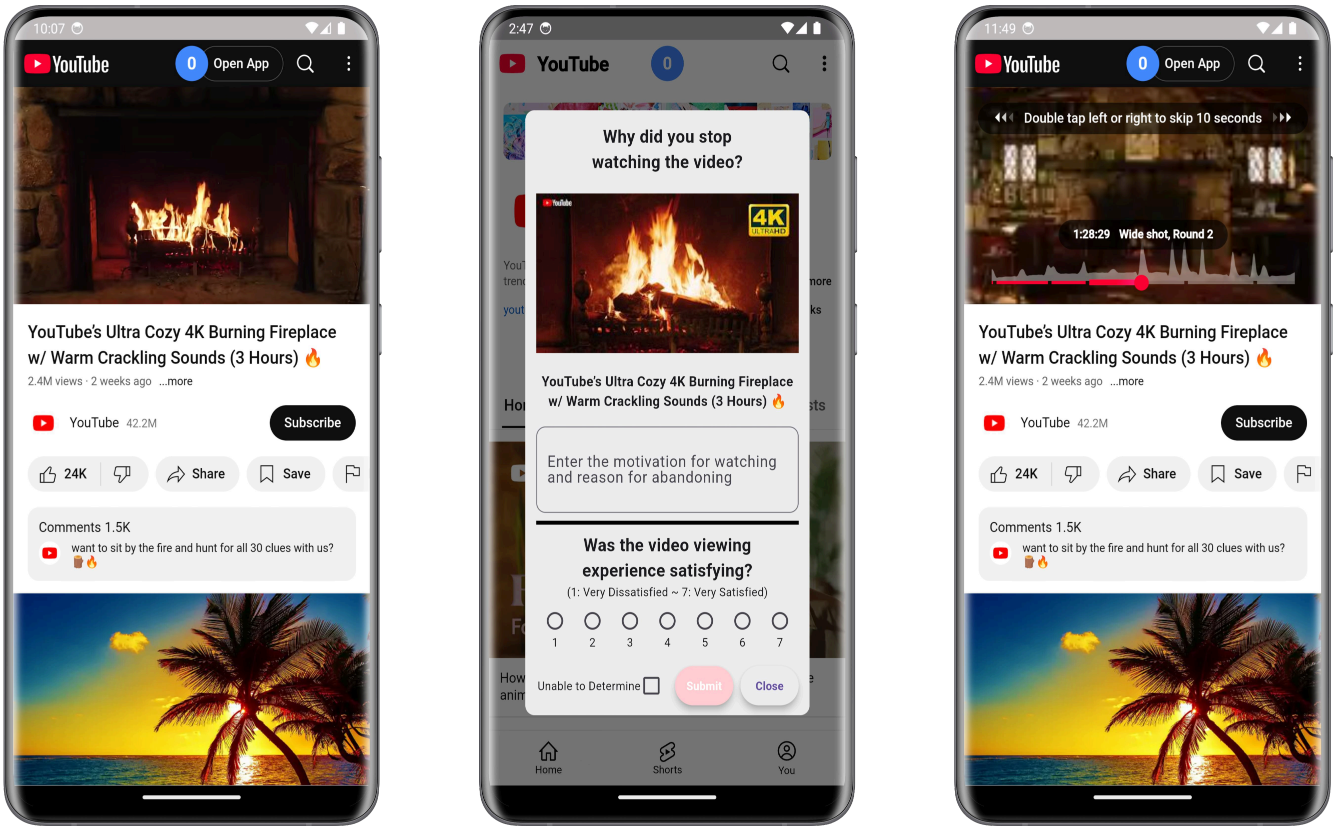

FIGURE 1. YouTube Mobile WebApp Wrapper

time, we can determine how long users remain engaged, and by logging the exact departure point, we can identify when they stopped watching.

We adopted the Experience Sampling Method (ESM) [43] to collect users' self-reports. If users do not watch the video until the end of the timeline—specifically, if they stop viewing at least 1.5 seconds before the video completes and then navigate away—the system considers the video unwatched to completion. At this point, a pop-up window appears to inquire about the user's viewing purpose and reason for leaving (see Fig. 1). The pop-up displays the video's title and thumbnail, followed by open-ended questions regarding the user's motivation for watching and the reason for exiting (minimum response length: 15 characters). Additionally, a 7-point Likert scale gauges satisfaction with the viewing experience, and an "Unable to Determine" option is provided for situations in which satisfaction cannot be meaningfully evaluated (e.g., boarding a bus). If the user prefers not to respond, they may close the pop-up without answering.

All data were stored in the Firebase Realtime Database. Because *Shorts* videos on YouTube do not permit skipping or speed adjustments and are typically very brief, this study excludes users' *Shorts* viewing data.

B. FIELD STUDY

In September 2024, we conducted a 10-days field study to collect the user data. A recruitment poster was created and distributed via the university's online communities and bulletin boards, inviting potential participants to complete the screening survey. The survey, administered using Google Forms, asked how many non-*Shorts* videos participants typically watch on their smartphones each day and how much time they spend doing so. We decided to recruit individuals who watch at least 10 YouTube videos and spend at least one hour on YouTube daily. A total of 22 people responded, and 17 were selected as final participants based on these criteria (6 females; age: $M = 22.65, SD = 2.37$; 6 Android users).

Each participant attended an orientation session before starting the field study. We provided guidelines for the study and explained the data collected. During the field study period, participants were asked to uninstall the standard YouTube app and install our YouTube mobile web wrapper App. To capture usage behavior as closely as possible to their normal YouTube viewing habits, participants were instructed to log into the app using their own YouTube accounts.

The participants was asked to use the YouTube mobile web wrapper app during the 10-day study period, while watching YouTube videos as they normally would on their smartphones. We requested that they watch at least five videos per day and respond to the ESM self-report regarding view-

TABLE 1. Demographic Characteristics of the Participants

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25
Age	24	20	23	19	20	26	19	21	24	23	23	23	23	21	25	23	22	24	26	25	26	20	24	24	21
Gender	M	F	F	M	F	M	M	M	M	M	M	M	M	M	F	F	M	M	M	M	M	F	F	F	M
OS	iOS	iOS	iOS	iOS	iOS	iOS	iOS	iOS	iOS	iOS	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A
Data Plan	5G	LTE	5G	5G	LTE	Unknown	5G	LTE	5G	LTE	LTE	5G	5G	5G	5G	5G	5G	LTE	5G	LTE	5G	LTE	5G	5G	5G

Note: OS = Operating System (iOS = iPhone, A = Android phone)

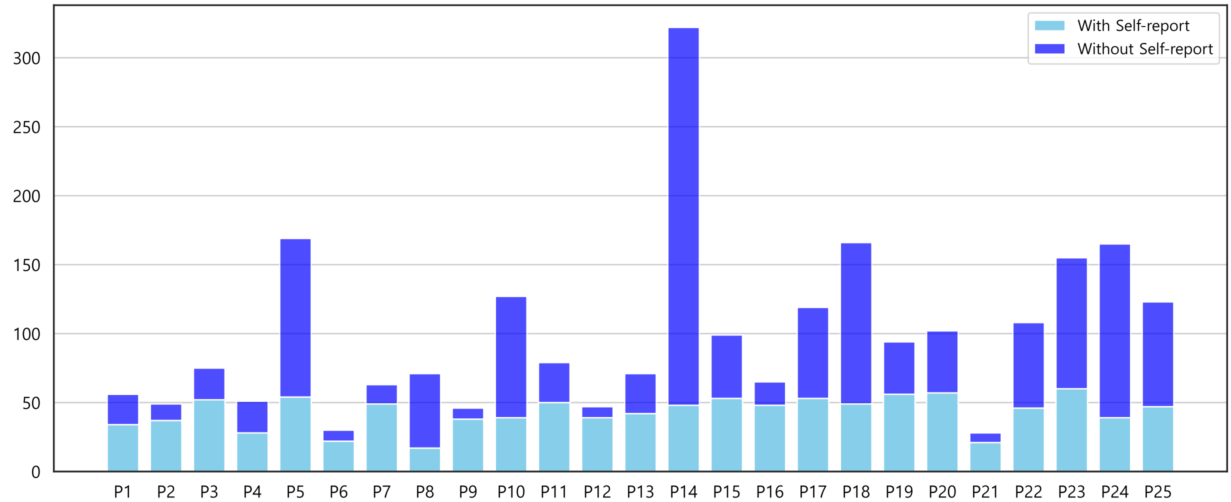

FIGURE 2. Collected Data from the Two Field Studies (P1–P16 in the first field study, P17–P25 in the second field study)

ing motivation, reasons for leaving a video, and satisfaction level. After submitting five responses per day, the participants could close subsequent ESM self-reports without providing additional answers.

Once the study was completed, we conducted individual one-hour semi-structured interviews with each participant. During these interviews, we discussed the app's usability, any inconveniences they experienced, and explored their ESM responses in greater detail to understand the reasons for video abandonment. We also asked about differences compared to the standard YouTube app, including whether their viewing patterns had changed during the experiment. All interviews were recorded with participants' consent and transcribed for thematic analysis. Each participant received KRW 30,000 (approximately USD 22) upon completion of the study.

During the study, we found that one participant did not use the app for several days, indicating a lack of sincere participation. After contacting this individual following the study, it was confirmed that the participant did not faithfully adhere to the study protocol. Consequently, we excluded the participant's data from the analysis. We collected 1,512 video viewing instances from 16 participants (681 included self-report responses).

In February 2025, we repeated the same field study to ensure a more robust sample size, aiming to strengthen the generalizability of our findings. A total of 15 individuals responded to the recruitment survey, and 11 met the selection criteria (4 females; age: $M = 23.73, SD = 2.38$; 11 Android users). During the study, we discovered that two participants did not use the app for several days: one did not follow the study protocol, and another lost her smartphone. After excluding both, we retained 9 participants, yielding 1,149 video viewing instances (453 with self-report responses). Combining these data with those from the first field study, we gathered a total of 2,661 video viewing instances from 25 participants (1,134 with self-report responses). The demographic characteristics of the 25 participants—including age, gender, operating systems, and mobile data plans for each participant's device—are presented in Table1.

We analyzed participants' free-text responses to the question, "Why did you stop watching the video?" to gain deeper insights into their viewing behaviors. Two authors collaboratively used ATLAS.ti[2] for affinity diagramming, performing open coding to assign labels to significant references or events. We iterated this process until consensus was reached, then examined relevant excerpts to develop detailed descriptions and illustrative examples of participant behaviors.

This study was conducted after obtaining approval from the Institutional Review Board (IRB) (approval number: *KHGIRB-24-409*). All participants were fully informed about the study's objectives, procedures, and data protection measures, and they provided voluntary consent to participate in the field study. They also agreed to the collection and use of their data for research purposes and were informed of their right to withdraw at any time.

[2]https://atlasti.com/

C. DATA COLLECTION AND PRE-PROCESSING

During the two 10-day field studies, we collected 2,661 video-viewing data points from 25 participants, as shown in Fig. 2. Among these, users provided 1,134 self-report responses regarding their viewing motivations, reasons for leaving the video, and satisfaction levels. The shortest video in the dataset was 10 seconds long, while the longest ran for 22,919 seconds (approximately 6.37 hours).

1) Filtering by Video Playtime

Using the 1.5 IQR criterion for video-length distribution, we removed 126 unusually long videos (2,179 seconds or longer), including 44 videos with user responses. This left 2,535 data points for analysis, which included 1,090 self-report responses.

2) Filtering Videos That Start in the Middle

We also excluded 55 data points (12 with self-report responses) where the user began watching from somewhere other than the beginning of the video. As a result, 2,480 data points remained for analysis, including 1,078 self-report responses.

Of these 1,078 self-reports, 20 indicated "Unable to Determine" satisfaction. Typical reasons for choosing this option included automatic transitions to the next video after one finished or leaving the video early to catch public transportation.

3) Redefining Abandonment

In the field study, if a user navigated away from a video 1.5 seconds before it ended, the system classified that action as "video abandonment" and triggered a pop-up self-report. However, upon reviewing these reports, 131 indicated that the user had actually finished watching. Therefore, we decided to classify a video as "fully watched" if the user viewed it through the "outro," when the main content was essentially complete and the recommended videos appeared. We reasoned that leaving during the outro does not necessarily signify abandoning the main content.

To operationalize this new definition, two authors manually checked each of the 2,480 videos' URLs to identify the exact outro timestamp. Any user who stopped watching before that timestamp was designated as having left early; otherwise, the video was considered fully watched.

Before we applied this updated criterion, the 2,480 data points included 1,967 "exited" and 513 "completed" instances. After applying the new criterion, these counts changed to 1,618 and 862, respectively.

D. KEY ENGAGEMENT METRICS USED IN THIS STUDY

Based on the preprocessed video viewing data and our redefined criteria for abandonment, we present four key metrics for user engagement as follows:

- *Abandonment rate*: The proportion of videos that were not watched until the end. It is calculated as the number of abandoned videos divided by the total number of video viewing instances. (For example, if there are 10 videos and 6 of them were not watched until the end, the abandonment rate is 60%.)
- *Dwell time*: The percentage of the video's total length that the user actually watched. It is calculated by dividing the time spent watching the video by the total video duration and multiplying by 100. (For example, if a user watches a 100-second video for 80 seconds, the dwell time is 80%.) Note that the dwell time can exceed 100% if the user repeatedly re-watches certain parts of the video, resulting in a total viewing time longer than the video's actual duration.
- *Abandonment point*: The point in the video at which the user stopped watching, expressed as a percentage of the total video length. This value may differ from the dwell time when users skip or rewind during playback. (For example, if a user watched until the 80-second mark of a 100-second video, regardless of skips or rewinds, the abandonment point is 80%. If they skipped parts and only spent 60 seconds total watching, the dwell time is 60%, but the abandonment point is 80%.)
- *Satisfaction*: The self-reported satisfaction score the user provides upon leaving the video, measured on a 7-point Likert scale (1 = very dissatisfied, 7 = very satisfied).

E. STATISTICAL ANALYSIS

We note that, in our statistical analysis of the four engagement metrics, the abandonment rate is a categorical variable (i.e., whether a video was abandoned or completed); therefore, we used a Chi-square test to compare differences across groups (e.g., skip vs. no skip). For the remaining three metrics—dwell time, abandonment point, and satisfaction—which are continuous variables, we employed Analysis of Variance (ANOVA) or non-parametric tests (e.g., Kruskal-Wallis), depending on the results of the Shapiro-Wilk test for normality. This approach ensured that each metric was analyzed using the most appropriate statistical method.

In addition, all statistical analyses were conducted at a significance level a of 0.05, corresponding to a 95% confidence level. Consequently, any p-value below 0.05 was deemed statistically significant. For clarity in the tables, we used one asterisk (*) to denote $p < 0.05$, two asterisks (**) for $p < 0.01$, and three asterisks (***) for $p < 0.001$. These procedures align with standard practices in the field and ensure a rigorous interpretation of our findings.

IV. RESULT

In this section, we present our analysis results based on the viewing logs and self-reports collected during the field study. We first examine users' skipping behaviors and their relationship to key engagement metrics. We then analyze how playback speed adjustments affect viewing patterns. Next, we explore users' self-reported reasons for abandoning videos. Finally, we investigate how content types, particularly video categories, relate to user interactions and engagement.

A. SKIPPING BEHAVIOR DURING VIDEO PLAYBACK

We conducted a statistical analysis of users' skipping behaviors and their relationship with four key engagement metrics: abandonment rate, dwell time, abandonment point, and satisfaction. Specifically, we compared these metrics across skip usage, skip types (e.g., 10-second skip vs. scrubbing), and skip directions (e.g., forward vs. backward).

1) Comparison of Viewing Patterns by Skip Usage

Regardless of the skip type or direction, 911 videos involved at least one skip, whereas 1,569 videos were viewed without skipping. Among the videos where skipping occurred, 622 were abandoned (i.e., the viewer did not watch until outro) and 289 were completed. In contrast, among videos with no skips, 996 were abandoned and 573 were completed. The results of the statistical analysis are presented in Table 2.

Abandonment Rate: The abandonment rate for videos with at least one skip was 68.28%, compared to 63.48% for those without skips. A chi-square test revealed this difference to be statistically significant ($\chi^2 = 5.638, p = 0.018, dof = 1$). Thus, regardless of skip type or direction, engaging in any form of skipping appears to be correlated with a higher abandonment rate.

Dwell Time: When at least one skip was used, the mean dwell time was 57.89 (SD = 56.04), whereas for videos with no skips it was 60.38 (SD = 51.71). The Shapiro-Wilk test indicated that both groups deviated from normality. Therefore, a Mann–Whitney U test revealed no statistically significant difference in dwell time between the two groups (U = 1.947, $p = 0.163$).

Abandonment Point: For videos with at least one skip, the mean abandonment point was 76.34 of the video (SD = 27.42). The mean for those without skips was 59.41 (SD = 39.71). The Shapiro-Wilk test again indicated that both groups were non-normal, prompting a Mann-Whitney U test. The difference in abandonment points was statistically significant (U = 49.984, $p < 0.001$). Thus, regardless of skip type or direction, videos that involved skipping tended to be abandoned later in playback.

Satisfaction: A comparison of satisfaction levels based on skip usage was conducted. For videos with at least one skip, there were 489 instances in which satisfaction was collected (M = 5.20, SD = 1.59). For the videos without skipping, there were 569 measurable instances (M = 5.03, SD = 1.51). A Shapiro-Wilk test again indicated that both groups were non-normal; therefore, a Mann-Whitney U test was used. The difference in satisfaction between the two groups was statistically significant (U = 4.507, $p = 0.034$), indicating that skipping was associated with higher satisfaction levels.

2) Comparison of Viewing Patterns by Skip Type

In the previous "Skip Usage" comparison, we examined video viewing logs that contained at least one skip versus those that contained none. Although this binary approach revealed broad patterns in user behavior, it may still overlook critical distinctions among different skipping methods. To address this issue, we now provide a more granular analysis by subdividing "Skipped" logs into "10-Second Skip Only," "Scrubbing Only," "Both," and "No Skip." This finer level of detail clarifies whether specific skipping types correspond to different viewing outcomes.

To compare viewing patterns across different skip types, we classified the data into four groups: (1) 10-Second Skip Only (forward or backward), (2) Scrubbing Only, (3) Both (10-Second and scrubbing skips), and (4) No Skips. The 10-Second Skip Only group consisted of 603 instances (399 abandoned, 204 completed), the Scrubbing Only group had 141 instances (103 abandoned, 38 completed), the Both group had 167 instances (120 abandoned, 47 completed), and the No Skip group consisted of 1,569 instances (996 abandoned, 573 completed). The results of the analysis are presented in Table 3.

Abandonment Rate: When ordered from lowest to highest abandonment rate, the groups were as follows: No Skip (63.48%), 10-Second Skip Only (66.17%), Both (71.86%), and Scrubbing Only (73.04%). A chi-square test showed a significant difference among these groups (χ^2 = 9.389, p = 0.025, dof = 3), but no significant pairwise differences emerged in the post-hoc analysis.

Dwell Time: When ordered from lowest to highest mean dwell time, the groups were as follows: Scrubbing Only (M = 45.50, SD = 63.98), Both (M = 53.22, SD = 86.88), 10-Second Skip Only (M = 62.08, SD = 40.68), and No Skip (M = 60.38, SD = 51.71). A Shapiro-Wilk test showed that all four groups deviated from normality; therefore, we employed a Kruskal-Wallis test, which revealed significant differences in dwell time (H = 42.816, $p < 0.001$). Post-hoc analysis indicated that there were significant differences between Scrubbing Only (M = 45.50) and 10-Second Skip Only (M = 62.08), Scrubbing Only (M = 45.50) and No Skip (M = 60.38), Both (M = 53.22) and 10-Second Skip Only (M = 62.08), Both (M = 53.22) and No Skip (M = 60.38).

Abandonment Point: When ordered from lowest to highest mean abandonment point, the groups were as follows: No Skip (M = 59.41, SD = 39.71), Scrubbing Only (M = 73.67, SD = 26.98), 10-Second Skip Only (M = 75.25, SD = 28.88), and Both (M = 82.52, SD = 20.87). A Shapiro-Wilk test again showed non-normality in all groups, and a Kruskal-Wallis test yielded a significant effect (H = 20.036, $p < 0.001$). Post-hoc analysis revealed that only two comparisons were statistically significant: No Skip (M = 59.41) compared with Both (M = 82.52), and No Skip (M = 59.41) compared with 10-Second Skip Only (M = 75.25).

Satisfaction: When ordered from lowest to highest mean satisfaction, the groups were as follows: Scrubbing Only (M = 4.45, SD = 1.86), Both (M = 4.98, SD = 1.83), No Skips (M = 5.03, SD = 1.51), and 10-Second Skip Only (M = 5.40, SD = 1.41). As all four groups violated normality in a Shapiro-Wilk test, a Kruskal-Wallis test was conducted, showing a significant difference (H = 20.036, $p < 0.001$). Post-hoc analysis indicated differences between Scrubbing Only (M = 4.45) and 10-Second Skip Only (M = 5.40), and

TABLE 2. Comparison of Viewing Patterns by Skip Usage

	Skipped (N=911)	Non-skipped (N=1,569)	Statistic
Abandonment Rate	68.28% (N=622)	63.48% (N=996)	χ^2=5.638, $\boldsymbol{p = 0.018}$*
Dwell Time	M=57.89 (SD=56.04), Median=50.00	M=60.38 (SD=51.71), Median=59.13	U=1.947, $p = 0.163$
Abandonment Point	M=76.34 (SD=27.42), Median=88.89	M=59.41 (SD=39.71), Median=71.28	U=49.984, $\boldsymbol{p < 0.001}$***
Satisfaction	M=5.20 (SD=1.59) Median=5 489 Self-reports	M=5.03 (SD=1.51) Median=5 569 Self-reports	U=4.507, $\boldsymbol{p = 0.034}$*

Note: Dwell Time and Abandonment Point = % of video length; Satisfaction = 1–7 scale.

TABLE 3. Comparison of Viewing Patterns by Skip Type

	10-Second Skip Only (N=603)	Scrubbing Only (N=141)	Both (N=167)	No Skips (N=1,569)	Statistic
Abandonment Rate	66.17% (N=399)	73.04% (N=103)	71.86% (N=120)	63.48% (N=996)	χ^2=9.389, $\boldsymbol{p = 0.025}$*
Dwell Time	M=62.08 (SD=40.68) Median=57.81	M=45.50 (SD=63.98) Median=17.17	M=53.22 (SD=86.88) Median=35.39	M=60.38 (SD=51.71) Median=59.13	H=42.816, $\boldsymbol{p < 0.001}$***
Abandonment Point	M=75.25 (SD=28.88) Median=89.80	M=73.67 (SD=26.98) Median=84.62	M=82.52 (SD=20.87) Median=91.62	M=59.41 (SD=39.71) Median=71.28	H=53.532, $\boldsymbol{p < 0.001}$***
Satisfaction	M=5.40 (SD=1.41) Median=6 335 Self-reports	M=4.45 (SD=1.86) Median=5 62 Self-reports	M=4.98 (SD=1.83) Median=5 92 Self-reports	M=5.03 (SD=1.51) Median=5 569 Self-reports	H=20.036, $\boldsymbol{p < 0.001}$***

Note: Dwell Time and Abandonment Point = % of video length; Satisfaction = 1–7 scale.

TABLE 4. Comparison of Viewing Patterns by Skip Direction

	Backward Only (N=92)	Forward Only (N=562)	Both (N=257)	No Skips (N=1,569)	Statistic
Abandonment Rate	42.39% (N=39)	73.67% (N=414)	65.76% (N=169)	63.48% (N=996)	χ^2=40.947, $\boldsymbol{p < 0.001}$***
Dwell Time	M=125.14 (SD=110.71) Median=107.52	M=44.69 (SD=33.88) Median=39.39	M=62.69 (SD=47.55) Median=56.53	M=60.38 (SD=51.71) Median=59.13	H=151.272, $\boldsymbol{p < 0.001}$***
Abandonment Point	M=82.41 (SD=27.55) Median=96.76	M=73.41 (SD=28.27) Median=84.80	M=80.56 (SD=24.54) Median=93.25	M=59.41 (SD=39.71) Median=71.28	H=64.184, $\boldsymbol{p < 0.001}$***
Satisfaction	M=5.97 (SD=1.38) Median=7 36 Self-reports	M=4.99 (SD=1.60) Median=5 325 Self-reports	M=5.52 (SD=1.50) Median=6 128 Self-reports	M=5.03 (SD=1.51) Median=5 569 Self-reports	H=26.344, $\boldsymbol{p < 0.001}$***

Note: Dwell Time and Abandonment Point = % of video length; Satisfaction = 1–7 scale.

between No Skip (M = 5.03) and 10-Second Skip Only (M = 5.40) were statistically significant.

3) Comparison of Viewing Patterns by Skip Direction

To compare the viewing patterns among different skip directions, we considered four groups: (1) Backward Only, (2) Forward Only, (3) Both (backward and forward skips), and (4) No Skips. There were 92 instances in the Backward Only group (39 abandoned, 53 not abandoned), 562 instances in the Forward Only group (414 abandoned, 148 not abandoned), 257 instances in the Both group (169 abandoned, 88 not abandoned), and 1,569 instances in the No Skips group (996 abandoned, 573 not abandoned). The result of the analysis are represented in Table 4.

Abandonment Rate: Ordered from the lowest to highest abandonment rate, the groups were Backward Only (42.39%), No Skips (63.48%), both skips (65.76%), and Forward Only (73.67%). A chi-square test revealed a significant difference among the groups (χ^2 = 40.947, $p < 0.001$, df = 3). Post-hoc analysis using Bonferroni multiple comparison correction indicated that the comparisons between Forward Only (M = 73.67%) and Both (M = 65.76%), and between Both (M = 65.76%) and No Skips (M = 63.48%) were not statistically significant. All other comparisons reached statistical significance.

Dwell Time: When ranked from the lowest to highest mean dwell time, the groups were: Forward Only (M = 44.69, SD = 33.88), No Skips (M = 60.38, SD = 51.71), Both (M = 62.69, SD = 47.55), and Backward Only (M = 125.14, SD = 110.71). A Shapiro-Wilk test indicated that all four groups deviated from normality, prompting a Kruskal-Wallis test. The results were statistically significant (H = 151.272, $p < 0.001$). Post-hoc analysis revealed that all comparisons were statistically significant, except for the one between Both (M = 62.69) and No Skips (M = 60.38).

Abandonment Point: Ordered from the lowest to highest mean abandonment point, the groups were: No Skips (M = 59.41, SD = 39.71), Forward Only (M = 73.41, SD = 28.27), Both (M = 80.56, SD = 24.54), and Backward Only (M = 82.41, SD = 27.55). As a Shapiro-Wilk test indicated non-normality in all groups, we conducted a Kruskal-Wallis test, which showed a statistically significant difference (H = 64.184, $p < 0.001$). Post-hoc analysis showed that all comparisons were statistically significant, except for the one between Both (M = 80.56) and Backward Only (M = 82.41).

Satisfaction: Ranked from the lowest to highest mean satisfaction, the groups were: Forward Only (M = 4.99, SD = 1.60), No Skips (M = 5.03, SD = 1.51), Both (M = 5.52, SD = 1.50), and Backward Only (M = 5.97, SD = 1.38). A Shapiro-Wilk test again showed that all groups departed from normality; therefore, we ran a Kruskal-Wallis test, which indicated a statistically significant difference (H = 26.344, $p < 0.001$). Post-hoc analysis revealed statistically significant differences between Both (M = 5.52) and No Skips (M = 5.03), Backward Only (M = 5.97) and No Skips (M = 5.03), Both (M = 5.52) and Forward Only (M = 4.99), and Backward Only (M = 5.97) and Forward Only (M = 4.99).

4) Motivation to Skip Behaviors

From our observations, we found that when viewers used skipping features during video playback, they tended to exit the video more quickly and frequently, especially when scrubbing through the progress bar at the bottom of the screen. Considering the direction of the skip, we observed that skipping backward (to rewatch a segment) was associated with a lower exit rate and higher satisfaction than skipping forward (to jump ahead in the video). To gain deeper insight into this phenomenon, we analyzed the post-interview data.

When asked why they used skip features, the most common responses were: (1) to find a specific scene of interest (N=21) and (2) to skip scenes they did not want to watch (N=15). If the participants were interested in a particular moment in the video, they used on-screen taps or dragged the progress bar to locate the scene. For example, one participant (P5) mentioned,

"When I watch idol videos, there is a specific part I really like, so I skip a lot to find it. Once I find it, I watch it and then just leave."

Another participant (P4) explained,

"I needed to buy shampoo, so I only watched the parts where the product appeared."

Participants also mentioned using skipping features to avoid ads or uninteresting segments, such as when they encountered boring or irrelevant content. For example, one participant (P5) stated,

"When there's a product placement (PPL), I skip it because I am not actually going to buy that product. It's not relevant to me."

Another participant (P12) stated,

"This video shows the process of cooking, but for example, once the chopping starts, you do not really need to watch the entire chopping process."

Additional reasons for skipping included quickly obtaining an overview of the entire video and skipping parts they already knew or had seen before.

Participants reported choosing between tapping the screen to skip or scrubbing the progress bar depending on how far they wanted to jump. If the current scene was boring or not what they were looking for, they would use a 10-second skip to jump ahead slightly. If they wanted to move to an entirely different section of the video, however, they would drag the progress bar. For instance, one participant (P15) explained,

"I use small skips when I predict that the desired scene is not too far away—like when there is a brief scene transition or someone says something uninteresting."

Another participant (P6) mentioned,

"If I use the progress bar to move too far, I end up missing a lot of the content, so I prefer using the 10-second skip by double tapping the screen."

On the other hand, the participants recognized that using the progress bar allowed them to locate the desired information more quickly over larger intervals. One participant (P24) said,

"When I want to get to the main point of the video quickly or just see what's mentioned in the title or thumbnail, I use the progress bar to skip. Skipping 10 seconds at a time doesn't feel fast enough to reach the part I want."

Other motivations for using the progress bar included checking the 'most-viewed' segments (as indicated by the playback graph on some platforms) and skimming the video by previewing thumbnails that appear when scrubbing through the progress bar.

Among the 2,480 data points, 349 involved at least one instance of a backward skip (233 used screen touch, 86 used the progress bar to move back, and 30 used both). A total of twenty-four participants used the backward skip feature. We asked them to explain why they chose to skip backward. The most common reasons were: (1) revisiting missed information (N=19) and (2) rewatching entertaining segments (N=10). Some participants mentioned that they were distracted or had to briefly step away during video playback and thus missed portions of the video. P14 said,

"Sometimes I leave the video running while I do something else like taking out the trash. When I come back, I rewind."

Another participant (P5) noted,

"Occasionally, if the video is boring, I lose focus and then realize I missed something, so I rewind to see what happened."

Others used backward skipping to rewatch enjoyable or funny moments. P5 and P13 said,

"Usually, if it's funny, I just watch it again. Sometimes, if there is a funny scene, I record it and send it to my friends. I also kept going back to catch the exact timing for the recording."

"When I'm reading comments while watching a video and I see someone saying, 'This part is hilarious', I sometimes rewind and watch that part again."

In addition, there were cases where participants skipped back to rewatch portions that they did not understand.

B. PLAYBACK SPEED ADJUSTMENTS AND VIEWING PATTERNS

1) Comparison of Viewing Patterns by Playback Speed Adjustments

Among the 25 participants, 17 used playback speed adjustments at least once during the field study. However, only 11 of these 17 used the feature regularly, whereas the remaining 6 employed it fewer than five times. Therefore, for analyses related to playback speed, we used only data from those 11 participants. The 11 speed-adjusting participants contributed 1,542 data points, comprising 542 vidos viewed with speed adjustments and 1,000 videos viewed without any speed changes. We identified four distinct types of speed adjustment: (1) starting the video at a sped-up rate (110 instances), (2) beginning at normal speed and switching to a faster rate mid-view (108), (3) starting at a faster rate and switching back to normal speed (3), and (4) changing the playback speed multiple times (321). Given the limited instances in some categories, we decided to compare only the presence or absence of speed adjustments (i.e., whether at least one speed change was made) to examine their potential impact on viewing behavior. Among the 542 sped-up videos, 320 were abandoned before the outro, and 222 were fully watched. Among the 1,000 videos viewed without any speed adjustments, 667 were abandoned, and 333 were completed. The results of the analysis are presented in Table 5.

Abandonment Rate: The abandonment rate was 59.04% when participants used speed adjustments at least once, compared to 66.70% without any speed adjustments. A chi-square test confirmed that the difference was statistically significant (χ^2 = 8.622, p = 0.003, dof = 1). This finding suggests that individuals who generally use faster playback are more likely to abandon the video when watching at normal speeds.

Dwell Time: When speed adjustments were used at least once, the mean dwell time was 53.30 (SD = 33.73). Without speed adjustments, the mean dwell time was 60.17 (SD = 65.38). A Shapiro-Wilk test indicated that both groups deviated from normality; therefore, a Mann-Whitney U test was performed. The difference was not statistically significant (U = 0.167, p = 0.685).

Abandonment Point: When speed adjustments were used at least once, the abandonment point was (M = 74.75, SD = 31.40), whereas without adjustments it was (M = 59.45, SD = 39.28). A Shapiro-Wilk test again showed deviations from normality for both groups, leading to a Mann-Whitney U test, which revealed a statistically significant difference (U = 43.526, $p < 0.001$). This suggests that individuals who normally use faster playback abandon videos later when they choose to watch at an adjusted speed.

Satisfaction: When speed adjustments were used, satisfaction was (M = 5.30, SD = 1.61). Without adjustments, satisfaction was (M = 4.87, SD = 1.45). A Shapiro-Wilk test showed that both groups were non-normal, prompting a Mann-Whitney U test. The difference in satisfaction level was statistically significant (U = 14.075, $p < 0.001$). Given that the overall satisfaction distribution skewed higher when using a faster playback, it can be inferred that viewing at an adjusted speed tends to yield greater satisfaction.

2) Motivation to Adjust Playback Speed

We observed that viewers who adjust playback speed may differ in both their likelihood of exiting a video early and their overall satisfaction compared to those who do not use this feature. To gain a deeper understanding of why participants chose to adjust playback speed, we asked those who had done so to explain their motivations during the post-study interviews.

The primary reason participants cited for adjusting playback speed was their desire to watch videos more quickly (N=7). Although skipping certain parts could also help shorten the viewing time, participants felt that skipping caused them to miss important scenes. By increasing the playback speed to a level that they could still comprehend, they believed they could watch the entire video without losing critical information. For example, P3 stated,

"Because it's an idol group I support, I did not want to skip anything and risk missing a member's appearance. So, I sped up the playback instead."

Another common reason was that the speaker in the video was talking too slowly, prompting participants to watch at

TABLE 5. Comparison of Viewing Patterns by Playback Speed Adjustment Usage

	Adjusted (N=542)	Non-adjusted (N=1,000)	Statistic
Abandonment Rate	59.04% (N=320)	66.70% (N=667)	χ^2=8.622, **$p = 0.003$****
Dwell Time	M=53.30 (SD=33.73), Median=53.50	M=60.17 (SD=65.38), Median=46.26	U=0.165, $p = 0.685$
Abandonment Point	M=74.75 (SD=31.40), Median=92.26	M=59.45 (SD=39.28), Median=71.44	U=43.526, **$p < 0.001$*****
Satisfaction	M=5.30 (SD=1.61) Median=6 210 Self-reports	M=4.87 (SD=1.45) Median=5 318 Self-reports	U=14.075, **$p < 0.001$*****

Note: Dwell Time and Abandonment Point = % of video length; Satisfaction = 1–7 scale.

TABLE 6. Reasons for Video Abandonment

	Definition	Statistic
Video Ended (N=127)	The viewer actually reached or perceived they had reached the end of the video due to signals such as an outro or closing remarks. (e.g., I thought I finished watching the video because the end credits appeared.)	M=6.37 (SD=0.86), Median=7
Desire Satisfied (N=316)	The viewer had a certain purpose or goal in mind, and once it was fulfilled, they left. (e.g., Watched a home-care video for skincare and left the video after obtaining the key information.)	M=5.88 (SD=1.07), Median=6
Wanted to Watch Something Else (N=90)	The viewer left to watch another video or different content, often with a similar goal or to explore a different topic. (e.g., Because I wanted to watch another video with the same purpose)	M=5.39 (SD=1.22), Median=5.5
Already Knew the Content (N=37)	The viewer realized during playback that they already knew the content or had seen similar content before, so they stopped watching. (e.g., I often watch baseball videos, but left when I realized this video was one I had already seen.)	M=4.84 (SD=1.50), Median=5
Undesired Content (N=73)	The viewer found the content unappealing, irrelevant, or unpleasant, leading them to exit. (e.g., I clicked on it thinking it was a Mukbang, but it hardly showed the actual eating and was mostly about daily life, so I left.)	M=4.08 (SD=1.82), Median=4
Decreased Interest (N=204)	The viewer lost interest or found the content less engaging than anticipated. (e.g., I wanted to travel to Japan and happened to see a newly uploaded video about it, so I started watching. However, it turned out to be less entertaining than I expected, so I left)	M=4.08 (SD=1.36), Median=4
Goal Not Achieved (N=83)	The viewer had a goal or expectation that the video did not meet, causing them to leave. (e.g., I watched a video to get tips on controlling my appetite during a diet, but it kept stating obvious points so I left the video.)	M=3.65 (SD=1.19), Median=4
Others (N=128)	In some cases, there was no clear reason for leaving, the video was too long, or external factors intervened. Some viewers also intended to finish watching later. (e.g., I was watching the video, but my mom called me, so I left the video.)	M=5.01 (SD=1.47), Median=5

1.5× speed. As P17 explained,

"I want to gather all the information from this video, but since normal speed feels too slow, I watch it at 1.5× instead."

However, some participants avoided using playback speed adjustments to preserve the quality or "feel" of the content—especially for music or dance performances. P16 said,

"If I speed up a dance performance, it loses its original vibe, so I prefer normal speed. It's the same as music—speeding it up makes it feel silly."

Additional reasons for not adjusting the playback speed included the video's speaker already talking quickly enough.

We also asked participants who rarely employed playback speed adjustments for their reasons for not doing so. They indicated that increasing playback speed often compromised their understanding of the content. For instance, P15 noted,

"When I speed up the video, I feel like I miss out on some fun parts—they just fly by. So I'd rather watch the interesting segments in their entirety and skip only the boring parts."

Another participant, P9, explained,

"When someone is speaking, speeding it up makes it hard for me to hear what they're saying."

Some also mentioned that the effort required to change speed settings was burdensome, so they simply never used the feature.

C. REASONS FOR VIDEO ABANDONMENT

From the 1,058 self-report responses in which a satisfaction level was selected, we categorized the reasons for video abandonment. For this, two authors manually examined the self-report responses using an affinity diagramming to iteratively develop a coding scheme, *Video Ended*, *Desire Satisfied*, *Already Knew the Content*, *Undesired Content*, *Decreased Interest*, *Goal Not achieved*, and *Others*. To validate and make our definitions of the coding scheme more robust, we used Cohen's Kappa [44]. We first examined 200 responses independently, and the consensus reached Cohen's kappa of 0.776. After reviewing all discord responses, we discussed together and built a concrete definition of the coding schemes. For the second round of the next 200 responses, our consensus reached Cohen's kappa 0.883, which is very high for multiple categorizations. Then, we divide *Others* into *Wanted to Watch Something Else* and *Goal Not Achieved*. After reviewing all the discord responses and reaching a consensus, we proceeded to the third round with the remaining 253 responses and our consensus reached Cohen's kappa 0.643. Finally, we examined the remaining 425 responses from the second field study, reaching a Cohen's kappa of 0.700. These kappa statistic values suggest that our consensus was substantial (above 0.60) or almost perfect (above 0.80) [45], especially given the complexity of multiple categorizations. After resolving all disagreements, we finalized eight themes in total. Table 6 presents these themes, their definitions, and the corresponding satisfaction levels.

When the users left video watching because the *Video Ended*, their level of satisfaction was highest. This is clear because they almost completed the video watching although they left before the actual end. The second highest reason to leave the video was their *Desire Satisfied*. Even though they left the video mid-way, this does not mean that it is a negative experience because they were satisfied with watching the video. When users left videos because they realized that the video was not what they expected, *Undesired Content*, the interest decreased, *Decreased Interest*, or they could not achieve the goal from the video, *Goal not Achieved*, the level of satisfaction was relatively low.

We conducted a statistical analysis to compare the level of satisfaction difference among the schemes, except for the *Others*. According to the Shapiro-Wilk test, none of the schemes met the assumption of normality. Consequently, the Kruskal-Wallis test was performed and was statistically significant ($H = 385.678$, $p < 0.001$). Post-hoc analysis revealed that 15 out of the 21 pairwise comparisons showed statistically significant differences. Fig. 3 shows the result of the statistical analysis using the Compact Letter Display [46], which is a statistical method to clarify the output of multiple hypothesis testing. It is a method that uses letters to indicate whether different groups are statistically distinct in an easy-to-read format. Each group is assigned one or more letters, and if two groups share a letter, it means they are not significantly different. For example, *Wanted to Watch Something Else* is 'ac' and *Already Knew the Content* is 'ae'. Then, the letter 'a' is shared, meaning that they are not significantly different. On the other hand, *Undesired Content* is 'de', so no letter is shared with *Desire Satisfied*, meaning that they are significantly different.

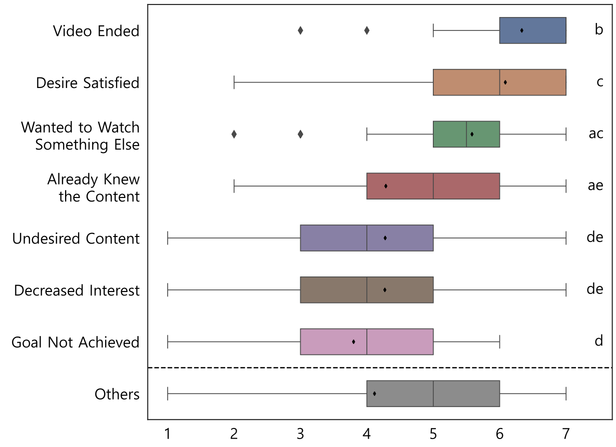

FIGURE 3. Reasons for Video Abandonment

D. INCORPORATING CONTENT TYPES ALONGSIDE USER INTERACTIONS

We found that skipping behaviors and playback speed adjustments correlate with user engagement, and that satisfaction levels vary based on users' reasons for abandoning videos. However, these findings may overlook additional factors, such as video category, view counts, thumbnails, or likes, because we did not control for them in our real-world field study. Consequently, our results risk being overly generalized if these considerations are ignored. To address this gap, we specifically examined how video categories relate to viewing behaviors (e.g., skipping and playback speed adjustments), as categories provide a broad, conceptual grouping of videos. This approach lets us explore systematic differences in user interactions without expanding the scope to every possible content variable.

1) Video Categorization and Data Distribution

We used the YouTube API[3] to categorize the collected videos from our viewing data. The top three categories—*People & Blogs* (N=596), *Entertainment* (N=485), and *Gaming* (N=307)—comprised 56.2% of the dataset. Expanding to the top six categories added *Comedy* (N=191), *Sport* (N=178), and *Music* (N=163), covering 77.8% of the dataset. Remaining categories (e.g., *Howto & Style*, *News & Politics*, *Film & Animation*) had smaller sample sizes. Because these remaining categories were underrepresented, we restricted our statistical analyses to the top six to investigate how they may influence user interactions. For instance, *Music* videos could exhibit distinctive interaction patterns, as users often listen passively rather than actively searching for highlights.

[3]https://developers.google.com/youtube/v3/getting-started

2) Skipping Behaviors and Playback Speed by Category

Next, we conducted statistical analyses to compare interaction usage rates for skipping behaviors (*10-Second Skip Only* vs. *Scrubbing Only*) across the top six categories. We found that most significant differences involved the Music and Gaming categories. For example, *10-Second Skip Only* was highest in Gaming and lowest in Music (Music < Sport; $p=0.002$, Music < Gaming; $p<0.001$, Gaming > Entertainment; $p=0.03$, Gaming > People & Blogs; $p=0.001$, Gaming > Comedy; $p=0.011$). By contrast, *Scrubbing Only* showed no significant differences, possibly due to its low overall usage. This pattern may reflect more passive listening in *Music* (e.g., during work) versus active searching for game highlights in Gaming. However, the Music category had a relatively small sample size, limiting generalizability—many participants mentioned they often use dedicated music apps (e.g., Spotify, YouTube Music) rather than YouTube.

We also examined skipping directions (forward vs. backward) across categories. Music had the lowest *Forward Only* usage, while Entertainment showed the highest. Significant differences were found in (Music > Entertainment; $p<0.001$, Music < Gaming; $p=0.008$, Music < Sports; $p=0.014$). Although backward skips were more common in Gaming, the overall number of backward skips was too small to yield significant results. For *Playback Speed Adjustments*, usage in Music was significantly lower than in all other categories.

3) User Engagement Across Categories

Finally, we analyzed user engagement metrics—abandonment rate, dwell time, abandonment point, and satisfaction—across these six categories. Only a few significant differences emerged in abandonment rate (People & Blogs > Comedy; $p=0.003$, Entertainment > Comedy; $p<0.001$, Entertainment > Sport; $p=0.046$), dwell time (Music > People & Blogs; $p=0.001$, Music > Entertainment; $p=0.008$, People & Blogs < Comedy; $p=0.002$), and abandonment point (Comedy > People & Blogs; $p=0.03$, Comedy > Entertainment; $p=0.037$), while no significant differences appeared in satisfaction. This indicates that although video categories may affect certain engagement metrics, they alone do not substantially predict user engagement—particularly satisfaction. Nonetheless, incorporating user interactions alongside categories could yield deeper insights. For instance, in Music videos, interactions already occur infrequently, so any observed interaction could hold greater weight in understanding user engagement.

V. DISCUSSION

A. BREAKING DOWN SKIPPING INTO TYPES AND DIRECTIONS

In our study, we collected users' playback interaction logs (e.g., skipping, playback speed adjustments) and video-watching logs (e.g., video abandonment and dwell time) in a field setting, then examined how these logs relate to user behavior, with a particular focus on video-seeking patterns.

We first identified significant differences in the video abandonment rate, abandonment position, and dwell time, depending on whether users skipped or not, regardless of skip type or direction. This suggests that users often engage in skipping interactions shortly before leaving the video. However, it is unsurprising that the abandonment position and dwell time vary depending on whether users actually abandon the video. Our finding is consistent with prior work [25], which indicates that seeking behaviors correlate with video abandonment. We then refined our analysis by separating skips into two types: a 10-second skip triggered by double-tapping the screen, and "scrubbing" by dragging or clicking on the progress bar.

Previous research on skipping behaviors [5], [22], [24] has largely focused on the act of skipping itself, rather than on different skip types. Scrubbing is generally more efficient for jumping to far positions than a 10-second skip. From our post-interviews, we found that 10-second skips are used to reach adjacent scenes without missing too much content, or to search incrementally for interesting parts. In contrast, scrubbing is more commonly employed to bypass large portions of a video, suggesting disinterest in intervening segments [47]. This distinction helps explain why our data show that dwell times were significantly shorter in scrubbing only instances, compared to those involving 10-second skipping or no skipping.

To deepen our understanding of skip behaviors, we also examined skip direction—backward vs. forward—regardless of whether users employed a 10-second skip or scrubbing. Backward skipping represents a highly active interaction because videos ordinarily play forward without user input. According to our post-interviews, backward skips often occur when users want to rewatch missed or intriguing scenes, indicating that these segments are sufficiently engaging to revisit. Consequently, backward skips may signal stronger engagement and intent to complete the video. In fact, our analysis revealed that the abandonment rate for *Backward-Only* skips was significantly lower than for the other skip types.

In contrast, forward skipping was positively associated with higher abandonment (73.67%) than no skipping (63.48%), and abandonment typically occurred later in the video (73.41% vs. 59.41%). This suggests that forward skipping may signal a user's desire for more engaging or relevant content, indicating a degree of dissatisfaction with the current portion of the video.

B. ACCELERATING OR ABANDONING IN VIDEO PLAYBACK

Interestingly, of the 25 participants in our field study, only eleven regularly adjusted playback speeds, whereas six did so only less than five times. Eight of our participants never used speed adjustments, despite being informed of their availability. Those who adopted speed adjustments preferred accelerating playback over skipping, to avoid missing potentially important or interesting segments.

Although our sample size for those who regularly adjusted playback speed was small (N=11), our findings indicate that videos viewed with speed adjustments (specifically faster playback) had a lower abandonment rate. This suggests that playback speed adjustment may serve as a strong indicator of heightened interest in ongoing content. Accordingly, incorporating speed-adjustment behavior into recommendation algorithms could help identify highly engaged viewers and offer more relevant suggestions (e.g., recommending related videos during the outro), or assign greater weight to videos of similar types as the current one for future recommendations.

Moreover, none of our participants chose a speed slower than 1.0×. Although reduced playback speed can be helpful in certain contexts (e.g., language learning [48], [49]), it appears less pertinent to general-purpose video platforms like YouTube. While many services offer increments for both faster and slower speeds (e.g., 0.5×, 0.75×, 1.0×, 1.25×, 1.5×), actual usage patterns may favor particular speeds over others. Consequently, identifying the most frequently used playback increments—such as 1.0×, 1.25×, 1.5×, and 1.75×—could refine the user experience for different platforms.

C. LEAVING SATISFIED: RETHINKING ABANDONMENT

Our analysis indicates that certain user interactions are correlated with satisfaction. For example, we observed significantly lower satisfaction when scrubbing was used (M = 4.45) compared with 10-second skipping (M = 5.40). Post-interview data suggest that scrubbing can be used to find more interesting scenes farther ahead. We also found that backward-only skipping (M = 5.97) was strongly correlated with higher satisfaction, whereas forward skipping (M = 4.99) and no skipping (M = 5.03) showed lower satisfaction. Such differences can be leveraged by recommendation algorithms in online video streaming services. For example, if a user scrubs to locate more engaging content, the platform may reduce the weight of the skipped portion in future recommendations. Conversely, if users skip backward, the system can infer a strong interest in rewound content and prioritize similar materials.

However, factors beyond user interaction also affect video abandonment. For example, psychological elements, such as a user's underlying motives and mental states, may be intrinsically linked to viewing behaviors. If users perceive that a video meets or surpasses their initial goals (e.g., gaining knowledge or being entertained), their overall satisfaction tends to rise [50], [51]. Satisfied users are more likely to continue consuming media over time, as satisfaction can be interpreted as a desired consumption outcome [52], and "over-gratification" has been linked to longer session durations [53].

By understanding these nuanced psychological and motivational dimensions, we can reframe abandonment not only as a negative outcome, but also as a possible sign of successful goal completion, even though many studies treat abandonment as a proxy for user dissatisfaction [3], [54]–[56]. Indeed, our results indicate that users sometimes leave a video despite feeling satisfied. Participants reported satisfaction scores of 6.33 (out of 7) when the *video ended* and 5.71 when their *desires were satisfied*, meaning they fulfilled their objectives before the video officially concluded (e.g., skipping a creator's closing remarks). Exiting a video, therefore, does not necessarily equate to dissatisfaction; rather, the user's departure time can represent a personal "completion" point. For this reason, platforms should be mindful when designing recommendation algorithms, ensuring that user abandonment is not automatically treated as a negative indicator [57], [58].

D. UNDERSTANDING USER ENGAGEMENT THROUGH MID-VIEWING BEHAVIORS: A U&G PERSPECTIVE

Many researchers studying media use have drawn on the Uses and Gratifications (U&G) theory to investigate why and how people engage with various forms of media [57], [59]. In particular, modern online media platforms such as YouTube and Netflix offer more complex interfaces than traditional television or film, allowing users to actively interact with video content through searching, selecting, and controlling playback. Moreover, these platforms are now accessible on mobile devices (e.g., smartphones), enabling more flexible usage. This expanded ecosystem fosters broader, more interactive engagement with content, granting users new ways to interact, such as skipping or adjusting playback speed. Consequently, there is a growing need to apply U&G theory to interpret these interactive behaviors in light of evolving online video streaming platforms [60], [61].

In much prior research on online video streaming platforms using U&G theory, user activity is typically analyzed across pre-viewing (video selection), during-viewing (interaction), and post-viewing (outcomes) stages. A number of these studies have explored why users choose certain videos on streaming platforms [31], [34]–[36]. In addition, prior work has investigated various factors that may influence user engagement, such as video category, view counts, comment counts, likes, channel popularity, and thumbnails [12]–[14], [33]. During viewing, users often skip forward if they feel bored or want a more satisfying scene, and rewind to revisit interesting moments [4], [39], [40], [62]. After watching a video, users may post comments, like, or search for another video if their needs are not fully met [34], [63].

Our study focuses on the during-viewing stage, examining users' playback interactions (e.g., skipping, speed adjustments). These behaviors reflect real-time user engagement because they are intentional responses driven by the user's current involvement. For instance, a backward skip may indicate heightened interest in a particular scene. Analyzing engagement through these interactions could be improved by considering pre-viewing factors such as video content. Indeed, we observed fewer skipping or speed adjustments for music videos, suggesting that video characteristics (e.g., category) combined with these interactions can effectively signal real-time engagement. If a user actively interacts with music content, this might reveal a different engagement pattern compared to other video categories.

Additionally, user characteristics also influence engagement [12], [35]. In our study, participants who regularly used playback speed adjustments exhibited distinct interaction and engagement patterns. For instance, using higher playback speeds often correlated with higher satisfaction and lower abandonment rates, meaning that users preference for playback speed with their playback interactions can be used together for infering user engagement.

Thus, a variety of factors can shape or correlate with user engagement. In our research, we focused on during-viewing playback interactions because they serve as strong indicators of real-time involvement. While we considered only video categories (a pre-viewing factor) alongside these interactions, other pre-viewing elements (e.g., comments, views, likes) and post-viewing behaviors (e.g., watching related videos) could further enhance the accuracy and utility of these engagement indicators. Incorporating these aspects may lead to a more comprehensive understanding of user engagement and ultimately support better user experiences.

E. LIMITATION AND FUTURE WORK

This study has several limitations. First, our sample comprised individuals in their twenties in South Korea, and the sample size was relatively small (N=25), which may limit generalizability. In particular, only 11 participants regularly used playback speed adjustments, indicating a need for larger samples to fully examine the effects of this feature. In addition, the number of video-viewing instances per participant was not evenly distributed, raising concerns that the results could be biased by individuals who contributed more data. To address this concern, we conducted an additional robustness check using a participant-wise balancing method. Specifically, we identified the participant with the fewest viewing instances (N=28) and applied bootstrapped sampling to randomly select 28 viewing instances from each participant (with replacement), repeating this procedure five times. We then reanalyzed the four key engagement metrics—abandonment rate, dwell time, abandonment point, and satisfaction—for each of the five balanced datasets. The results were highly consistent across all samples. Only three comparisons showed changes in statistical significance—two in abandonment point and one in satisfaction—all within the skip type analysis (scrubbing only vs. no skip). All other results remained stable, suggesting that our findings are generally robust and not substantially affected by imbalances in viewing volume across participants. Future research with a larger and more diverse participant pool (e.g., different age groups and occupations) will help enhance the generalizability and depth of user engagement insights.

Second, Our findings may have been influenced by various external factors, such as emergencies, network latency, and video buffering, because we conducted a field study. Participants may abandon a video due to an unforeseen situation, rather than dissatisfaction with the content. An in-lab environment would have more effectively controlled these potential confounds; however, we chose a field approach to allow participants to watch any video they preferred and interact naturally, thereby capturing more authentic viewing patterns and self-reports [4], [64]–[66]. Furthermore, by collecting a relatively large dataset in this real-world setting, we believe any sporadic emergency situations had a limited impact on our overall findings.

With regard to Quality of Service (QoS), South Korea benefits from a highly developed internet infrastructure, including fast and stable mobile (5G) and Wi-Fi networks. For example, in 2024, South Korea ranked highest in Asia for its 5G video experience, indicating that users were generally able to stream 1080p or higher video with fast loading times and minimal stalling [30]. In addition, South Korea placed fourth worldwide in median internet download speed [28] and sixth in Ookla's Speedtest Global Index for mobile performance, which ranks countries by median download speeds [29]. We therefore believe that QoS-related impacts were at least partially mitigated in our study.

Next, we used a custom mobile web wrapper rather than the official YouTube app because of data collection constraints. The official YouTube app allows users to minimize a current video while searching for other content; in our setup, users had to exit the video entirely when they sought new content, potentially diverging from real-world scenarios. In addition, YouTube native app has recently updated its playback speed adjustment interface to include more granular playback speed controls, which were not captured in our study.

Future work should consider collecting more data on users' interactive behavior. For example, users may jump to the specific timestamps mentioned in the video description or comments—actions we did not track. Similarly, gathering more information on video categories, user comments, likes, mobile sensor data (e.g., accelerometer, screen orientation) [25], and video quality [10], [67] could enrich our understanding of mobile video engagement and satisfaction. For instance, analyzing sudden changes in screen orientation could reveal additional nuances in skip or abandonment behaviors, offering deeper insights into user preferences and the overall QoE.

VI. CONCLUSION

In this study, we examined how mobile video interactions—specifically skipping (including its types and directions) and playback speed adjustments—are associated with user engagement, such as video abandonment and satisfaction. Across a 10-day field study with 25 participants, our findings revealed that skip mechanisms (e.g., 10-second skips vs. scrubbing) and directions (backward vs. forward) show strong associations with engagement. Notably, some instances of video abandonment reflected fulfilled viewing goals rather than dissatisfaction, and frequent playback speed adjustments appeared to signal deeper engagement. These insights underscore the importance of refining online video interfaces and incorporating video content characteristics into online video streaming platforms.

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