FoodCensor: Promoting Mindful Digital Food Content Consumption for People with Eating Disorders

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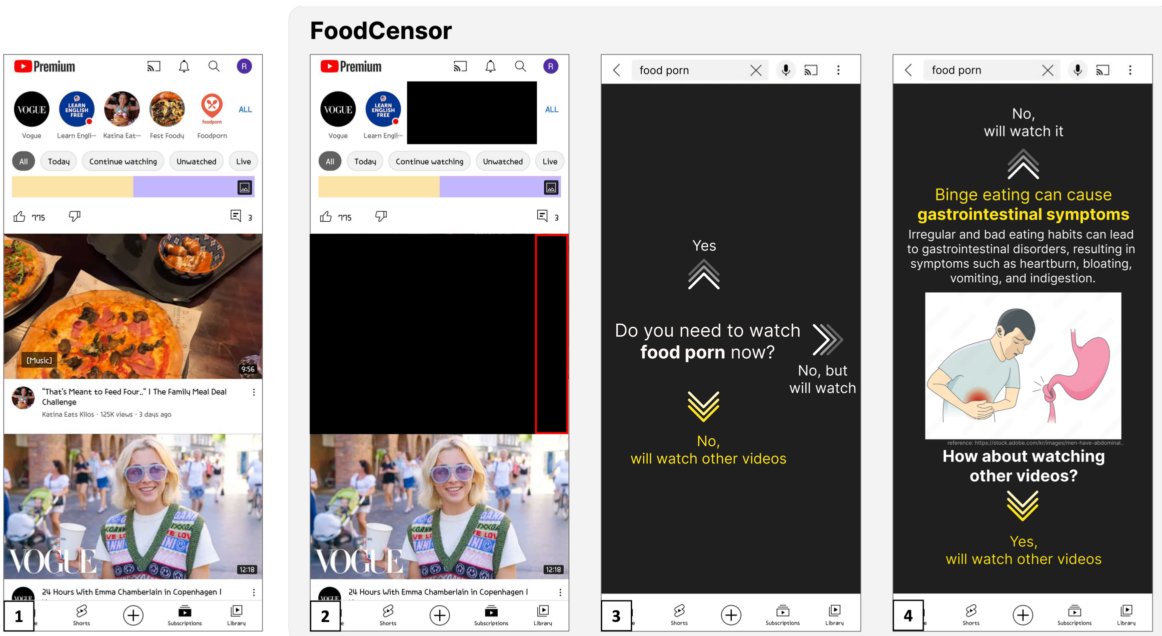

Figure 1: Snapshots of YouTube Subscriptions page including food content without (1) and with *FoodCensor* (2). *FoodCensor* hides channel thumbnails and video previews showing food content. The red vertical box in (2) is touchable for users' scrolling convenience but other parts of the screen are untouchable. Snapshots of *FoodCensor*'s interventions, prompt reflective question (3) and pictorial warning of negative consequence (4), triggered by a food-related search query (i.e., food porn) on YouTube Search page.

ABSTRACT

Digital food content's popularity is underscored by recent studies revealing its addictive nature and association with disordered eating. Notably, individuals with eating disorders exhibit a positive correlation between their digital food content consumption and disordered eating behaviors. Based on these findings, we introduce *FoodCensor*, an intervention designed to empower individuals with eating disorders to make informed, conscious, and health-oriented digital food content consumption decisions. *FoodCensor* (i) monitors and hides passively exposed food content on smartphones and personal computers, and (ii) prompts reflective questions for users when they spontaneously search for food content. We deployed *FoodCensor* to people with binge eating disorder or bulimia (n=22) for three weeks. Our user study reveals that *FoodCensor* fostered self-awareness and self-reflection about unconscious digital food content consumption habits, enabling them to adopt healthier behaviors consciously. Furthermore, we discuss design implications for promoting healthier digital content consumption practices for vulnerable populations to specific content types.

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CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**; **Interactive systems and tools**; **Field studies**.

KEYWORDS

food content, eating disorder, intervention, bulimia, binge eating disorder

1 INTRODUCTION

Caution: *This paper addresses eating disorders and contains content that might serve as a trigger for individuals managing such conditions. Please use discretion when reading this paper.*

In today's digital age, the pervasive influence of various forms of digital content has led to growing concerns about their impact on health. Particularly, the relationship between viewing certain digital content (e.g., promoting eating disorders and thinspiration content) and eating disorders has garnered attention [66, 94]. Among the various digital content, *food content*, such as cooking demonstrations, restaurant reviews, and eating broadcasts, have raised alarms due to their potential contribution to problematic eating habits and dietary health [51, 77, 80, 83, 85, 111].

Research has underscored that various digital food content holds the potential to elicit addictive behaviors, with their visually enticing presentations, immersive experiences, and auditory stimuli contributing to the triggering of cravings and the reinforcement of unhealthy eating patterns [53, 88, 114]. In addition, watching food images and videos has been repeatedly associated with unhealthy food choices [8, 82], overeating [9, 35], and inadequate eating habits [88, 114] through various visual and social factors [97]. Of particular concern is the heightened susceptibility of individuals with disordered eating behaviors (e.g., binge eating and purging) to the addictive qualities of these digital food content [41, 58]. The popularity and prevalence of digital food content may amplify their potential to exacerbate these individuals' challenges.

One of the primary challenges that individuals with eating disorders already face is the constant struggle against the allure of unhealthy eating behaviors. These individuals are particularly vulnerable to the captivating qualities of food-related media, which can intensify their cravings and reinforce harmful patterns [41, 112]. The ready availability of such media, combined with the immersive sensory experience they provide, may add a layer of complexity to the existing battle these individuals wage against their disorders.

In the face of these concerns, there has been a noticeable absence of adequate support to mitigate the detrimental effects of digital food content on individuals with eating disorders. Consequently, we introduce a just-in-time intervention, *FoodCensor*, which provides pivotal support, enabling them to consume digital food content more thoughtfully and to promote healthier food content consumption behavior on personal devices (i.e., smartphones and personal computers). Drawing inspiration from the Dual Systems Theory [64], which posits two distinct cognitive decision-making systems—System 1, involving fast and automatic responses, and System 2, encompassing slower and more reflective thinking—we aim to harness these cognitive mechanisms to address the challenges posed by digital food content (Figure 2).

FoodCensor endeavors to sever the potential connection between visual and auditory cues in digital food content and disordered eating practices. By hiding content thumbnails with covers and muting auto-played content (Figure 1 (2)), *FoodCensor* introduces a cognitive trigger that encourages users' awareness of their exposure to digital food content and prompts them to actively engage in the process of uncovering hidden content when seeking consumption. This shift marks a transition from the automated response of System 1 control to the conscious evaluation of System 2 (Figure 2 ① and ②). The second facet of the intervention encourages users to pause and reconsider their choice when searching for food-related content (Figure 1 (3) and (4)), fostering a moment of reflection, signaling the expected value of control and steering their focus toward healthier alternatives (Figure 2 ③).

We performed a three-week between- and within-subjects field study (n=22) in South Korea to understand the effect of *FoodCensor* on people with binge eating disorder (BED) or bulimia nervosa (BN).[1] The control group (n=13) was given a version of *FoodCensor* that only tracks food content. For the experimental group (n=9), *FoodCensor* monitored exposure to food content for the first week and intervened for the rest of the two weeks by hiding the food content and intervening with users when searching for food content.

In the experimental group, *FoodCensor* significantly reduced exposure to food content on YouTube by censoring them and implicitly tuning YouTube's content suggestion algorithm. Conversely, in the control group, there was no reduction; instead, exposure to food content increased. Notably, experimental group participants stated that *FoodCensor* played a crucial role in interrupting their automatic reactions to click on food-related content, prompting them to become more conscious of their choices, which demonstrates that *FoodCensor* discourages System 1 control and promotes System 2 control of the Dual Systems Theory. Additionally, the intervention's reflective questions and information regarding the expected value of control encouraged conscious evaluation and fostered greater self-awareness of their behaviors, aligning with System 2 control. Experimental group users' subjective feedback further suggests that *FoodCensor* mitigates the obsession with food in daily lives and thus leads to better life quality. From our findings, we articulate future directions for the design of an adaptive intervention that helps users balance their engagement with digital content and self-control. Additionally, we propose user-centric content moderation approaches that foster intentional behavior changes, beyond mere content censorship.

The main contributions of our paper are summarized as follows.

- We developed *FoodCensor*, a digital food content monitoring system for Android devices and the Google Chrome web browser. *FoodCensor* monitors food content by reading UI components without directly manipulating targeting services. To the best of our knowledge, *FoodCensor* is the first attempt to track content users consume or encounter in *real-time* at the *content level*, from *user's side*, not the platform's

[1]Binge eating disorder is characterized by recurrent episodes of excessive eating in a short timeframe (e.g., 2 hours) and feeling a loss of control over their eating behavior [25]. Bulimia nervosa involves a cycle of binge eating and compensatory behaviors, such as self-induced vomiting [27].

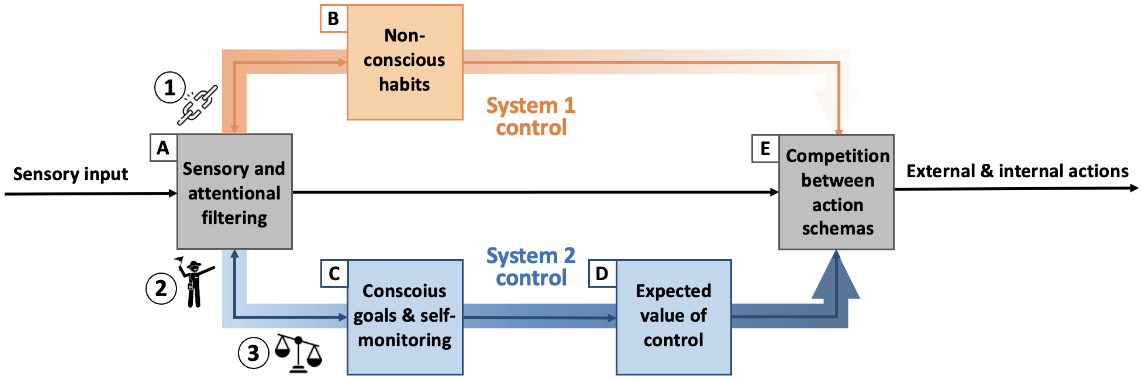

Figure 2: An extended Dual Systems Theory of self-regulation [79, 100]. System 1 control is swift and non-conscious, while System 2 control is slower, conscious, and capacity-limited. *FoodCensor* tries to attenuate the influence of stimulating sensory input by hiding digital food content ①, and to facilitate a shift from System 1's automatic response to System 2's conscious evaluation by prompting users to actively engage in the process of searching for and revealing the hidden content through reflective questions when they want to consume ②. Additionally, *FoodCensor* informs potential consequences of eating disorder behavior to increase the expected value of control ③.

side. Our technology could be leveraged to track and support other types of content consumption.

- Drawing inspiration from the Dual Systems Theory, we designed an intervention system incorporated in *FoodCensor* to sever the potential connection between sensory cues in food-related content and impulsive disordered eating behaviors for people with BED and BN.
- We conducted a three-week field study with people with BED or BN (n=22) and compared *FoodCensor* against a baseline. Our results indicate that *FoodCensor* encourages awareness of potentially problematic habitual behaviors and the benefits of changing such behaviors. This increased awareness, in turn, enables users to make informed choices when consuming digital food content.
- Based on our findings, we share insights into the design of adaptive interventions that support users in managing their interaction with digital content. We also propose user-centric content moderation approaches to enact behavior change beyond mere content censorship.

We believe that *FoodCensor*, when incorporated with medical services, has the potential to improve the ED symptoms of people with BED and BN.

Ethics. Our work aims to reduce the prevalence of triggering online content and its potential harm to people with EDs. Our research extends efforts in social computing research that aim to provide tailored support to marginalized groups (e.g., eating disorders). Many people could benefit from such computer-mediated support. In the meantime, we acknowledge that there could be unexpected conflicting and negative effects from well-intentioned and health-minded design, such as content moderation. We appreciate the insights into the ethics of this type of research [28] and took precautions to conduct this study as ethically as possible. The Institutional Review Board (IRB) approved our study. In addition, we informed study participants that they could exit from the study at any time for any reason, including unpleasant experiences with our system that moderates digital food content.

2 RELATED WORK

The pervasiveness of digital food content in today's digital age has raised significant concerns about its impact on individuals' dietary health and behaviors [8, 51, 80, 83, 85, 105, 111]. This section discusses the addictive nature of digital food content and its implications, highlighting the need for interventions like *FoodCensor* for individuals who are often vulnerable in digital food content interaction.

2.1 Addictive Consumption of Digital Food-related Content

Digital food content, such as recipe tutorials, eating broadcasts, and culinary travel, has become widespread in today's media landscape. These digital food content offer users a source of recreational enjoyment and opportunities for inspiration, culinary exploration, and social engagement [5, 60]. However, beneath the surface lies an inherent addictiveness that has garnered increasing attention in recent years [20, 52].

The visually enticing presentations, immersive experiences, and sensory stimuli associated with digital food content contribute to its widespread popularity [5, 19]. These qualities, while engaging, also pose a potential risk. Research has illuminated the addictive nature of digital food content, linking it to overeating, unhealthy food choices, and inadequate eating habits [53]. According to the compensatory internet use model, individuals utilize online activities to compensate for unmet offline needs, and those who satisfy their needs using a specific online activity can become excessive consumers of that particular activity [48]. From this perspective, watching digital food content expecting gratifications can be transformed into excessive and problematic consumption for some viewers. An empirical study has demonstrated that people who watch eating broadcasts suffer from addiction-like symptoms due to these broadcasts and that the frequency of watching eating broadcasts was correlated with problematic eating broadcast watching [52]. This addiction-like response to digital food content can have profound implications for individuals' eating behaviors, especially those with preexisting disordered eating patterns [53].

2.2 Impact of Digital Food Content Consumption on Disordered Eating

Research has uncovered the potential detrimental effects of digital food content on viewers' dietary health. Various forms of digital food content, such as glamorized food pictures and captivating eating broadcasts, have been positively associated with a range of unhealthy and disordered eating [8, 51, 80, 83, 85, 105, 111]. The visually enticing food displays on social media have been associated with viewers' unhealthy food choices [82, 97] and eating habits [114]. Moreover, food videos disseminated through the media can encourage and stimulate overeating [9, 35, 105]. Besides, increased exposure to eating broadcasts has been associated with a stronger effect on dietary health [47].

The concept of *visual hunger* [103] is explained as "the natural desire, or urge, to see food images and the subsequent array of neural, physiological, and behavioral responses that result from an individual's exposure to food images – typically implying unisensory (visual) stimulation in the absence of any actual food." Remarkably, such visual stimulation substantially impacts individuals with BED and BN [57, 96]. Research indicates that the particularly potent addictiveness of such content to individuals with eating disorders intensifies their struggles [53]. Moreover, a growing body of evidence suggests a positive correlation between higher frequencies of consuming digital food content, longer viewing times, and elevated eating disorder symptoms, including binge eating and vomiting [112]. These findings underscore the need for interventions to help individuals with eating disorders consume digital food content more consciously and healthily.

2.3 Dual Systems Theory and Digital Self-Control

The Dual Systems Theory provides a foundational framework for understanding human decision-making processes [45]. This theory posits two distinct cognitive systems: System 1, characterized by swift, automatic responses rooted in habits and instincts (e.g., opening social media apps habitually), and System 2, marked by slower, more reflective thinking guided by conscious goals and rational analysis (e.g., goal-oriented reflection to overcome habitual responses or temptations).

In the context of digital self-control, the Dual Systems Theory offers insights into how individuals engage with digital content, such as food-related media, and how interventions can leverage these cognitive systems to overcome habitual behavior [64]. The swift and captivating nature of digital food content can activate System 1, leading to unconscious consumption of digital food content. System 2, on the other hand, represents a more reflective approach to media consumption, where individuals consciously evaluate their choices and their potential consequences. In Section 3.1, we provide an illustrative scenario to demonstrate how Dual Systems Theory applies to digital food media consumption, offering insights into the interplay between System 1 and System 2 in individuals' decision-making processes.

In light of the Dual Systems Theory, *FoodCensor* aims to address the challenges digital food content poses. By enhancing users' awareness and promoting self-regulation of their digital food content consumption, *FoodCensor* aims to empower individuals, particularly those with eating disorders, to make conscious and healthier choices in their media consumption habits.

3 *FOODCENSOR*

3.1 Dual Systems Theory and Digital Food Media Consumption: An Illustrative Scenario

The digital food content consumption behavior aligns seamlessly with the Dual Systems Theory. Imagine a person, Taylor, struggling with bulimia nervosa and often finds themselves drawn to watching food-related content on social media. When Taylor encounters a video of a mouth-watering dessert being prepared (Figure 2 (A)), their initial response is immediate interest and curiosity. System 1 drives this automatic reaction, as the captivating visuals and sensory cues trigger an impulse to engage with the content (Figure 2 (B)).

However, Taylor also has a conscious goal of self-regulating digital food content consumption, which they have recognized can sometimes trigger their eating disorder behavior, such as binge eating. This goal represents System 2's influence (Figure 2 (C)). As Taylor contemplates whether to watch the video, their cognitive processes unfold within the framework of the extended dual systems model of self-regulation. The expected value of control, a key component of System 2, comes into play. Taylor evaluates the potential outcomes of their decision: If they watch the video and succumb to the cravings it might trigger, the immediate gratification could be rewarding, but it could also delay progress towards their health goals (Figure 2 (D)). This evaluation introduces a moment of reflection, enabled by System 2, where Taylor weighs the short-term satisfaction against the long-term benefits of adhering to their dietary goals (Figure 2 (E)).

In this scenario, the implications of watching the food-related content are multifold. If Taylor's automatic response controlled by System 1 prevails, they might indulge in unhealthy eating patterns. Alternatively, suppose System 2's influence prevails, and Taylor refrains from watching the video. In that case, they maintain their self-control, enhance their ability to overcome impulsive habits, and align their behavior with their conscious health goals.

This scenario illustrates how the interaction between System 1 and System 2 and the concept of the expected value of control shape the decision-making process in response to digital food content. It highlights the potential impact of the intervention's design goals, which aim to support individuals like Taylor in making thoughtful and healthier choices in the face of automatic impulses triggered by digital food content.

3.2 Design Goals

Building on the scenario of digital food content consumption behavior aligned with the Dual Systems Theory, the design goals of the intervention emerge to support individuals in overcoming addictive and habitual consumption of digital food content. The intervention seeks to achieve this by:

G1. Prevent non-conscious habits and support self-awareness. We employ passive censorship techniques to disrupt the automatic engagement with digital food content. The censorship introduces a cognitive trigger that prompts users to actively search for and reveal hidden content, marking a transition from System 1's automatic response to System 2's conscious evaluation. Meanwhile, censorship does not entirely disrupt the automatic response; it instead seamlessly fosters an awareness of exposure to digital food content by covering, not removing it.

G2. Strengthen conscious goals and weigh the expected value of control. To support individuals making conscious decisions with digital food content, we adopt intervention that nurtures reflecting thinking and emphasizes the expected value of control. Through the intervention, we aid users to strengthen their System 2 control.

These design goals draw on the extended dual systems model of self-regulation [79, 100], aiming to redirect individuals' responses to digital food content towards more deliberate and goal-aligned behaviors.

3.3 Preventing Non-conscious Habits and Support Self-awareness

This study explicitly targets digital food content consumption on YouTube, a prominent multimedia platform. To target and prevent non-conscious habits associated with impulsive responses triggered by digital food content as a sensory input, *FoodCensor* systemically conceals and hides digital food content (e.g., food-related videos, posts and channels) in YouTube.

Rather than opting for outright replacement of digital food content, a strategic decision was made to employ covers to hide them (Figure 1 (2)). This approach harmonizes with the framework of the Dual Systems Theory in two significant ways. First, the black cover makes users aware of the presence of food content in their feeds. This awareness prompts users to acknowledge the automatic, instinctual responses of System 1. Replacing food content with other content would have eliminated the stimuli entirely, eliminating users' chances to become aware of System 1's involvement. Second, we introduce an intentional interruption that triggers System 2's involvement by employing covers to hide the content. Users are prompted to actively engage in the process of revealing the concealed content (e.g., intentionally search for such content and answer to *FoodCensor*'s reflective questions described in the following Section 3.4) if they want to watch them. This deliberate action aligns with the reflective thinking and conscious evaluation fostered by System 2.

In the context of self-regulation, this design choice carries added significance. The use of covers underscores the importance of users' cognitive engagement and serves as a visual representation of their content consumption habits. Based on the proportion of content covered in black covers, users can gain a tangible measure of their exposure to food content, thereby facilitating their ability to monitor and regulate their content consumption behaviors. This approach, rooted in the interplay between System 1's automatic responses and System 2's reflective decision-making, provides users with a tool to enhance their digital self-control and align their actions with their conscious goals.

3.4 Strengthening Conscious Goals and Weighing Expected Value of Control

FoodCensor aims to support users to make conscious decisions in the process of actively searching for and revealing hidden digital food content. Once *FoodCensor* identifies users' intentional searching for digital food content by detecting food-related search queries on YouTube, it prompts reflective questions to strengthen users' conscious goal of self-regulating digital food content consumption.

Our intervention design follows a similar approach to the *Negotiating Unblocking* design, which promotes self-reflection through questions, allowing users to determine their actions while answering them [109]. To allow users to make autonomous choices regarding digital food content consumption, *FoodCensor* adopts a flexible intervention design that offers options when asking reflective questions. By prompting a question, '*Do you need to watch {search keyword} now?*' (Figure 3 (I1)), *FoodCensor* tries to enable self-reflection by asking users to examine the underlying reasons driving their digital food content behavior. In response to this question, users can make decisions (e.g., continuing or quitting the behavior). By ensuring volition and enhancing users' autonomy, *FoodCensor* can promote their intrinsic motivation to change and strengthen conscious goal [93].

FoodCensor also aims to increase the expected value of control to strengthen System 2 control. The expected value of control is enlarged when people perceive that they would obtain a greater reward or avoid a greater loss through effective self-control [1, 101]. Thus, *FoodCensor* alerts potential loss from consuming digital food content by informing negative consequences of binge eating and purging behaviors (Figure 3 (I2)). This strategy, informing the negative consequences and symptoms of EDs, has been used to enhance awareness and prevent disordered eating behaviors in traditional EDs research [7, 15, 75, 102, 107]. In addition, reminding the potential negative consequences of EDs can help users reflect on their symptoms and increase motivation to change [38]. We collected negative consequences of EDs (i.e., binge eating) by referring to the literature examining the health problems resulting from binge eating [2, 11, 22, 36, 59, 65, 68, 76, 81, 91, 106].[2]

To effectively deliver the expected value of control, we leveraged pictorial warning, a widely used method to notify the dangers of discouraging behaviors, such as smoking. Pictorial warnings are significantly more effective in discouraging a target behavior than text-based warnings [18, 43, 50, 78]. The first and second authors independently collected five pictures describing each consequence. They then reviewed every picture together, discussed whether the picture was intuitive enough to indicate the corresponding consequence, and finalized the list of negative consequences and corresponding pictures. In addition to the pictorial warning, *FoodCensor* briefly explains each consequence to help users understand the potential negative consequences of binge eating. We leveraged the descriptions of each negative consequence the Seoul National University Hospital provides [37].

[2]We provide the list in the Supplementary Materials.

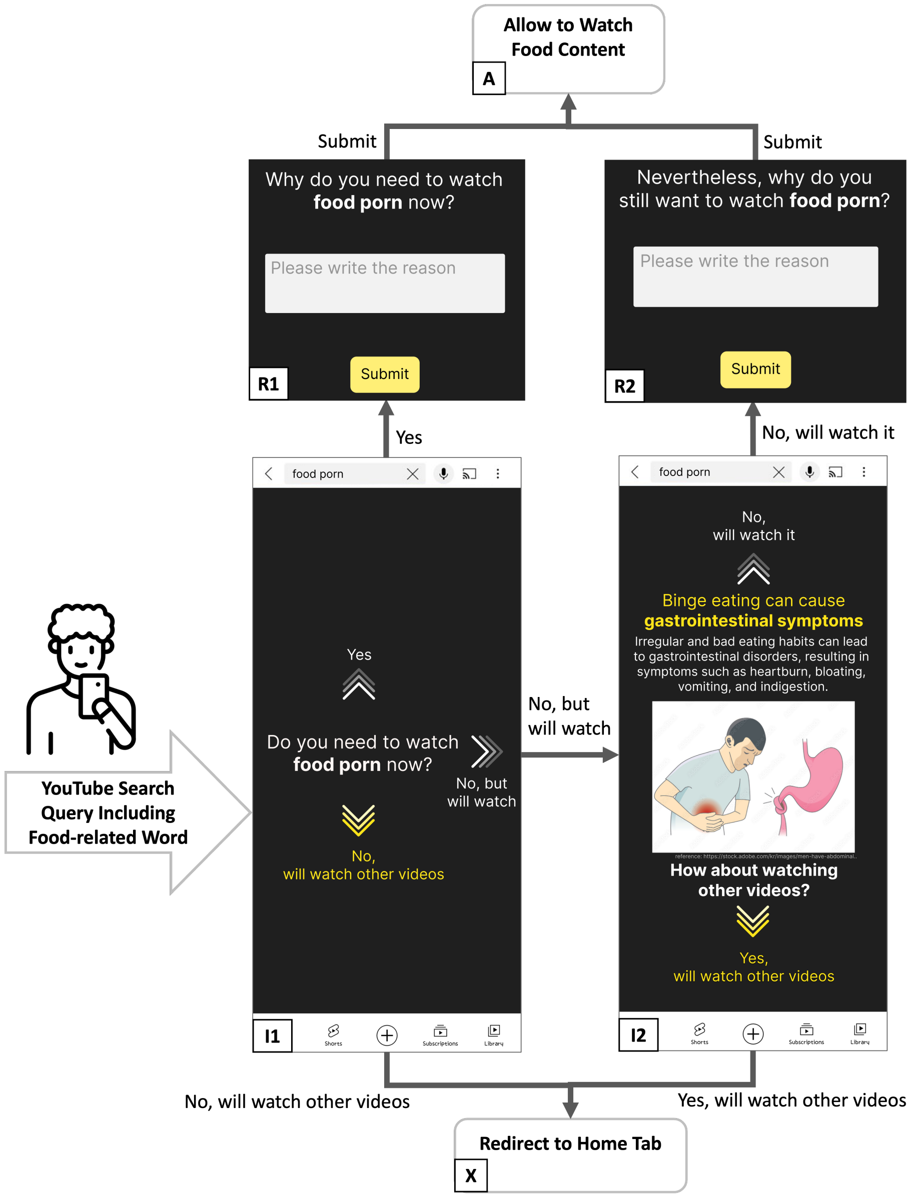

Figure 3: Diagram of the *FoodCensor* intervention for active consumption of food content

3.5 Implementation

FoodCensor consists of a mobile application for Android smartphones and tablets and a Google Chrome Extension for the Chrome browser. The mobile application and Google Chrome Extension are connected to a cloud data storage, Google Firebase, to store log data, information on food content exposure, and daily symptom self-reports. All log data and self-reports are pseudonymized with random identifiers.

3.5.1 Mobile Application: Monitoring. *FoodCensor* monitors the content that users view on the YouTube app. The monitoring function is developed by implementing a custom callback function for the Android Accessibility API [24]. When there is a change in the displayed screen due to the user's touch input, scrolling action, or video streaming, the UI component that caused the change (e.g., button, video player) fires an Accessibility Event. Once an Accessibility Event is fired, *FoodCensor* identifies the app currently in use by reading the package name, which is a unique identifier for an app.

From the YouTube app, we identified 12 features (e.g., VIDEO_PREVIEW, SHORTS) that can display food content from 11 pages (e.g., Subscriptions, Explore).[3] Considering threats to user privacy and the limited computing power of mobile devices, we employ a computationally light rule-based method to identify food content so that

[3]The list of target features and pages are in the Supplementary Materials.

most data processing is done on-device. We built two dictionaries, *food name dictionary* and *food-related keyword dictionary*, and considered a feature to contain food content if its text description contains any word from the two dictionaries. The *food name dictionary* includes 38,843 food names collected from public recipes and food image datasets [10, 40, 74]. The *food-related keyword dictionary* contains 1,457 food-related words, which are non-food name words (e.g., lunch, eat, delicious) and lexical variants (e.g., eeeeeats), crawled from 1,362 YouTube titles that appeared with search keywords 'food' in English and Korean.[4]

When users open the YouTube app, *FoodCensor* reads the UI component tree provided by the Android Accessibility API. *FoodCensor* continuously reads UI components displayed on the screen to detect any targeting features shown on the screen. When a target feature is detected, *FoodCensor* reads the associated text descriptions and determines whether the feature is food-related by searching for matching words in our dictionaries. The feature name and the content type of the feature (i.e., non-food vs. food) are sent to the cloud data storage. To protect users' privacy, *FoodCensor* does not collect text descriptions of features that do not provide food content.

3.5.2 Mobile Application: Intervention. When a detected target feature is determined to provide food content, *FoodCensor* obtains the bounds of the feature (coordinates of the best-fit rectangle containing the feature) and overlays the feature with a rectangular black view of the same size to prevent users' passive exposure to food content. *FoodCensor* also mutes food videos played through the video players.

FoodCensor detects the user's attempts to consume food content intentionally and provides intervention. *FoodCensor* regards including food and food-related words in the search query as an effort to intentionally consume food content. To identify the user's search query, *FoodCensor* reads the text in the search box view. If the search query contains food-related words, *FoodCensor* displays an intervention screen and sends the search query to the cloud storage. When such an attempt is detected, *FoodCensor* displays an intervention screen that covers the entire screen (Figure 3). When a user is persuaded not to consume food content, *FoodCensor* relaunches the YouTube app to its Home tab. If the user is not persuaded, *FoodCensor* asks the user for a reason for consuming food content and logs the content information (i.e., the title of the YouTube video or the name of the food delivery app). The user's response and food content logs are sent to the cloud storage. During active consumption, when *FoodCensor* detects package names of other pages in the YouTube app or other apps, *FoodCensor* considers it a transition to a new context and the end of intentional searching for digital food content.

3.5.3 Chrome Extension: Monitoring. Our Google Chrome Extension targets the YouTube website only on computers. The YouTube website dynamically rewrites the currently loaded web page with new data instead of reloading an entire page. Hence, *FoodCensor* leverages the `MutationObserver` to monitor the content on YouTube upon every change (e.g., insertion, deletion) of HTML DOM elements (e.g., div, video tag). When a change is detected, *FoodCensor* parses the URL to identify the current page (e.g., Home, Subscription). *FoodCensor* then extracts text descriptions of targeting features from the DOM elements. Finally, *FoodCensor* determines whether a feature provides food content by the same rule-based method used for the mobile application, searching for food or food-related words in the food dictionaries. *FoodCensor* stores feature types and the content type of the feature in the cloud data storage. The title text is stored only when the feature provides food content.

3.5.4 Chrome Extension: Intervention. *FoodCensor* censors food content on YouTube website to prevent non-conscious habits of consuming recommended content. *FoodCensor* determines the content type of element by assessing the text in the title element. If the content is identified as food content, *FoodCensor* inserts a custom CSS class that makes the corresponding DOM element transparent and non-clickable (Figure 4). *FoodCensor* also mutes food videos by updating the mute attribute of the video element.

FoodCensor detects the users' intentional search for food content and displays an intervention screen. Our system extracts the search query and identifies an inclusion of food-related words referring to the food dictionaries. If a search query contains food or food-related words, *FoodCensor* inserts an intervention screen to the DOM elements. If the user is persuaded, *FoodCensor* redirects the user to the YouTube Home page. Otherwise, *FoodCensor* allows the user to access food content. When `MutationObserver` encounters the URL of pages other than the search result and the watch video pages, *FoodCensor* considers the new URL as a transition to a new context and the end of an intentional search for digital food content.

4 USER STUDY

4.1 Participants

We recruited 22 participants (aged 18~41, mean=26.7 years; 21 identified as female and 1 as male) through advertisement posts on the South Korean online social support communities for people with EDs [21, 46]. Table 1 provides an overview of the participants' demographics and their ED information from pre-survey and post-survey. Participants were required to provide consent forms stating that they agreed to disclose their data. To be eligible for the study, participants were required to (1) be over 18 years old, (2) have an ED (symptoms of BED or BN), and (3) use an Android smartphone and Google Chrome browser on their computers. Since many people do not seek treatment for their EDs, eligibility for this study was not contingent upon a diagnosis. Participants, however, had to identify themselves as having BED or BN. In addition, we let users subscribe to the YouTube Premium plan for the user study period to minimize the impact of food ads. The compensation for each participant was approximately USD 122, including the price of a YouTube Premium plan subscription for one month.

4.2 Study Procedure

All phases of our IRB-approved user study were conducted remotely due to the high social stigma of EDs [87]. Prior to the study, we explicitly communicated to participants the potential for experiencing negative emotions, including stigma, discomfort, and depression, as a result of engaging in surveys and interviews with potentially sensitive questions. Participants were informed of their unequivocal

[4] We included the keyword in Korean considering further user study region.

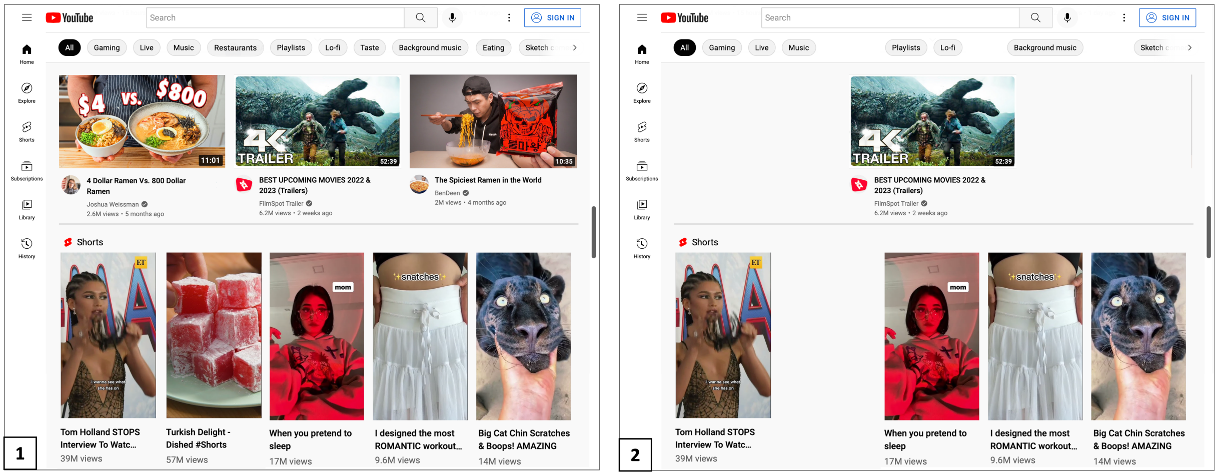

Figure 4: *FoodCensor* deployed on a Chrome browser. Snapshot of the YouTube Home page including food content without *FoodCensor* (1) and with *FoodCensor* (2). *FoodCensor* conceals Filter buttons, video thumbnails, and Shorts video thumbnails showing food content and disables clicking them. The source code for Chrome extension version of our *FoodCensor* is available at https://github.com/Ryuhaerang/FoodCensor.

Table 1: Participants demographic and ED information.

P	Age (yrs)	Gender	Eating Disorder Population		Eating Disorder Duration	EDE-Q Score		User Group
			BED/BN	Diagnosis		Pre	Post	
1	18	female	BN	self	1 year	4.9	2.5	control
2	20	female	BN	self	1 year	4.7	4.9	control
3	20	female	BN	self	3 months	3.8	4.8	control
4	21	female	BN	formal	2 years	4.4	3.9	control
5	22	female	BN	formal	3 years 1 month	5.3	4.3	control
6	23	female	BN	self	3 years	2.7	4.2	control
7	24	female	BN	formal	6 years	5.3	3.1	control
8	25	female	BN	self	5 years	4.8	4.4	control
9	29	female	BED	self	2 years	4.5	5.2	control
10	33	female	BN	formal	7 years 3 months	5.2	5.1	control
11	33	female	BN	formal	15 years	5.0	4.4	control
12	34	female	BN	self	15 years	4.3	5.0	control
13	22	female	BN	formal	10 years	5.1	3.3	experimental
14	22	female	BED	self	3 years	4.4	4.3	experimental
15	23	female	BN	formal	4 years	4.6	4.7	experimental
16	24	female	BED	self	2 years	4.2	3.7	experimental
17	26	female	BED	self	2 years	5.4	4.3	experimental
18	26	female	BN	self	2 years	4.7	3.7	experimental
19	29	female	BN	self	1 year	5.0	1.7	experimental
20	34	female	BED	formal	10 years	5.0	5.1	experimental
21	39	male	BED	self	10 years	2.7	2.8	experimental
22	41	female	BN	self	20 years	0.7	0.3	experimental

right to withdraw from the study at any point without providing specific reasons. This safeguard was put in place to prioritize the well-being and autonomy of participants, acknowledging the sensitive nature of the topic under investigation. Figure 5 illustrates the study procedure. Participants responded to a preliminary survey via email before the study. The preliminary survey included the EDE-Q and questions about their demographics and ED symptoms.

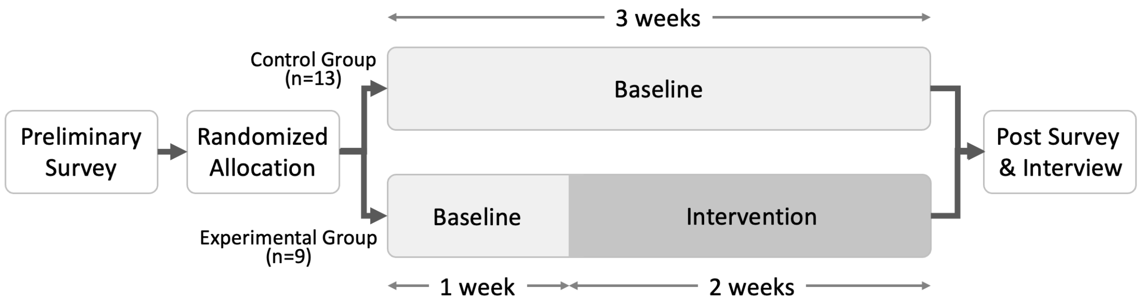

Figure 5: Study procedure diagram.

We designed a three-week field study for two user groups; control and experimental groups. We aimed to uncover the differences in exposure to digital food content videos, perceived changes in digital food content consumption, and disordered eating behaviors between groups with and without *FoodCensor*. Additionally, we used a within-subject design to observe changes in these measures over the field study period. In a quasi-experimental design [14], participants were divided into control and experimental groups based on their ED types, ages, duration of their ED, and their use of YouTube. The control and experimental groups were matched as closely as possible to reduce potential confounding variables, with participants being assigned to either group based on their characteristics. However, two participants (P17 and P13) initially assigned to the experimental group were re-assigned to the control group as the *FoodCensor* intervention displays did not show on their smartphones. *FoodCensor* intervenes in users' digital food content consumption process from the second week of the study period only for the experimental group.

Over the whole field study period, we collected log data on users' exposure to digital food content and ED symptoms from both user groups. The collected data were timestamps, pages, search queries, responses to intervention, and pictorial warning information. Note that titles and search queries were collected only when they were food content. We informed the types of log data *FoodCensor* collected to all participants before the user study started. To merge the log data from the *FoodCensor* mobile app and Google Chrome extension from each participant, we stored the log data pseudonymized with nicknames randomly assigned to every user. For ED symptom information, we asked the number of times binge eating and purging they engaged in for a day through two questions [26]: 'How many times did you have a sense of having lost control over your eating (at the time you were eating) today?' and 'How many times did you make yourself sick (vomit) as means of controlling your shape or weight today?' Questions are formulated by referring to EDE-Q questions 14 and 16. To nudge daily symptom reports, *FoodCensor* sent a push notification every 9 PM. To minimize the self-reflection effect of self-reporting [23], we did not show users the history of symptom self-reports.

After the field study, we asked every participant to respond to a post-survey consisting of EDE-Q 6.0 and questions about the perceived changes in digital food content consumption via e-mail. We asked about the overall experiences of using *FoodCensor* only to the experimental group. We also conducted semi-structured interviews with all participants on Zoom. We allowed participants to turn off their cameras. Every interview was recorded and transcribed.

4.3 Analysis Method

4.3.1 Quantitative Analysis. We evaluated the *FoodCensor*'s food content detection accuracy with 1K YouTube videos. To begin with, we crawled the metadata (i.e., titles, channel names, and URLs) of the videos sampled from YouTube in incognito mode. Afterward, we advertised a call for video annotators in our institution's bulletin to build ground truth labels to determine whether each video is about food. We randomly distributed metadata into ten batches: 100 videos per batch. We also paired twenty annotators randomly. Next, we assigned one batch to each pair. The annotators watched the videos individually and labeled them as digital food content or not. Additionally, we asked them to comment tags (e.g., `eating_broadcast`, `food_recommendation`, and `eating_segment`) when the content is annotated as digital food content.

We also evaluated the *FoodCensor*'s food content detection performance with video metadata from our user study. We assessed 200 randomly sampled YouTube videos from the log data that were identified by *FoodCensor* as containing food content. Four human annotators who did not participate in annotating 1K videos watched these videos and labeled them whether they were related to food. Each pair of annotators independently assessed the same one hundred number of videos. We asked them to comment tags when the content is marked as digital food, just as we did for the annotation of 1K videos. We assessed *FoodCensor*'s accuracy in detecting food content by using labels obtained from annotators.

We conducted Friedman tests and Wilcoxon Signed Rank Test (WSRT) on the proportion of food videos played and suggested food videos on YouTube and the number of food content searches every week to investigate the trends in each user group over the user study period. We also conducted WSRT on the number of times users engaged in objective binge eating and purging per week to examine the clinical outcomes of *FoodCensor* interventions.

4.3.2 Qualitative Analysis. We conducted inductive thematic analysis [42] on the responses to the descriptive questions in the post-survey and the interview. We initiated our data familiarization process by transcribing the interviews. Subsequently, the first and second authors individually reviewed all transcriptions to gain a comprehensive understanding of the interview data. The authors then generated the initial code independently. Following the initial coding, the authors iteratively discussed emerging themes, addressed inconsistencies, resolved disagreements, and ensured that the identified themes were firmly grounded in the data. Before finalizing the analysis, all authors participated in comprehensive discussions. Upon completion of the analysis, each theme and subtheme was titled and given a description.

5 RESULTS

5.1 Food Video Detection Accuracy

We evaluated *FoodCensor*'s food video detection algorithm. As detailed in Section 4.3.1, we had twenty annotators work in pairs to independently assess whether 100 videos were related to food. The overall agreement between annotator pairs was considered good (mean κ=0.77, std=0.07) based on Cohen's kappa coefficient [55].

For algorithm accuracy, we considered a video as food-related only if both annotators labeled it as such, resulting in an accuracy of 0.83 (F_1=0.84, precision=0.68, recall=0.62). Even when we considered a video as food-related, if either one of the annotators labeled it such, *FoodCensor* achieved an accuracy of 0.79 (F_1=0.62, precision=0.78, recall=0.51). Most misclassified food videos were music playlist videos with titles containing food-related location words (e.g., cafe and restaurant) or singers who have food-related words in their names (e.g., Punch and Spice Girls). A few channel names containing food-related terms (e.g., Potato sister and Tasty) also led to misclassification. Particularly, *FoodCensor* sometimes struggled to detect videos tagged with `eating_segment`.

5.1.1 Performance on User Study Data. We also evaluated the in-the-wild performance of *FoodCensor*'s food content detection using the user study data. As outlined in Section 4.3.1, four annotators worked in pairs and independently assessed whether 100 videos were related to food. On average, the agreements between their final labels were considered good (mean κ=0.76, std=0.16) based on Cohen's kappa coefficient [55].

The precision of the video detection algorithm varied depending on the criteria for considering a video as related to food. When a video was classified as food with agreement from both annotators, the precision was 0.80. However, when a video was labeled as food if at least one of the two annotators labeled it related to food, the precision increased to 0.86. With such precision, *FoodCensor* would not significantly affect user experience as it would ensure low false positives and avoid unnecessary censorship of non-food content. We could not measure the true negative cases where *FoodCensor* failed to censor food content because we did not collect descriptions of non-food content to preserve users' privacy, but no participants reported such cases in our interviews.

5.2 *FoodCensor* Intervention Impact on Exposure to Food Content

5.2.1 Food Video Played on YouTube. We measured the proportion of food and non-food videos played on YouTube on smartphones and computers for each user.[5] Figure 6 presents the proportion of food videos played during the user study period. A non-parametric

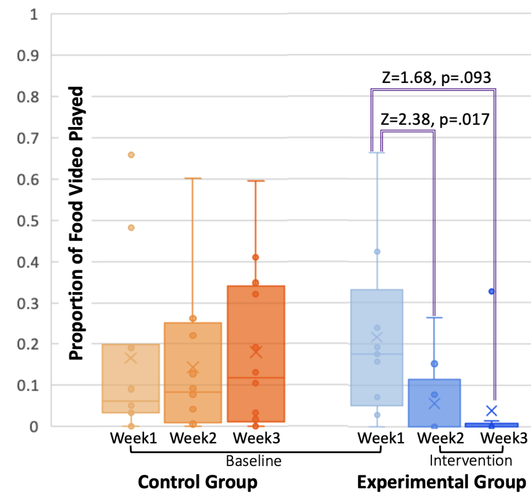

Figure 6: Proportion of food video played per week in the control and experimental groups.

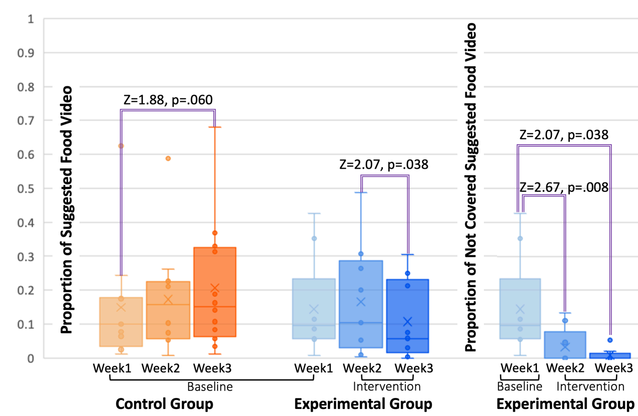

Figure 7: Proportion of suggested food video per week in the control and experimental groups, and not covered suggested food video per week in the experimental group.

Friedman test showed significant drops in the proportion of food videos played per week in the experimental group ($\chi^2(2)$=6.50, p=.039) while not in the control group. This indicates that *FoodCensor* significantly reduced the number of views of food content every week only in the experimental group. According to the WSRT results, in the experimental group, there was a statistically significant reduction between the first and second weeks (Z=2.38, p=.017), indicating that *FoodCensor* immediately and significantly reduced the view of food content on YouTube. There also was a marginally significant reduction between the first and third weeks (Z=1.68, p=.093), demonstrating the sustained effect of *FoodCensor* on users' food video views.

[5] `WATCH_VIDEO_PLAYER`, `PIP_PLAYER`, `SMALL_VIDEO_PLAYER` and `SHORTS` features for YouTube app, and `WATCH_VIDEO_PLAYER`, `PIP_PLAYER`, and `SHORTS` features for YouTube website are considered. Please refer to the Supplementary Materials for each feature.

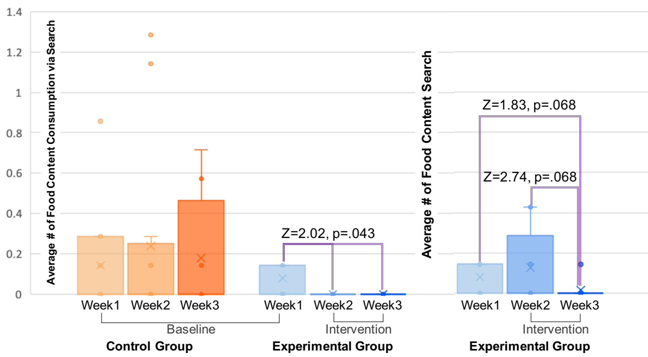

Figure 8: Average number of (1) food content videoplay after search per week in the control and experimental groups and (2) food content search per week in the experimental group.

5.2.2 Suggested Food Videos on YouTube. We also investigated the proportion of food and non-food videos suggested by YouTube on smartphones and computers during our user study period. Both the Friedman test ($\chi^2(2)$=9.55, p=.008) and WSRT showed significant reductions in the proportion of suggested food videos in the experimental group (Figure 7). However, a WSRT result indicated a significant increase in the proportion of suggested food videos for the control group.

These results highlight an intriguing finding. While the experimental group, benefiting from *FoodCensor*'s intervention, actively reduced their consumption of food videos, their actions appeared to influence YouTube's suggestion algorithm promptly. As a result, the algorithm began to recommend fewer food-related videos to this group. This observation is particularly significant as it underscores how *FoodCensor* can effectively assist users in preventing the snowballing habit of consuming food videos, which might otherwise perpetuate the YouTube algorithm's inclination to suggest more food-related content. Furthermore, when analyzing the proportion of YouTube-suggested food videos actually exposed to users, the statistical results, including the Friedman test ($\chi^2(2)$=10.17, p=.006) and WSRT, demonstrated that *FoodCensor* significantly boosted the impact of reducing the proportion of YouTube-suggested food videos that users were actually exposed to by concealing food content. In contrast, the control group, even though their viewing habits remained statistically unchanged (Section 5.2.1), saw an increase in the suggested food video proportion. This emphasizes the importance of *FoodCensor* in disrupting the algorithmic feedback loop that could potentially contribute to excessive food video consumption.

5.2.3 Food Content Search on YouTube. In the experimental group, food content plays via search significantly reduced during the intervention period compared to the baseline (Figure 8). Unsurprisingly, experimental group users never played food content videos via search during the intervention period. In summary, *FoodCensor* significantly reduced the number of food videos that were suggested, watched, and searched.

5.2.4 Perceived Impact of FoodCensor Intervention. We explored the perceived impact of the *FoodCensor* intervention among participants in the experimental group through post-surveys and interviews. Table 2 shows perceived changes in consumption of digital food content and perceived effect of *FoodCensor*. In addition, our qualitative analysis of interviews revealed themes that provide nuanced insights into participants' experiences in the experimental group with the *FoodCensor* intervention. Table 3 outlines the codes for the perceived impact of *FoodCensor* intervention and associated *FoodCensor* intervention design.

Reduced Passive Exposure to Food Content. The experimental group participants reported that *FoodCensor* was somewhat helpful (n=1) or very helpful (n=8) in regulating exposure to food content (mean=3.89, stdev=0.33) (Table 2, Q2). In interviews, many experimental group participants reported a noticeable reduction in their exposure to food content with *FoodCensor*. P22 expressed, "*I really felt the reduction (of exposure to food content) a lot. No food-related content showed up at all (on my YouTube feed). When I accessed YouTube, I noticed no food thumbnails among the videos displayed.*" In addition, some recognized a decrease in the proportion of suggested food content on YouTube over the study period, as indicated by changes in the number of black covers. P19 highlighted, "*Definitely. Initially, the entire screen was black. Now, there are very few black covers. Decreased for sure*," illustrating a tangible reduction in suggested food content.

These observations suggest that *FoodCensor* stimulated System 2 control, promoting users' self-monitoring of their exposure to food videos on YouTube by visualizing the prevalence of food-related videos on users' suggested feeds. Some experimental group participants claimed that *FoodCensor* "*removed food videos from the YouTube's suggestion algorithm, permanently discouraging YouTube from suggesting food videos*" (P22).

Promoted Self-Reflection and Self-Awareness of One's Behavior. *FoodCensor* prompted experimental group participants to pause and reflect on their choices. The presence of black covers made our participants consciously consider whether they wanted to watch food videos or explore non-food videos. P13 described, "*I had a habit of watching eating broadcasts. FoodCensor covered eating broadcasts on YouTube in black, so I did not touch them on purpose. Black covers made me focus more on the (non-food) content, and the habitual watching of eating broadcasts disappeared. I thought, 'Do I want to watch this (eating broadcast)? It's more fun to watch other content.'* "

The reflective questions *FoodCensor* posed when users attempted to access food content also made experimental group participants experience a moment of self-reflection, promoting self-awareness of their behavior. P20 said, "*While responding to a question, I paused and became aware of my behavior and thought, 'Why do I watch this (food content)?'*." P18 mentioned *FoodCensor* encouraged awareness, stating, "*I became aware of my behavior when FoodCensor asked if I needed to watch a food video. I used to do (a food content search) subconsciously. By becoming more aware of my behavior, I thought I might be able to reduce the (food content search) behavior.*"

The self-reflection and self-awareness induced by *FoodCensor* underscore its pivotal role in initiating users' conscious behavior, in line with the principles of System 2 control of the Dual Systems Theory.

Table 2: Post-survey results of the questions about perceived changes in digital food content consumption (Question 1) and perceived effect of *FoodCensor* (Questions 2 and 3 were asked only to the experimental group). Every question is set up with a five-point scale rating (For Q1, 1: Significantly Decreased, 2: Decreased, 3: Stay the Same, 4: Increased, 5: Significantly Increased, and for Q2-3, 1: Not at All Helpful, 2: Not So Helpful, 3: Somewhat Helpful, 4: Very Helpful, 5: Extremely Helpful).

	Questions	User Group		Mean	Kruskal-Wallis
		Control	Experimental	Diff	p-value
1	How has your consumption of food content videos on YouTube using your smartphones and computers changed compared with three weeks ago?	2.77 ± 0.58	1.44 ± 0.58	1.32	0.003
2	How much do you think *FoodCensor* regulates exposure to food content videos on your smartphones and computers.	-	3.89 ± 0.33	-	-
3	How much do you think *FoodCensor* prevents the development of your BED/BN symptoms?	-	3.56 ± 1.13	-	-

Table 3: Codes for perceived impact of *FoodCensor* Intervention. The circled numbers correspond to *FoodCensor* components detailed in Figure 2. Check icons (✔) in the "Associated Intervention Design" column are paired with codes in the adjacent "Codes for Perceived Impact" column, indicating that each was associated with the code by participants. The last two codes represent the perceived impact of reduced food content watch with *FoodCensor*, with no specific associated intervention design.

Codes for Perceived Impact	Associated Intervention Design		
	① Black Cover	② Reflective Questions	③ Pictorial Warning
Reduced passive exposure to food content	✔		
Promoted self-reflection and self-awareness of one's behavior	✔	✔	
Nudged expected value of control			✔
Prevented non-conscious habitual watch	✔	✔	✔
Annoyance from undesired content blocking		✔	✔
Reduced obsessive thoughts about food		-	
Promoted self-awareness of food content impact		-	

Nudged Expected Value of Control. The *FoodCensor* prompt that informs potential consequences of disordered eating could shape the expected value of control. This shaping could enable individuals to make conscious decisions about whether to engage with food content. P19 stated, "*Although I already knew about the negative consequences, seeing it from FoodCensor made me realize there's an additional layer. It prompted me to make up my mind once more.*"

Prevented Non-Conscious Habitual Watch. All experimental group participants responded that their food content consumption on YouTube decreased (mean=1.44, stdev=0.58) (Table 2, Q1). In contrast, participants in the control group exhibited varying responses (mean=2.77, std=0.58). Results indicate a significant difference in perceived changes in food video consumption on YouTube between the two groups (p=.003).

Many experimental group participants shared their experiences in which *FoodCensor* prevented their non-conscious habitual watch of food content. Some mentioned that the visual restrictions could prevent them from habitually watching such content. P20 said, "*I used to watch (food videos) like a ritual. I recognized that the visual restriction (of food videos) helps me not to watch (food videos) while using FoodCensor. Now I feel like I don't really need it that much.*" These results suggest that *FoodCensor* effectively prevents non-conscious habits, which fall under System 1 control in the Dual Systems Theory, by weakening the sensory input associated with food videos.

In addition, some noted *FoodCensor*'s prompts prevented their habitual view of food content. P19 described, "*I watched habitually, but the questions and information about the negative consequences of binge eating that FoodCensor provided made me turn off the app.*" This result is consistent with prior research, which suggests that just-in-time interventions can disrupt habitual smartphone usage patterns by enhancing user awareness [113].

Interestingly, even though *FoodCensor* hides food content only on smartphones and personal computers, the reduced interest in food content also resulted in "*watching less food content on a smart TV*" (P20). This change could be attributed to their increased exposure to different types of content, leading to a shift in preferences. This phenomenon aligns with the Mere Exposure Effect, a psychological tendency where increased familiarity leads to preference, explaining the participants' newfound preference for the content they were exposed to more often [116].

Annoyance from Undesired Content Blocking. While *FoodCensor* was generally helpful, few participants found the questions asked for non-food-related content annoying. P15 expressed, "*When trying to listen to a new song titled 'Cookie', it (FoodCensor) kept blocking the song. I was irritated because I wasn't trying to watch food content.*" Moreover, a few participants found it inconvenient when they needed to watch food content (e.g., search for a nice restaurant to meet a friend) but were blocked.

Reduced Obsessive Thoughts about Food. With the reduced exposure to food content with *FoodCensor*, some experimental group participants noted a corresponding reduction in their obsessive thoughts about food. P20 remarked, "*I used to constantly think about eating all day. . . . As I stopped watching them, I unconsciously continued my daily life. I don't think much about food; phrases like 'I*

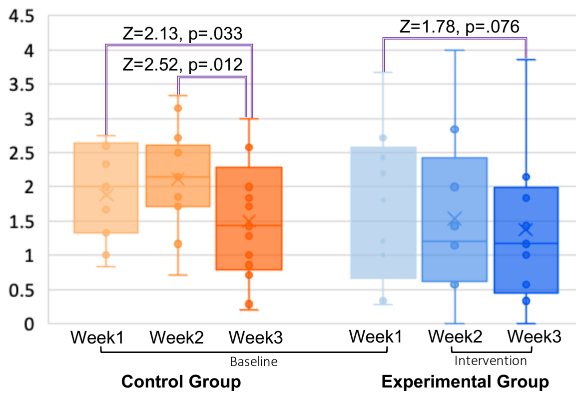

Figure 9: Avg. number of binges per week.

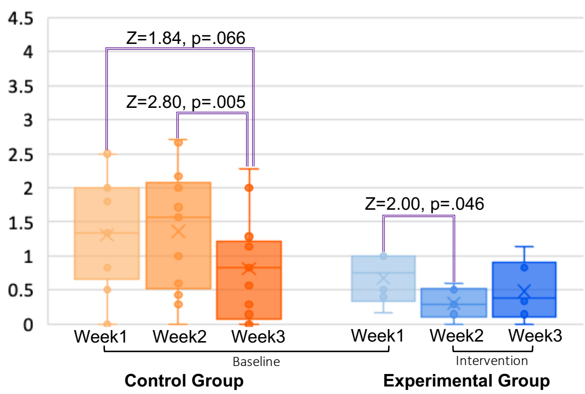

Figure 10: Avg. number of purges per week.

want to eat something' don't come to mind often. I realized that I was unknowingly leading a healthier lifestyle."

Promoted Self-Awareness of Food Content Impact. *FoodCensor* also contributed to the self-awareness of the impact of food content. P20 described, "*I couldn't understand binge-eating while watching eating broadcast, but as FoodCensor prevented me from viewing the content, I realized how much they were influencing me.*"

To conclude, by passively censoring displayed food videos, *FoodCensor* interrupted the automatic reaction to click on food videos, making users more aware of their choices and promoting System 2 control (G1). Furthermore, through reflective questions and the expected value of control prompts, *FoodCensor* encouraged conscious evaluation and expected values of control, ultimately helping users become more aware of their behaviors (G2).

5.3 *FoodCensor* Intervention Impact on Eating Disorder Symptoms

To examine the outcomes related to clinical improvement in ED psychopathology in the experimental group with *FoodCensor*, we examined changes in scores of EDE-Q. We could see a greater decrease in global scores of EDE-Q in the experimental group (pre: 4.1±1.5, post: 3.4±1.6) than in the control group (pre: 4.6±0.7, post: 4.2±0.8). Note the scores range from 0 to 5, and a higher score suggests more problematic eating behaviors and attitudes. We also collected the number of objective binge eating and purging instances daily during the user study period. The WSRT results indicated significant decreases in the number of binge eating and purging episodes in both user groups (Figure 9 and 10). As many participants said that they participated in our user study with the motivation to improve their ED symptoms, such motivation might have resulted in improving ED symptoms for both control and experimental groups. In addition, a few control group participants mentioned that daily self-reporting helped improve their symptoms.

Regarding the perceived impact of *FoodCensor*, many experimental group participants evaluated *FoodCensor* as somewhat helpful (n=2), very helpful (n=3), or extremely helpful (n=2) in preventing the development of their ED symptoms (Table 2, Q3). Participants said that *FoodCensor*'s intervention helped them get away from thinking too much about food in their daily lives. P20 described, "*Before, all I thought about all day was eating. My fear of gaining weight clouded my thoughts, and I kept on watching eating broadcasts without much thought. When I stopped watching those broadcasts, suddenly, I was going about my ordinary life. I stopped thinking about my cravings for food, which didn't seem possible before.*" Some participants noted that *FoodCensor* "*prevented binge eating and purging triggered by watching eating broadcasts*" (P13).

Many users found *FoodCensor* helpful in regulating their ED symptoms as it increases self-awareness of their behavior and the negative effects of such behavior. After the user study, P15 and P19 voluntarily expressed their desire to continue to use *FoodCensor*.

6 DISCUSSION

6.1 Toward Adaptive Intervention Balancing Engagement and Self-control

6.1.1 Scaffolding Conscious System 2 Goal to Automatic System 1 Habit. Our participants reported a shift in their thought process when using *FoodCensor*. They actively reflected on their choice and found other content more enjoyable by consciously considering whether they wanted to watch food videos or explore non-food content. This shift reflects the characteristics of System 2, which involves slower, conscious, and reflective decision-making. In this context, *FoodCensor*'s black covers acted as a cognitive trigger, encouraging users to engage System 2 control. It prompted them to consciously evaluate their desire to consume digital food content. This change from habitual watching to more intentional content selection demonstrates how *FoodCensor* effectively facilitates System 2 control, helping users make more considered choices regarding their digital food content consumption.

Additionally, recent intervention studies in digital behavior change have emphasized the importance of scaffolding the transition of conscious System 2 goals to automatic System 1 habits [64]. While *FoodCensor* successfully enacted System 2 goal during the user study period, it could be further improved to make the conscious System 2 goal settle into an automatic System 1 response.

6.1.2 Supporting Autonomy and Adapting to Individual's Stage of Change. *FoodCensor* is designed to preserve users' autonomy by supporting them to make informed decisions, rather than merely blocking food content consumption, based on the Dual Systems Theory. Our qualitative findings underscore that *FoodCensor* encouraged self-awareness and self-reflection regarding unconscious digital food content consumption behaviors. This, in turn, allows users to consciously make healthier choices in their digital content consumption.

FoodCensor could be further improved by being adaptive to an individual's transtheoretical model of behavior change (TTM) stages [86]. TTM, also known as the stages of change model, is a theoretical framework that posits that individuals go through a series of stages when attempting to modify their behavior. For instance, during the *pre-contemplation* stage, in which they are unaware that their behavior produces negative consequences, intervention could focus on raising awareness through informative content and gentle nudges towards self-reflection. For example, *FoodCensor* could provide sporadic prompts with one's food content consumption history to initiate contemplation about their digital food content consumption habits: e.g., "In this week, you watched digital food content for 8 hours. Consider the impact of viewing digital food content on your overall well-being. Are there any changes you would like to make?" These prompts could be designed to gently guide individuals in the pre-contemplation stage toward recognizing the impact of digital food content and contemplating potential changes.

For individuals in the *contemplation* and *determination* stages, where they recognize their behavior might be problematic and intend to change it, *FoodCensor* could incorporate designs that motivate them to voluntarily change their habitual digital food content consumption behavior before censorship. *FoodCensor* could, for instance, share others' experiences of changing their habits of consuming digital food content. By witnessing others' successful experiences, users can be motivated to take action [89].

During the *action* and *maintenance* stages, *FoodCensor* could support users' self-agency to reduce reliance on the system's control and promote self-control on top of censoring food content. This approach aligns with the emphasis on avoiding over-reliance on interventions in decision-making to ensure users' autonomy in behavior change across various domains [6, 12]. The current design, with black covers, enables users to sense the presence of digital food media, activating System 1 control while preventing habitual content consumption through censorship. To further empower users, *FoodCensor* could replace the black covers with labels, retaining the option to censor while allowing users to confront larger and more natural stimuli, thereby making informed decisions. Furthermore, offering fewer interventions could assist users in reducing reliance on system control and developing self-control. Meanwhile, as the stages of change are cyclic [86], systems should also be designed to prevent individuals from relapsing to problematic behaviors.

6.1.3 *Considering Message-Framing Effects in Tailored Health Interventions.*

FoodCensor strategically integrates pictorial warning to increase the expected value of control within the Dual Systems Theory by leveraging the effectiveness of loss-framing messages in encouraging the awareness of perceived negative consequences of a behavior. A loss-framing message has been found to be superior to gain-framing, especially when targeted behavior and taking action involve risk or uncertainty [29, 72, 90].

The broader discourse on health message framing has been a subset of ongoing debate [67, 92, 99]. Some studies have examined the advantages of each framing method according to individual attributes, such as age, attitude, intentions, need for cognition, or emotional risk [44, 54, 56]. Acknowledging the diversity in individual attributes, reflective questions and pictorial warnings in *FoodCensor* could also be perceived as judgemental by some individuals, possibly inducing feelings of shame associated with eating behavior and stress that are positively associated with the severity of eating disorder symptoms [13]. Therefore, we suggest integrating support for flexible configuration in message framing. This adaptive approach, harmonizing with user-centric design principles, could effectively enhance engagement and promote self-control by customizing framing options within the framework of *FoodCensor*.

Furthermore, we propose automated switching of message framing considering the individual's context (e.g., being in a social place, watching the screen with others). This implication is motivated by a participant's shared experience of feeling embarrassed when encountering a pictorial warning in a public space (i.e., the subway), with concerns about revealing her eating disorder to strangers nearby. While most discussions on message framing have focused on individuals' attributes and scarcely considered momentary context, which might affect users' affective response, our findings suggest the importance of incorporating individuals' temporal social context into the framing strategy.

6.1.4 *Considering Individual's Digital Context.*

Our participants stated several different purposes for consuming digital food media, and a few (e.g., find a nice restaurant to meet friends) were necessary. We think future just-in-time interventions for EDs should consider the digital context in determining intervention delivery opportunities. One could exploit various general ties between different services, indicating the purposes of use. For example, opening a food delivery app right after watching food videos might indicate the urge to binge. On the other hand, frequent switches between searching for restaurants on social media and using chat services might imply necessary use. Based on such relationships across apps, intervention systems could infer users' intention of the target behavior and prevent unnecessary nudges. In addition, as previous research suggested [104], intervention systems should offer users controllability over the timing as temporal contexts could indicate different purposes of the target behavior. For instance, the system could provide pre-scheduled options to reflect individual patterns [39].

6.2 User-centric Content Moderation to Enact Behavioral Changes

6.2.1 *Personalized Content Moderation at User-side.*

Most content moderation efforts have been made at the platform side, such as placing human and machine moderators to detect, address, and remove harmful content for the general audience [31, 32, 95]. For EDs, there have been a few attempts to moderate pro-ED content [16, 17]. A recent study examined that individuals with different identities show nuanced differences in toxicity annotations of comments in online communities [34]. By the same token, recent research found that digital food content negatively impacts people with eating disorders while having various positive aspects for the general public [53, 112]. *FoodCensor* interventions aim to moderate a specific content (i.e., food content) to specific target users (i.e., people with BED and BN). Our method involves users activating the moderation, thus enabling personalized content moderation.

FoodCensor's approach to censoring food content on digital media could be leveraged to study how specific content affects a specific population. For instance, with our approach, one could examine how violent content influences people's linguistic expression by monitoring exposure to aggressive content and users' text input on digital devices.

6.2.2 Shaping Behavioral Intentions. According to the theory of planned behavior [3], individual behavior is determined by the intent to perform the behavior and, thus, the willingness and motivation to perform the behavior. Three elements shape individuals' behavioral intentions: attitude, subjective norms, and perceived behavioral control. We found that food content moderation affects an individual's *attitude* toward food content consumption by promoting self-awareness of potentially problematic behaviors. Moderating food content enacts attitude changes, ultimately affecting the intention and preventing food content consumption. Future research could empower individuals by encouraging greater *perceived behavior control* and shifting *subjective norms* surrounding the consumption of certain content. For example, users could be given greater control over the content moderation process, such as the ability to censor uncensored content or adjust the levels of content moderation to suit their individual needs.

6.2.3 Self-agency of Algorithm Out-Of-Reach. While recommendation algorithms are utilized to attract users [33, 71, 108, 110] and provide a better user experience [61], there is a pitfall; users are highly likely to be repeatedly exposed to harmful content that is similar to a viewed content, as recommendation algorithms are based on the user's viewing history [84]. This pitfall also leads users to lack self-agency [63]. During our field study, *FoodCensor* restricted content passively exposed to users and significantly reduced exposure. The recommendation algorithm could gradually reduce the suggestion of such content by censoring specific types of content (and thus, users not viewing it). Recently, digital media allows users to specify their preferences by fine-tuning the suggestions through '*Don't recommend this channel*' or '*Not interested*' on YouTube and '*Hide post*' on Facebook [70, 115]. However, such manual user effort can be easily overridden with one-time relapse (e.g., watching digital food content), which is not desirable to support self-control [63]. Some do not even know fine-tuning by themselves is available [73]. Further content moderation could be improved by incorporating features to proactively provide self-agency to users [62].

Moreover, by hiding food content from users, users were more exposed to other kinds of content, and consequently, their interests shifted from food content to other content. This is in line with the Mere Exposure Effect phenomenon by which people develop a preference for things merely by being repeatedly exposed to them [116]. Our experimental results showed food content moderation reduced excessive thoughts about eating and helped some users improve their ED symptoms. Moreover, the reduced thoughts of eating brought a better quality of life. Our findings suggest that regulating food content could ameliorate the effect of clinical care by eliminating one of the triggers.

In addition, a participant highlighted that *FoodCensor* influenced content consumption in YouTube app on another device. Since users often use the same account for a platform, YouTube in our study, across different devices, the reduced food content suggestions with *FoodCensor* on a device (e.g., smartphone) could be seamlessly extended to other devices (e.g., smart television). Building upon this observation, extending from cross-devices to cross-platforms, there is an opportunity to improve the self-agency feature by enabling users to seamlessly transfer their fine-tuned algorithm across different content platforms. For example, designers could incorporate a self-agency feature that allows users to extract an articulation of their fine-tuned algorithm in natural language on a platform (e.g., '*Prefer animal and music content. Dislike food and violent content.*' from YouTube) and update algorithms by using the articulation in different platforms (e.g., TikTok and Instagram).

However, providing users with self-agency could pose a risk of biased or potentially harmful content suggestions. Users may misuse their self-agency to guide the algorithm toward suggesting content that promotes wrong body image and thinspiration. In conjunction with the Mere Exposure Effect phenomenon [116], such manipulation could amplify the negative impact of harmful content. Platform-side efforts are necessary to prevent users from intentionally or accidentally steering the content suggestion algorithm in an undesirable direction. Platforms could raise awareness about how user fine-tuning shapes the algorithm and encourage users to recognize when their fine-tuning practices may be unhealthy. Additionally, platforms could ensure a certain degree of diversity in the suggested content topics. This dual approach could empower users while safeguarding against potential negative consequences of unchecked self-agency.

6.3 Limitations

The coverage of *FoodCensor* is focused on YouTube on smartphones and personal computers. We believe expanding the coverage to other digital media, such as Instagram and TikTok, could be achieved. Relying on content descriptions to censor food content has algorithmic limitations. Although no participant stated cases where *FoodCensor* failed to hide food content and accuracy was fairly good, with an accuracy rate of 79-83%, a more sophisticated content moderation technique based on NLP [4, 69] and vision [4, 16] could be integrated to improve our method. Our participants' demographics are limited to South Koreans aged 18 to 41. Although the worldwide interest in eating broadcasts is increasing [5], our results might not be generalized as eating broadcasts have higher popularity in Asian countries. In addition, our study population was mostly female as the demographic of people with BED and BN is statistically biased to female (87.4% of identified BED patients were female in South Korea) [30, 49, 98].

7 CONCLUSION

We proposed a just-in-time intervention, *FoodCensor*, to encourage users to make informed decisions in watching digital food videos potentially associated with disordered eating (i.e., binging and purging) on smartphones and personal computers. We conducted a three-week field experiment with 22 participants with binge eating disorder or bulimia nervosa to evaluate the effect of *FoodCensor* on exposure to food content and eating disorder symptoms. *FoodCensor* significantly discouraged users' food content consumption by encouraging self-awareness of exposure to digital food content and enacting conscious and reflective decision-making. Our findings highlight the value of interventions in response to potentially harmful behavior in a particularly vulnerable population for providing opportunities for self-reflection and awareness. Based on these findings, we provide design implications for an adaptive intervention to balance engagement and self-control in digital media and for content moderation to enact behavioral change beyond passively preventing undesirable behavior. We encourage future researchers to further explore how computer-mediated just-in-time intervention supports eating disorder patients.

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