Functionality and User Reviews Analysis of Mobile Apps for Mindfulness Eating and Eating Disorders

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ABSTRACT

A growing number of mobile apps have focused on healthy or problematic eating, albeit limited research has focused on evaluating such apps from users' perspectives. To address this, we evaluated the functionalities of 27 apps on mindfulness eating, and eating disorders from the Apple App, and Google Play Stores, and conducted a content analysis of 1248 user reviews, totaling over 60,000 words. Findings indicate the main functionalities of tracking data on eating behaviors, emotions, thoughts, bodily sensations, symptoms, as well as triggers of eating disorders, and of providing interventions such as mindfulness, goal setting, psychoeducation, CBT, and holistic ones. Findings also highlight key usability and ethical challenges, which we used to inform five design implications namely tracking and reflecting on multiple aspects of mindfulness and healthy eating, supporting personalized interventions and AI-based ones, as well as the sensitive design for diagnosis, and for tracking and monitoring problematic data.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**.

KEYWORDS

Eating Disorders, Healthy Eating, Mindfulness Eating, Mobile Apps, User Reviews, Tracking, Interventions, mHealth

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1 INTRODUCTION

Eating disorders (EDs) are a significant health issue due to prevalence and associated health risks, leading to high mortality rates [90]. Studies show that compared to men, both young and adult women will encounter a diagnosable ED during their lifetime, due to bodily dissatisfaction [69, 90]. Despite evidence-based clinical guidelines [45], accessing professional therapy is limited due to the stigma around EDs [82], fear of losing control [38], and cost of in-person therapy [89]. As a result, EDs patients often prefer to self-manage their treatment [95].

The advancement of technology has impacted mental health treatments, particularly for EDs [66]. The prevalence of mobile devices and smartphones supports and facilitates EDs symptom monitoring [32, 52, 95], increases patients' treatment adherence, and alleviates stigma associated with in-person psychotherapy [51]. When properly developed, mobile health (mHealth) interventions contribute to behavior change by allowing users to self-monitor personal data, and reflect on moods, thoughts, physical activities, and eating behaviors [95], to share their progress with therapists or access psychoeducation materials [31, 32].

A growing body of HCI research has focused on promoting healthy eating through persuasive technologies [11, 48, 64], and mobile apps [8, 16, 28, 65, 97]. Given the value of mindfulness eating for physical and emotional health [99], HCI research has also started to explore aspects of mindfulness eating such as slow eating through smart tableware [54, 57, 101], wearables [58], AR/VR [73, 85], 3D printed food [63] or apps for mindfulness eating [44].

Despite HCI work investigating the impact of online platforms [14, 77, 80, 98] and mobile app interventions [24–26] on EDs, limited research has focused on users' perspectives. To address this gap, we evaluated functionalities and analyzed 1248 user reviews sampled from 27 apps for mindfulness eating, and EDs, available in the UK Apple App and Google Play Stores. The aim was to identify users' perspectives, challenges, and unmet needs in order to articulate design implications for such apps. For this, we focused on the following research questions:

- What are the main functionalities of top-rated apps for EDs, or mindfulness eating?
- How do these apps support users' needs, as reflected in users' reviews?
- What are the key challenges of these apps and how can they be addressed?

The contribution of our work is three-fold. First, we describe the breadth of functionalities for mobile apps focused on eating behaviors and interventions in support of mindfulness eating and EDs. Second, we provide nuanced accounts of users' experiences with these apps as reflected in their reviews. Third, we advance the design space of technologies for eating behaviors with new design implications.

2 BACKGROUND

We draw from HCI research on mindfulness eating, healthy eating, and their specific focus on EDs.

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2.1 HCI Research on Healthy and Mindfulness Eating

Growing HCI work has focused on healthy eating, mostly through persuasive technologies for children, or mobile apps helping adults to track and regulate eating behaviors [41]. Persuasive technologies usually include interactive tableware leveraging gamification by motivating children to eat more vegetables [48], tracking eating through sensors embedded in a tray to reduce meal completion time [64], or smart chairs to help children focus and promote proper mealtime behavior [15]. Studies with adults have primarily investigated mobile apps that monitor calories, nutrients, and physical activities [8]; as well as the use of photo-based tracking within social media [16]. Furthermore, digital diaries such as the Crumbs app provide lightweight food-based daily challenges to promote mindfulness around healthy food choices through nutritional information [28], while the TableChat app extends the family dinner table environment to the virtual realm to encourage healthy eating [65].

HCI researchers have also argued against the obsessive self-tracking of calories in the context of weight loss, given its association with EDs, and for supporting instead nutritious diet through food literacy [8]. For instance, the Garden app uses gamification and behavior change techniques to support healthy eating [2], while the CHEW app aims to cultivate awareness of healthy food shopping while providing psychoeducation on nutrition [97]. Apps have also explored eating behavior while monitoring thoughts and feelings for the management of symptoms associated with EDs [22], or digestive disorders [17, 87].

Although HCI research on mindfulness eating technologies is currently limited, some systems developed to promote healthy eating have addressed elements of mindfulness eating, such as slow eating. Most research in this domain involves capturing eating gestures or chewing movements to offer real-time feedback, encouraging deliberate and slow chewing, often facilitated by wearable technologies [58] or smart tableware such as forks [54, 102] or trays [59]. Other work has explored 3D food printing technologies to alter food's density [63] or AR/VR for slow eating through small bites or portion sizes [73, 85]. A recent study found that top-rated commercial apps for mindfulness eating target aspects such as healthy eating, physical activity, emotions, and thoughts, albeit with limited focus on bodily sensations of hunger and satiety cues. Moreover, while support for mindfulness meditation or healthy eating is prevalent, few such apps are informed by MB-EAT interventions or integrate mindfulness eating per sei [44].

To conclude, the breadth of research focused on healthy eating technologies has looked at persuasive technologies, mobile apps, smart tableware, wearable, AR/VR, and 3D printing but not particularly for supporting mindfulness eating. Moreover, while design research has started to investigate the functionalities of commercial apps for mindfulness eating, users' reviews of such apps have been limitedly explored.

2.2 HCI Research on Eating Disorders

A growing body of HCI research on mental health has also focused on EDs, particularly on online platforms [77, 80] to predict disorders' severity [14], identify EDs' communities [98], forecast the severity of associated mental health conditions [13]; or investigate how social norms and behaviors change within online platforms regarding EDs [34]. HCI scholars have also looked at the interaction between content creators and moderation practices on online platforms [12, 14, 20, 79–81], or clinicians' perspectives on technologies' impact on people living with EDs [78].

Besides social media platforms, research has also looked at how wearable sensors could recognize eating behaviors [98], and the role of nutrition and fitness apps in influencing unhealthy behaviors [24, 25]. For instance, Eikey and Reddy investigated the use of weight loss apps by individuals identifying as having an ED, and examined their use cycle, recovery, and relapse [26]. Their findings showed that apps can exacerbate EDs by triggering unhealthy eating and by creating a dependence on food logging, exercise, and weight. Findings also showed that such apps could also contribute to EDs recovery, by promoting healthy eating and physical activity goals for obesity-related health conditions [26].

Devakumar and colleagues' work provided an analysis of the design space of commercial apps for EDs, and developers' approaches to collecting and reflecting on user data [22]. They looked at 55 apps, and their findings indicate functionalities for tracking users' meals, emotions, thoughts, or EDs symptoms mostly through text or icons, and of supporting reflection on tracked data, mostly through text, icons, charts, or media. Our work explores only one (A20) of these 55 apps, and additional 26 apps, 10 of which target mindfulness eating, which we also extend with the analysis of users' reviews.

To conclude, while HCI research aimed to explore the impact of social platforms, mobile interventions, and wearable technologies on people living with EDs, limited research has focused on users' reviews of mobile apps for mindfulness eating and EDs.

3 METHOD

To address this gap, two data sets have been used for this study: (i) a set of top-rated commercial apps, and (ii) a set of users' reviews of these apps. Now we describe how these two data sets were collected and in the subsequent section their analysis. The study received Institutional Ethics approval.

3.1 Data Set 1: Mobile Apps Selection

To identify the apps we searched the two main app stores in the UK: Apple App Store and Google Play Store, from October-November 2023 (Fig. 1). For this search, we used the following keywords: "binge eating", "binge eating disorder", "eating disorders", "anorexia nervosa", "anorexia", "bulimia nervosa", "bulimia", "obesity", "stress eating", "emotional eating", "mindfulness eating", "mindful eating", and "intuitive eating".

From the initially identified 772 apps, we included those that met the following inclusion criteria: highly rated free apps scoring 4 out of 5, having at least 20 user reviews in the Apple App Store or Google Play Store, belonging to the Health and Fitness category, and whose title or description on the marketplace mentioned at least one of our keywords. We particularly focused on apps in the Health and Fitness category based on previous findings indicating that these categories typically contain longer reviews [96], and the proportion of likely fake reviews is minimal [68]. Future work could explore additional categories such as Medical and Lifestyle.

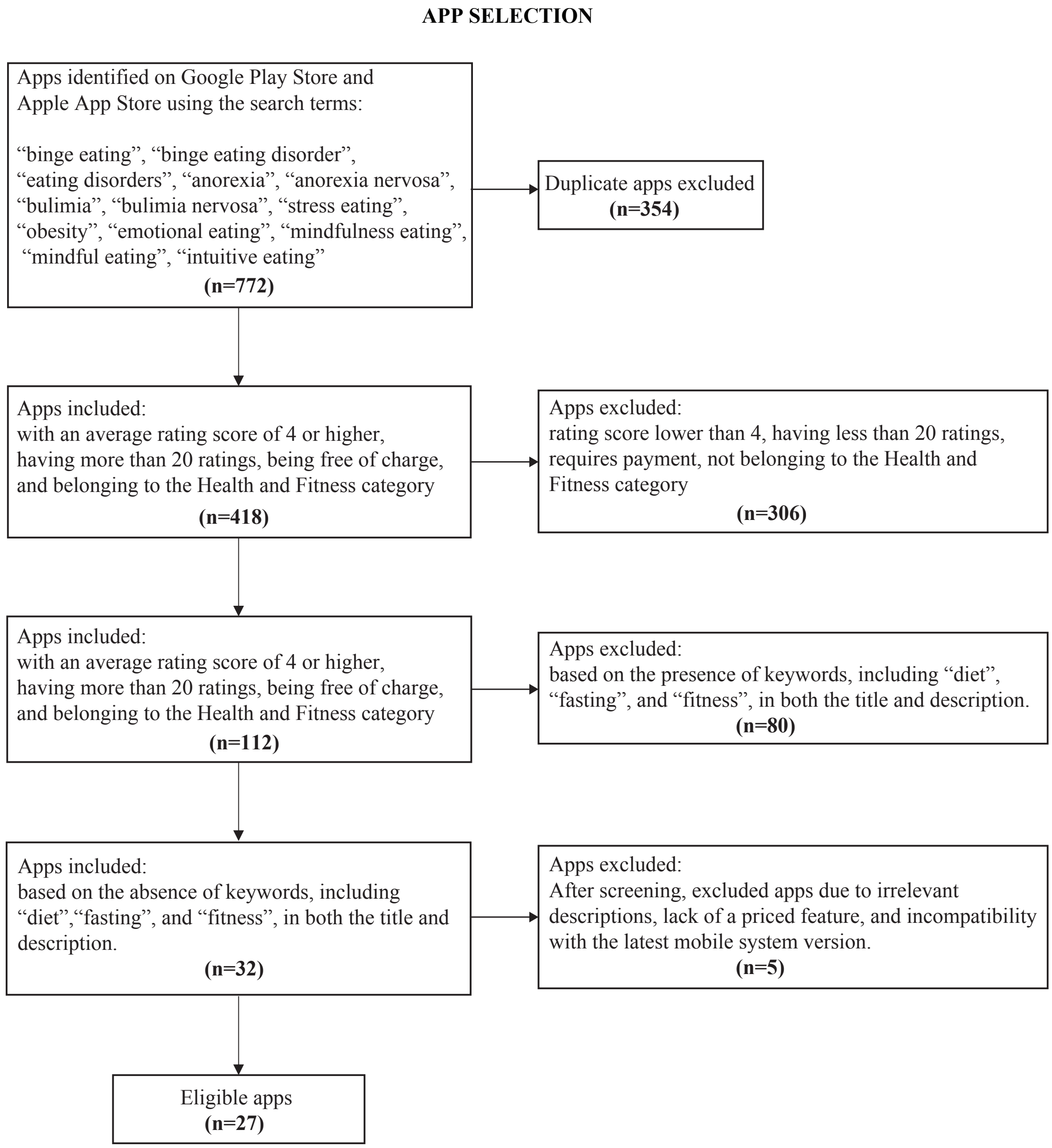

Figure 1: The criteria for selecting apps from both mobile stores.

Apps were excluded from our analysis if their main focus was on aspects like “diet”, “fasting”, and “fitness” as mentioned in their title or description.

This led to 32 apps, but after the screening, 5 apps were further excluded because they supported neither mindfulness eating nor users living with EDs (2 apps), or both of these main features were behind the paywall (2 apps). In addition, during our study, one further app showed technical issues after an update, so we cannot use it. Thus, the final set of apps that we analyzed consisted of 27 apps from Apple Store, with 7 of these being also available on Google Play Store (A1, A2, A6, A10, A11, A12, A14) (Table 4). We note that while all these apps are free to download, most of them do provide in-app purchases for advanced functionalities.

3.2 Data Set 2: Users' Reviews Selection

We searched for users' reviews for each of the 27 selected apps. A script was used to extract all the apps shown in the search results (Fig. 5). The script automatically downloaded data for each app from both the Apple App Store, and Google Play Store, including name, category, marketplace description, price, review score, and reviewer number. We employed the following selection process to ensure a balanced sample of more recent and longest reviews across all 5 ratings. Users' reviews were included if they met the following two criteria: (i) recent reviews posted within the last 3 years, and (ii) the top 100 longest reviews with the number of characters between 150 and 5000. The first choice was made to ensure that reviews reflected the more recent versions of the apps, similar to the ones downloaded by us. The second choice was grounded in the expectation that longer reviews are more likely to provide a rationale for users' ratings. A similar character range has been used in previous studies for instance on users' reviews of depression apps [9]. Future work could further explore how our findings extend to shorter reviews.

Users' reviews were excluded from analysis if they lacked textual content, consisting for instance only of "emojis" (783 reviews), were not in English (134 reviews), or did not mention user's experiences but provided for instance only the name of apps' functionalities, i.e., "food diary app"(19,665). Similar exclusion criteria have been used in previous studies on users' reviews of commercial apps [9, 88, 91]. This led to 2496 user reviews, totaling 121,016 words from which we randomly selected half so that we worked with a more manageable corpus of user reviews, similar in size to those from previous studies, i.e., 77,500 words [9]. As a result, we had a final set of 1248 users' reviews from both marketplaces (419 from Apple Store, and 829 from Google Play Store), totaling over 60,508 words (35 average word number per review) (Fig. 2). These users' reviews were exported to Atlas/ti software [1] for qualitative analysis.

3.3 Analysis of Data Set 1: Apps' Functionality Review

To evaluate the functionalities of the selected apps, we as HCI experts followed previous approaches [18, 44] integrating auto-ethnography and expert evaluation. Thus, all apps were used at least three times a day, for a week, by the first author on iPhone 14.

For the expert evaluation, instead of considering solely the usability of the interface based on Nielsen's heuristics and the Mobile Application Rating Scale (MARS) [92], we employed a top-down approach involving key concepts from both EDs and mindfulness eating literature. A predominant such intervention is MB-EAT: a mindfulness intervention commonly used for training mindfulness eating, with benefits in reducing binge eating [61]. At its core lies guided eating meditation, integrated with aspects of other interventions such as mindfulness-based stress reduction and cognitive behavioral therapy (CBT) aimed to increase awareness and acceptance of bodily sensations in particular bodily cues for hunger and satiety, together with emotional (i.e., anger, anxiety), cognitive (i.e., thoughts), or physical triggers (i.e., texture, flavor), impacting the less mindfulness eating [61].

In the light of MB-EAT and EDs interventions, we looked for functionalities supporting awareness of, and acceptance of bodily sensations, before, during, and after eating, particularly hunger and satiety, as well as various triggers for eating. For the 27 apps, we identified each app's main functionalities such as tracking, and interventions, similar to main functionalities in other HCI studies of mobile apps [4, 83]. Within each functionality, we looked for sub-functionalities as they emerged, namely tracked content in the form of eating behaviors, feelings, thoughts, bodily sensations, triggers, or symptoms; the format of tracked data such as text, charts, or emojis; and specific interventions such as mindfulness meditation, mindfulness eating meditation, goal setting for healthy eating, psychoeducation, CBT, and holistic interventions.

3.4 Analysis of Data Set 2: Users' Reviews

For the analysis of users' reviews, we employed hybrid coding [33], using deductive codes informed from MB-EAT such as bodily awareness, slowly chewing, small bites, small portions, savoring food, non-judgemental attitude, healthy food, gratitude, not-multitasking, relationship with food and body [30, 37, 47, 50, 62, 67, 71], which we extended with inductive codes emerging from users' reviews such as types of interventions, tracking symptoms, eating behaviors, and triggers (Table 1, 2).

After sampling, we grouped users' reviews based on their numerical rating, and coded them as "positive", "negative", or "ambivalent", following Bowie and colleagues' approach [9] where the first two codes reflect users' reviews capturing positive and negative aspects of the apps, respectively, while "ambivalent" code captures both positive and negative aspects of the apps as described in users' reviews. In our analysis, we used users' reviews from the full breadth of scores, rather than only those with the highest (5) or lowest (1) rating scores, to capture the full spectrum of users' voices. The first author coded the users' reviews and iteratively revised the coding scheme through weekly discussions with the second author over several months to reach agreement. New codes were developed based on interventions for EDs including the relationship with the body and, the relationship with food.

3.5 Positionality and Reflexivity

We believe that qualitative study is not value-free [36] and that positionality is significant, particularly for research on health technologies [75]. Therefore, we unpacked our positionality and how it might influenced our research process and outcomes. The first author has a background in product design and HCI, focusing on mobile and interactive health technologies. The second author has expertise in HCI, with a focus on technologies for eating experiences, wellbeing, mindfulness, and mental health, as well as their ethical aspects. Regarding research methods, both authors have knowledge of mixed methods. While the first author has primarily engaged in quantitative methods, the second author has extensively employed both qualitative and quantitative data analysis. The first author's limited work with qualitative analysis provided them with a fresh perspective and less biased approach, while the second author leveraged their expertise to critically reflect and engage in each stage of data analysis.

4 FINDINGS

Findings are organized based on the functionalities of the apps, which we further detailed with findings from users' reviews. These functionalities include tracking eating behaviors, tracking EDs symptoms, and providing interventions, together with additional themes cross-cutting these functionalities such as apps' usability, and ethical concerns. This section integrates findings from the analysis of two data sets. Table 1, 2, 3 present these codes and their

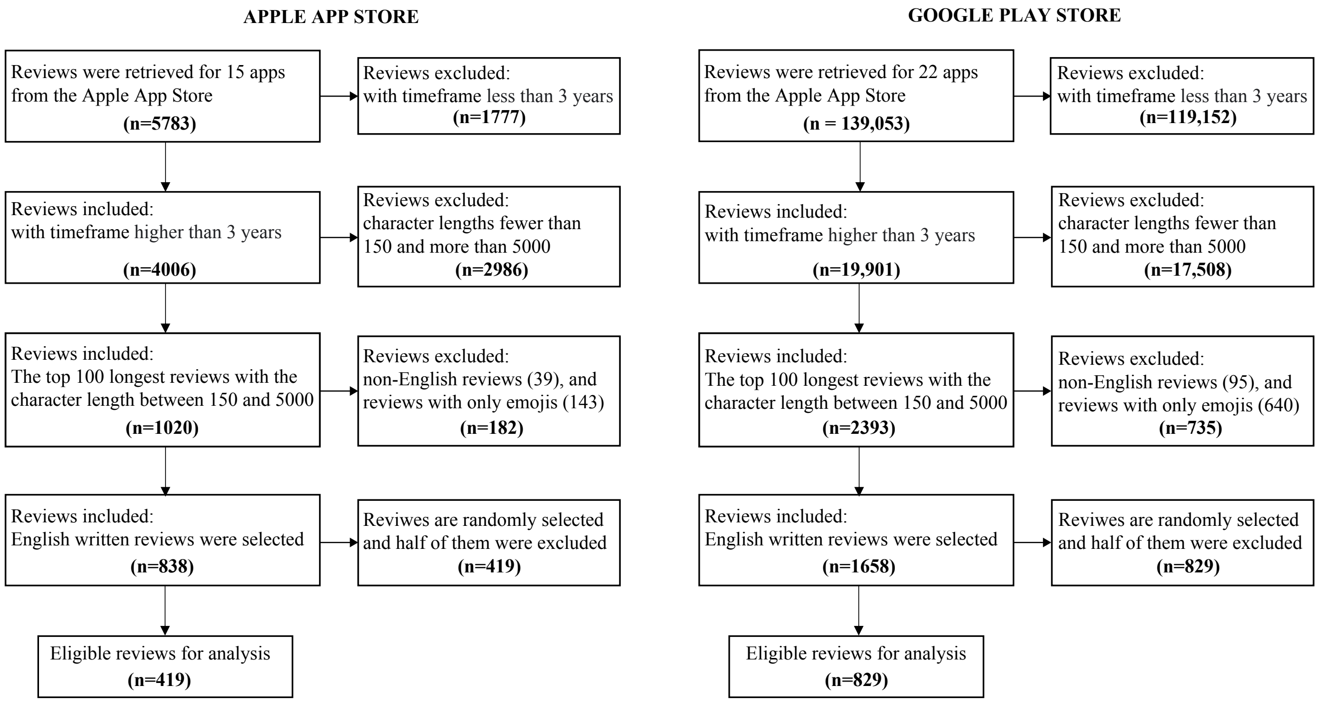

Figure 2: Users' reviews selection criteria from both Apple App Store and Google Play Store marketplaces.

total distribution of 100%, while Fig. 3 presents a word cloud of users' reviews. To protect users' identities, in the Findings section we paraphrased quotes from the users' reviews.

4.1 Tracking Eating Behaviors

Out of the 27 apps, only 6 apps ask about meal details such as type, time, location, size, thoughts, emotions, and behaviors around it. The main formats for meal logs include free text (6 apps), photo (4 apps), checkmark by tagging it as unhealthy-ok-healthy (A10), and barcode scan (A25). Users' reviews (26/1248) equally liked the photo entry and barcode scanning due to ease of use: "*I enjoyed its simple diary format without any diet features. Easy to use and liked the simplicity. Quickly track and get a big picture meals review*", albeit they found barcode scanning limited:"*barcodes are easy to scan but not all items are available. The good side is that the food products database can be updated by the crowd*".

Further support for healthy eating is provided through step-by-step picture-based instructions for food preparation including duration, ingredients, portion size, nutritional information, calories, and allergens (A7, A10, A16). Users' reviews show that users praised these apps for the usefulness of the digitized food journals: "*they are easier to use than paper ones. It provides responsibility for recording and reflecting on any behavioral patterns*".

Our findings show that 15 apps provide tracking functionality for healthy eating behaviors, including tracking of emotions, thoughts, behaviors, and bodily sensations, as described below. An important outcome is the low number of apps providing support for measures associated with eating behaviors such as *physical activity* (7 apps); *meals* (6 apps); *sleep* (6 apps); *water intake* (5 apps); *energy level* (5 apps); *number of steps* (5 apps); *menstrual cycles* (4 apps); *weight* (3 apps); *macronutrients* (e.g., carbohydrates, proteins) and *micronutrients* (e.g., vitamins, minerals) (2 apps) (Table 1). Users (54/1248) highlighted the positive impact of tracking healthy eating on their well-being "*the app motivates me to adopt a healthy morning routine, manage stress throughout the day, and unwind from a long day's thoughts*".

Common formats for tracking these aspects include stand-alone, or combined charts and calendar views. For instance, *water intake* and *physical activity* are tracked through progress bars (A10) or calendar views with bar charts (A6); *steps* through line charts (A16) or calendar views with bar charts (A6, A12); *energy level* through calendar views with line graphs (A22) or with emojis (A16); and *sleep* through calendar views with line graphs (A22) or bar charts (A6). None of the users provided feedback on the visualization formats. Alongside eating behaviors, our apps also track associated aspects including emotions/moods, thoughts, and bodily sensations.

4.1.1 Tracking Emotions or Moods. Findings indicate that only 4 apps track emotions (A2, A4, A21, A26) through free text (A2, A26) or emoji (A4, A21). Users' reviews (4/1248) indicate that users liked the calendar views with emojis "*the app is great for reflecting on my emotional state. The calendar view allows me to easily track daily and weekly mood updates*". Apps also provide diverse visualizations including calendar views with line graphs (A21, A26), calendar views

Figure 3: Word clouds are generated based on users' reviews analysis.

with emoji (A4), or bar charts (A2) (Table 1). Chatbot functionality is supported by the A4 app, which a small number of users (3/1248) appreciated: "*when I feel stressed I know the chatbot is there for me, ready to listen with prompt responses*".

4.1.2 Tracking Thoughts. Findings show that 3 apps (A14, A17, A21) track thoughts through free text in the form of journal entries (Table 1). Interestingly, the A14 app provides an AI-generated journal and prompts questions to support reflection or gratitude such as "*I'm blessed with an abundance of ...*".

4.1.3 Tracking Emotions/Moods & Thoughts. Findings indicate that 5 apps allow users to track both thoughts and moods related to mindfulness eating (A23), or EDs (4 apps) on a 5-point emoji scale which prompts users how they feel (e.g., happy, confident, sick, overwhelmed), and to reflect on the factors causing such feelings (e.g., family, work, food, exercise): "*reflecting on my thoughts after eating helps me understand my overall mood at the end of the day*". Apps also employ stand-alone, or combined charts and calendar views to capture moods, for instance through line graphs with emojis (A6), calendar views with line graphs (A6, A12), or calendar views with emojis (A16) (Table 1). Additionally, A6 integrates AI into the journal and prompts daily reflective questions such as: "*What helps you focus when you work or study?*" to which users can respond through text input, voice recording, or photo upload: "*it's got a smart AI tool that asks me daily questions when I answer it, generates a new one that helps me talk in depth about what's on my mind*". A small number of users (3/1248) mentioned their preference for voice recording: "*sometimes, I don't like typing and I think voice messages express the mood in the moment more effectively*".

4.1.4 Tracking Behavior, Moods & Thoughts. Findings show that 3 apps allow users to track behaviors, as well as thoughts and moods for mindfulness eating (A23), or EDs (A1, A20). Only one app (A20) also tracks dysfunctional thoughts concerning a given situation by providing multiple distortion options such as all-or-nothing thinking, overgeneralization, mental filter, discounting the positives, mind reading, fortune telling, personalization, magnification or minimization, emotional reasoning, "should" statements, or labeling and mislabeling. This app also provides a 10-point Likert scale to help users reflect on their beliefs and related emotions (e.g., guilt, disgust, anxiety, sadness) (Table 1).

4.1.5 Tracking Bodily Sensations: Hunger and Satiety Cues. An important outcome is that surprisingly, only 3 apps (A1, A16, A23) track data for bodily sensations (Table 1). These apps use self-reports of bodily cues for hunger and satiety such as stomach emptiness, growling, and low energy. Moreover, apps prompt users to self-report their emotional triggers for eating such as boredom, sadness, stress, or craving specific tastes or textures. The tools that such apps use for self-reports include craving checkbox (A1), or 5-point Likert scales (A23) completed before and after eating, as well as 10-point Likert scales for hunger and satiety, or customized hunger checks completed before, during, and after meals (A16, A23). A16 supports chatbot functionality, offering predefined responses for both eating behavior (e.g., "*I have strong cravings*") and mood (e.g., "*I feel stressed*").

Additionally, the app provides options to reflect on moods through emoticons and hunger scales. When users select a predefined response like "*I have strong cravings*", the app suggests general interventions such as going for a walk or journaling about feelings, rather than more specific ones like guided mindfulness eating meditation. These findings are important as they align with the primary goal of the MB-EAT intervention which is supporting people to cultivate awareness of, and balancing bodily sensations, emotional states, and external triggers for eating. MB-EAT also incorporates CBT elements such as meal diaries for self-monitoring eating behaviors [72] which can support awareness of the relationships between eating behavior, emotions, and thoughts [72, 95].

Main codes	Sub-codes	App numbers (/ 27)	Users' reviews content	Reviews number (/1248)	App names
Tracking Eating Behaviors	meals	6 (22%)	Cultivate awareness of factors impacting eating behavior - (P)	50 (4%)	A10, A13, A20, A23, A24, A25
	emotions/ moods and thoughts	5 (19%)			A6, A10, A12, A16, A23
	emotions or moods	4 (15%)			A2, A4, A21, A26
	moods, thoughts and behaviors	3 (11%)			A1, A20, A23
	thoughts	3 (11%)			A14, A17, A21
	bodily sensations (hunger/ satiety cues)	3 (11%)	Cultivate awareness of cravings, and hunger & fulness levels - (P)	11 (0.9%)	A1, A16, A23
Tracking Healthy Eating	physical activities	7 (26%)	Cultivate awareness of eating behavior, healthy food choices - (P)	39 (3.1%)	A5, A6, A9, A10, A20, A22, A25
	sleep	6 (22%)			A6, A9, A10, A16, A17, A26
	water intake	5 (19%)			A9, A10, A17, A22, A25
	energy level	5 (19%)	Limited food data - (N)	10 (0.8%)	A16, A6, A22, A25, A26
	steps	5 (19%)			A6, A9, A12, A16, A22
	menstrual cycles	4 (15%)			A6, A22, A25, A26
	weight	3 (11%)	Calorie intake as customized option - (S)	5 (0.4%)	A1, A15, A22
	macro & micronutritents	2 (7%)			A3, A22
Tracking Eating Disorders	triggers and symptoms	4 (15%)	Cultivates awareness of problematic eating behaviors and its factors, support food choices - (P)	69 (5.5%)	A6, A25, A26, A27
	medication/ supplements	3 (11%)			A22, A25, A26
	triggers and behaviors	2 (7%)			A1, A20

Table 1: Distribution of main codes for tracking functionality with sub-codes for tracking eating behaviors, emotions/moods, thoughts, bodily sensations; tracking healthy eating with sub-codes for tracking physical activities, healthy eating, sleep, water intake, energy level, steps, menstrual cycles, weight, macronutrients, and micronutrients; and tracking eating disorders with sub-codes for tracking triggers, symptoms, medication, and behaviors. The table also shows the number of positive (P), negative (N), and suggestions (S) from users' reviews for each functionality.

4.1.6 Tracking Symptoms and Triggers of Eating Disorders. Findings indicate that the reviewed apps provide limited tracking related to EDs such as tracking of *triggers and symptoms* (e.g., anxiety, depression) (4 apps); *triggers and behaviors* (e.g., purging, binging, counting calories) (A1, A20); *medications and supplements* (4 apps) (Table 1). EDs include a range of conditions such as anorexia nervosa, bulimia nervosa, and binge-eating disorder each with specific symptoms (e.g., preoccupation with food, nausea, vomiting, stomach pain), triggers (e.g., emotions, environment, body dissatisfaction), and behaviors (e.g., excessive exercise, strict dieting, or fasting, food labeling). Apps that capture medications and supplements use text entry for their time (e.g. day and hour), quantity (e.g., number of cups, drops, tablets), duration (e.g., regular, occasional), and targeted symptoms (e.g., obesity). Apps provide such information alongside details about meals, thoughts, and other activities. By collecting real-time data on EDs symptoms, apps help users self-monitor their eating habits and related activities. Users' reviews (69/1248) (5.5%) indicate appreciation for these tools: "*I appreciate the ability to monitor my fullness levels, it helps me recover from EDs as I have a hard time understanding when I'm actually full*".

Apps provide a range of tools for tracking triggers or problematic behaviors such as 5-point (A13) or 10-point (A25) Likert scales, or drop-down lists to select common EDs symptoms (A27). Our findings surprisingly indicate that apps do not integrate standardized scales into their interventions. An interesting finding is that 5 apps (A13, A22, A25, A26, A27) allow users to explore possible correlations between symptoms, triggers, and behaviors (e.g., sleep and mood, behavior and meal type). For instance, A13 supports users with anorexia nervosa to evaluate correlations between meals for which they experienced an urge to binge, and the type of meal that they consumed for a given week. Thus, they can identify the cause or trigger, and subsequently use that output to manage their condition better "*It enhances my understanding of how my symptoms relate to my diet. The app includes features for anxiety and stress, which often impact my nutrition negatively. I plan to use it to monitor and improve this aspect*". Apps visualize correlations with line graphs (A25, A27), bar charts (A20, A22, A27), or point graphs (A26) (Fig.4).

Findings also show that 5 apps (A13, A20, A23, A25, A27) provide an export option for the tracked data in three formats including PDF, CSV, and web reports to share with doctors. Although users (7/1248) did not specify the format type, they expressed satisfaction with being able to export their data: "*I like being able to keep track of different things together and the option to export my data to CSV for detailed analysis*".

To conclude, despite users' reviews (69/1248) showing appreciation for the tracking and monitoring functionalities provided by the apps as they may support awareness of bodily sensations and eating behaviors or motivate users to build healthy habits (e.g., physical activity, sleep quality); some reviews (4/1248) also highlighted challenges for tracking rich data (e.g., eating pattern): "*this app's relentless data tracking has become a major drawback. The constant reminders and exhaustive calorie, portion, and ingredient tracking feel intrusive*". Furthermore, 10/27 apps provide tracking functionality without interventions (A3, A9, A13, A14, A15, A22, A24, A25, A26, A27).

4.2 Interventions

Findings indicate that apps provide a range of interventions which we grouped into those supporting mindfulness meditation (12 apps), mindfulness eating meditation (8 apps), goal setting (11 apps), psychoeducational (9 apps), CBT (8 apps), and holistic (7 apps).

4.2.1 Guided Mindfulness Meditation. Findings show that 12 apps support guided mindfulness meditation both for EDs and mental health. Such guided mindfulness meditations interventions include body-centered ones (12 apps) (i.e., body scan, yoga, walking); heart-centered (10 apps) (loving-kindness, gratitude, compassion), and relaxation-focused (12 apps) (visualization, breath, letting go, calm) (Table 2). These interventions are mostly delivered in audio format (12 apps), and less so in text (A1, A6, A16), or video (A10, A16, A17), although the latter is particularly appreciated (4/ 1248): "*the animated video guidance is quite beneficial for visualizing messages and grasping concepts. I believe understanding these ideas would be hard without the help of such visuals*". The number of provided sessions varies from 1 to 10, each lasting between 3 and 40 minutes, and users (148/1248) expressed satisfaction with their diversity: "*I appreciate the wide variety of meditations available, catering to different moods and activities. It's fantastic to have such a diverse selection to choose from*".

4.2.2 Guided Mindfulness Eating. Our findings show that apps provide mindfulness eating meditation both for EDs (A1) and healthy eating (8 apps) (Table 2). The main finding is that all these 8 apps provide both mindfulness meditation and mindfulness eating. Most of these apps appear to be informed by MB-EAT interventions usually featuring the guided mindful eating of a small piece of fruit such as a raisin to fully engage with its sensory qualities [53]. Sensory appreciation is cultivated through slow observation, such as seeing the fruit for the first time, paying attention to its sight, smell, taste, sound, and texture; slowly chewing and swallowing, and if thoughts or emotions arise, noticing them non-judgmentally and return attention to the fruit [53]. These apps support guided mindfulness eating meditation by focusing on fruits such as raisins (A1, A8, A21), grapes (A8, A16, A21), cranberry (A16), or orange (A21), sweet treats such as chocolate (A1, A2, A16, A21), and candies (A1, A8), or savory food such as snacks (A1) or pasta (A21). Also, 3 apps provide generic guided meditation that can apply to any food (A4, A17, A21). Apps use different formats for mindfulness eating meditations namely calm music (A1, A2, A4, A8, A16, A21), encouraging the introduction of mindful moments into everyday meals (A16), and videos or animations showing the importance of each mindfulness eating aspect (A2, A17).

Interestingly, only 1/27 apps (A1) supported mindfulness eating interventions for people living with EDs. It features 28 modules including (i) psychoeducational videos on environmental content, emotional triggers for eating, foods that may boost cravings, and mindful awareness of physiological cues and eating habits; (ii) mindfulness interventions in audio format (e.g. body scan, self-compassion), and (iii) interventions addressing cravings and stress such as brief mindfulness exercises to cultivate awareness of one's body and emotions, and if the latter aligns with stress, eating patterns, mental habits, or hunger.

4.2.3 Goal Setting for Healthy Eating. An important finding is that 11/27 apps allow users to set healthy eating goals related to healthy and mindfulness eating, as well as physical activity, sleep, and water intake, supported by reminders through push-up notifications, or motivational quotes (Table 2). Users (38/1248) appreciated such apps: "*it helped me change my life by setting a new goal, now I drink water more regularly, and have better sleep quality*". In terms of format, most of these apps support the monitoring of goal progress through visualizations such as progress bars (A9, A12, A23, A26), checks integrated with calendar view (A16, A22), or icons (A19). For supporting engagement with goals, two apps provided rewards such as milestone badges (A19, A23) or celebration animations (A16), while 6 apps allow users to set calendar reminders which some users (11/1248) found problematic: "*whenever I fall short of my daily target, I receive reminders that demotivate me. They lack positive reinforcement and seem designed to crush motivation. It's normal not to have the same motivation every day*".

To support motivation, 11/27 apps provide text or image-based inspirational quotes: "*if you are feeling low and can't do it that day, prompts you to fill it in without any pressure*". Users (11/1248) reported that such apps supported them achieve daily goals (e.g., physical activity, water intake, meditation) which led to improved wellbeing or mental health. Surprisingly, only 1 app (A20) supports EDs recovery by setting goals such as monitoring and self-managing

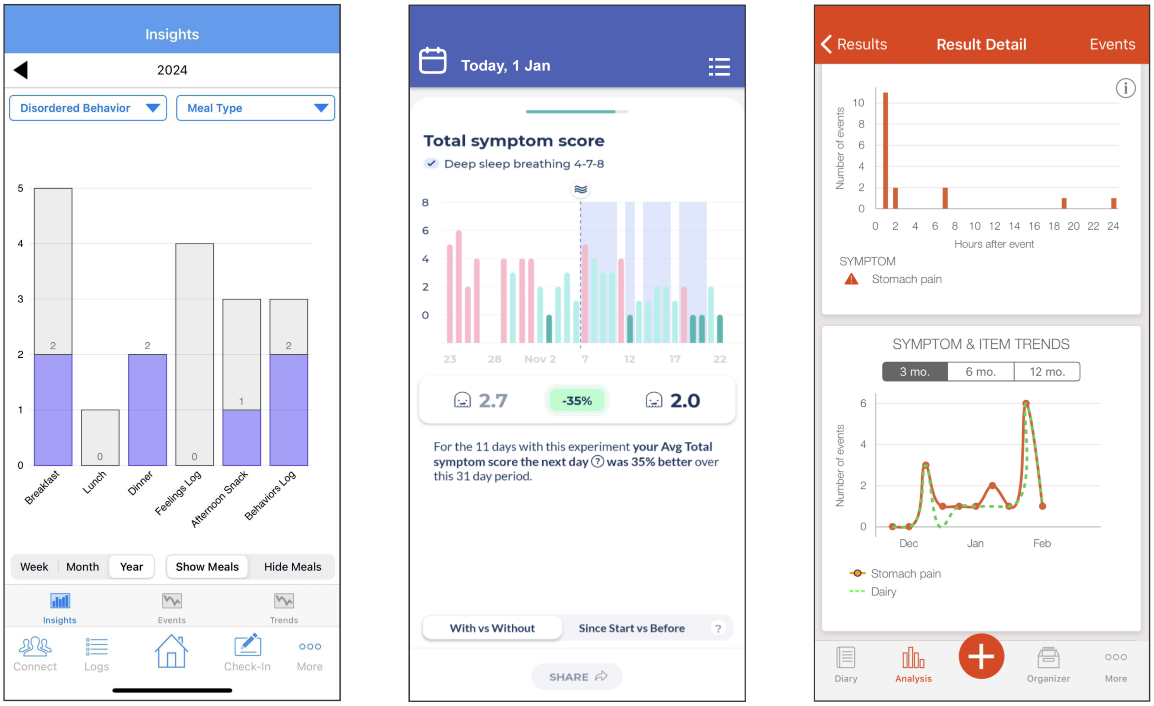

Figure 4: Screenshots showing visualizations of different tracked data to support reflection on the relationship between symptoms, triggers, and behaviors from apps (A20, A22, and A26 respectively). ©Copyright held by the developer(s) and used with permission.

meals, physical activity, triggers and urges, self-care, and body image, avoiding restrictive food intake, and strengthening motivation.

4.2.4 Psychoeducation. Most psychoeducation is provided with respect to interventions such as guided mindfulness meditation (12 apps) or mindfulness eating (3 apps) (A1, A2, A21). We have found surprisingly limited psychoeducation tailored to EDs, while 9/27 apps provide psychoeducation on broader aspects of healthy eating (Table 2). Such information is usually in text format (7 apps), videos (A1, A19), or audio (A21).

4.2.5 CBT-based Interventions. Study outcomes indicate that 6/27 apps provide CBT support for mental health, through motivational content, goal setting, mood, and thought tracking to help users better manage depression, anxiety, or stress (Table 2). In particular, such apps support the identification of behaviors that impact mood and thoughts through mood trackers, AI-based journals (A6, A14), or chatbots (A16). These apps also support mood regulation through visual and audio content aimed to relax, or boost mood, while 5 apps provide positive affirmations (A4, A6, A12, A14, A17); social (A6, A17), and clinical support (A6) to aid in the treatment.

Furthermore, 2 apps (A12, A16) allow users to set goals where they can track progress for a range of goals within domains such as social and romantic relationships, career and education, personal, family, social, and financial. For instance, the A12 app supports users to select such goals or define them themselves, alongside psychoeducation on goals and personal development.

Our findings also indicate a limited focus on CBT support for people living with EDs. Only 2/27 apps leverage CBT to support users' self-monitor meals, emotions, behaviors, and thoughts (A10, A20) which is surprising, given that CBT is the most explored and empirically supported treatment for EDs [29, 95]. Noticeable, the A20 app allows users to personalize their coping skills and indicate when they want to support with a coping skill (e.g., someone with anorexia reports they have the support for coping strategies to manage the urge to binge). This app also employs two validated scales for symptom identification: Eating Pathology Symptoms Inventory (EPSI) [35], and Eating Disorder Examination Questionnaire (EDE-Q) [70], which users can leverage to assess monthly progress.

4.2.6 Holistic Interventions. Alongside mindfulness interventions, 7 apps offer self-soothing content including relaxing and calm sounds (A2, A4, A10, A11, A19, A21), wellbeing text (A6), and sensory-textural games (A11) (Table 2). While users expressed their satisfaction with the various interventions provided by the apps, they also expressed dissatisfaction (negative reviews 58/1248) due to generic and non-personalized content, and particularly limited support for EDs: "*Instead of providing insightful data on eating disorders, it seems the developers opted for a one-size-fits-all method, resulting in a superficial and unhelpful resource for users*".

4.3 Usability Issues and User Experience

Usability concept captures how apps support users to achieve their goals with effectiveness, efficiency, and satisfaction [49] and has

Main codes	Sub-codes	Target	App numbers (/ 27)	Users' reviews content	Reviews number (/1248)	App names
Interventions	Mindfulness Meditation	Mental health	7 (26%)	Unable to change narrators' voice - (N)	14 (1.1%)	A2, A4, A6, A8, A11, A17, A21
				Customization of meditations - (S)	11 (0.9%)	
		EDs	5 (19%)	User satisfaction with diverse mindfulness meditations - (P)	152 (12.2%)	A1, A10, A12, A16, A20
	Goal Setting	Healthy eating	10 (37%)	Helps to build healthy habits - (P)	38 (3%)	A1, A6, A9, A12, A16, A17, A19, A22, A23, A26
		ED recovery	1 (3.7%)	Overwhelming reminders - (N)	11 (0.9%)	A20
	Psychoeducation	Healthy eating	9 (33.3%)	Helps with learning healthy food preparations and choices - (P)	29 (2.3%)	A1, A2, A6, A10, A16, A17, A18, A19, A21
	Cognitive Behavior Therapy (CBT)	Mental health	6 (22%)	Daily affirmations improve mental health; journals for reflection and mindfulness - (P)	136 (10.9%)	A4, A6, A12, A14, A16, A17
		EDs	2 (7%)	Immediate access to therapeutic support - (S)	7 (0.5%)	A10, A20
	Mindulness Eating Meditation	Healthy eating	7 (26%)	Help with slow eating and awareness of eaten foods - (P)	5 (0.4%)	A2, A4, A8, A12, A17, A21, A23
		EDs	1 (3.7%)			A1
	Holistic approaches	Wellbeing	7 (26%)	Help with calm sounds and sensory games for relaxation - (P)	23 (1.8%)	A2, A4, A6, A10, A11, A19, A21

Table 2: Distribution of main codes for providing interventions with sub-codes for types of interventions: mindfulness meditation for mental health and eating disorders, goal setting for healthy eating and eating disorder recovery, psychoeducation for healthy eating, cognitive behavior therapy for mental health and eating disorders, mindfulness eating meditation for healthy eating and eating disorders, holistic approaches for wellbeing.

emerged as the most prevalent theme in users' reviews, reflected in both positive (22/1248) and particularly negative experiences (307/1248). Considering the increased vulnerability of some of these users, usability is an important aspect impacting the delivery of apps' interventions and apps' adoption which in turn poses risks for harming users. Usability's main issues relate to apps' performance, user interface design, tracked data, and limited support.

4.3.1 Apps' Performance. Users' reviews reflected significant issues with apps' stability (184/1248) which ranged from poor responsiveness to app failure, including failing to record completed parts of interventions due to bugs (106/1248), slow running or buffering throughout use (36/1248): "*I used to enjoy with this app but recently they keep making it worse. Everything is super slow, sometimes the app doesn't launch at all or things get stuck at buffering*". Some of these issues could show early on during signing up or logging in (42/1248): "*I see a lot of potential, but full of bugs. It says that I don't have an internet connection, I can't log my meals*". Such limitations could give rise to heightened frustration, increased anxiety, and a sense of losing control, thus limiting the apps' effectiveness for self-monitoring and improving one's eating behavior.

4.3.2 User Interface. With respect to the design of the apps' interface, users reported mostly negative experiences in their reviews (87/1248). These are related to problematic color schemes perceived as "*overpowering [which] hinders the user experience. The blend of colors makes focusing on content difficult, especially with multiple symptoms, resulting in a chaotic graph*", or perceived complexity of graphics or animations, and text-based content: "*it becomes excessively complex with lengthy paragraphs and complex drawings and animations, resulting in a sensory overload*". Such findings indicate the value of ensuring simplicity of user interface to support users understand tracked data and their visualizations.

4.3.3 Tracked Data: Limited Accuracy and Judgemental Monitoring. Users' reviews (36/1248) expressed concerns regarding the richness of tracked data, and in particular its limited accuracy and judgmental monitoring. While some users appreciate that apps provide functionalities to track eating behaviors, sleep, weight, physical activity, or triggers and symptoms, others highlighted concerns regarding inaccurate tracked data: "*any height you put in it goes to overweight and especially in this era, this could lead to eating disorders and more dangerous ways*". Users also expressed concerns about what they perceived as judgemental monitoring through foods being labeled as "*good*" or "*bad*": "*the biggest disappointment was that this app ignored low carbs as an option. It would be great for diabetics who count carbs to monitor blood sugar and insulin requirements*".

4.3.4 Limited Support: Technical and Therapeutic. Another aspect emerging from users' reviews was limited developers' technical support, or in-app therapeutic support (25/1248). Findings indicate that some users (19/1248) faced challenges in accessing developers' help, expressing frustration at the limited responsiveness to their queries related to usability or payment issues. This frustration eventually led them to abandon app usage. In contrast, only a few users (2/1248) reported positive experiences, expressing satisfaction with developers' responses for addressing their reported issues.

Users (6/1248) also mentioned therapeutic support provided by in-apps through AI-based chatbots, or online qualified counselors. A few reviews outlined concerns with chatbot communication, in which users stated that it was not functioning properly or lack of support. The main issue is that the conversation between the chatbot and the user feels robotic, and misinterpretation of the questions can lead to misdiagnosis: "*the chatbot usually misinterprets my questions and returns with irrelevant responses*".

4.4 Ethical Concerns

Ethical aspects related to the risk of harm particularly for vulnerable users, fair access to these apps due to problematic costing practices, privacy of users' data, and users' trust in these apps, which are further outlined.

4.4.1 Risk of Harm: Vulnerable Users. Our analysis of apps' descriptions and user reviews' highlighted concerns about the potentially harmful impact of these apps, particularly for the most vulnerable users, such as those living with EDs, mental health conditions of any age, and especially children. A key outcome is that only 11/27 apps offer *medical disclaimers*, while 16 apps do not provide such disclaimers although some of them target vulnerable users. Users' reviews reflect such concerns: "*framed as an anorexia recovery app, but aimed at people with BED. It can be very triggering for individuals with bulimia and anorexia*" (Tables 5 and 6).

Findings also indicate concerns with using apps for *self-diagnosis* of EDs, with few users' reviews (7/1248) emphasizing the risk that invalid results may trigger EDs. These concerns include the reliability of the assessments, which if not valid may generate false results due to the restricted choice for answers: "*[there is] no way to take continuing health problems or medications into account when assessing symptoms. I had trouble answering questions because the answer options were limited and you could only pick one when multiple answers might apply*".

Our findings also show that 6/27 apps (A3, A4, A9, A10, A15, A16) do not highlight in their Policies their *suitability for children.* The remaining 21 apps mentioned in their Privacy Policies their suitability for different age groups: for those older than 13 years (8 apps), those older than 14 years (A25); those older than 16 years (A22, A27), or older than 18 years (4 apps). These apps also mentioned in their Privacy Policies the intention to protect children's data although the age group in such policies may be inconsistent with the apps' age rating on the marketplace (Tables 5 and 6). Moreover, 18 apps suggest the app's usage with parental guidance, and similar such concerns are also reflected in users' reviews: "*children shouldn't try this app, it's tracking weight and seeing themselves as underweight can make them unhappy*".

Another key finding relates to *problematic peer support*, with 4 apps allowing users to post anonymously in online user groups (A9, A13, A18), or by providing daily community questions (A6) which users can react to using emojis (A6, A13, A18). Regarding community support, users (4/1248) stated that it is important for them to share their progress with others and feel that not being alone in their journey positively impacts mental health. However, for some vulnerable users (7/1248) peer feedback impacts are negatively perceived due to increasing self-comparison to others which might impact the severity of mental health issues: "*given the presence of many early teens, sensitivity is crucial. A filter system for discussing and seeking help on potentially triggering topics would be beneficial*".

Not least, findings highlight concerns regarding *interventions' validity*, since only 8/27 apps were promoted on the marketplace with the claim that their design is based on evidence-based interventions including mindfulness (3 apps), CBT (7 apps), Acceptance and Commitment Therapy (A4, A16), self-compassion (A16), psychology (A6), or positive psychology (A14). The remaining 19 apps provide no such claims, and 5 apps provide interventions without tracking (A4, A8, A11, A18, A19). These findings are also reflected in users' reviews, with only a small number of users (13/1248) mentioning satisfaction with some apps' clarity regarding the validity of the provided interventions "*I was looking for an app backed up by science, and happy that I found this app simple yet effective*". Other apps were recommended to users by their health practitioners, after meeting validity requirements: "*My dietitian recommended it (reliability is key). It has made me honest with my eating patterns and the psychology behind my eating problems. A really good prompt to open a discussion about my eating disorder with her and my psychologist*".

4.4.2 Users' Fair Access: Apps' Problematic Costing Practices. With respect to fair access, key findings relate to apps' costs. A positive outcome is that most apps are free to download, and 7/27 apps do not request in-app purchases (Tables 5 and 6). The remaining 20 apps offer in-app purchases for specific functionalities, with subscription prices between $4.99 and $129.99 per month. Apps' cost was one of the most common themes in users' reviews, including perceived deception concerning costing practices, and users' rights (173/1248) which echoes previous findings on users' reviews for apps for depression [9]. In this respect, some users argued that such apps should offer all features for free (13/1248) since their cost is not affordable (28/1248) which in turn prevents long-term use. Users (19/1248) also shared concerns regarding unfair costing practices such as limited payment plans, which make subscriptions unaffordable. Such users appear to lack the financial means to afford these costs, or are doubtful about making such payments, perceiving the costs as disproportionately high compared to the value offered by the apps (36/1248).

Main codes	Sub-codes	App numbers (/27)	Users' reviews content	Reviews number (/1248)	App names
Usability	App performance	27 (100%)	Time lag/ slow loading, intermittent freezing/buffering, unresponsive interface, bugs with login/sign up - (N)	184 (14.7%)	All apps
	User interface	27 (100%)	Poor colour scheme, animations, non-responsive buttons, lack of menu/ control buttons, lack of customization - (N)	87 (7%)	All apps
			User satisfaction due to ease of use, simplicity - (P)	22 (1.76%)	
	Accuracy of tracked data	27 (100%)	Inaccurate multiple data being tracked, food labelling, or weight - (N)	36 (2.9%)	All apps
Ethical Concerns	App trust	27 (100%)	Paywalls, unexpected charges, misleading advertisements of app content - (N)	82 (6.6%)	All apps
	Sensitive user data	23 (85%)	Limited protection and security as sensitive data may be shared with third parties - (N)	16 (1.3%)	A1, A2, A3, A4, A5, A7, A9, A10, A11, A12, A14, A15, A16, A17, A18, A19, A20, A21, A22, A23, A24, A25, A26
	User age	21 (78%)	Not suitable for certain age groups due to harmful content - (N)	1 (0.1%)	A1, A2, A5, A6, A7, A8, A11, A12, A13, A14, A17, A18, A19, A20, A21, A22, A23, A24, A25, A26, A27
	App cost	17 (63%)	High costs, excessive advertisements, limited payment plans, lack of payment transparency - (N)	148 (11.9%)	A1, A2, A3, A4, A5, A6, A8, A11, A13, A14, A15, A16, A17, A19, A22, A23, A26
			Apps should be free - (S)	13 (1%)	
			Satisfaction with free content - (P)	12 (0.9%)	
	Medical disclaimer	11 (41%)	Does not provide appropriate treatment for the EDs despite being mentioned in app's description - (N)	1 (0.1%)	A1, A4, A6, A12, A13, A14, A16, A17, A20, A21, A25
	Peer support	4 (15%)	Self-comparison and negative peers' comments - (N)	11 (0.9%)	A6, A9, A13, A18
User Support	Developer's support	27 (100%)	Customer support is unreachable and unresponsive - (N)	19 (1.5%)	All apps
	In-app support	4 (15%)	AI-based diary not working or wrong answers, limited answer option available for questions - (N)	6 (0.5%)	A4, A6, A14, A16

Table 3: Distribution of main codes for usability issues including sub-codes for app performance, user interface, and accuracy of tracked data; as well as main codes for ethical concerns including sub-codes for sensitive user data, user age, app cost, medical disclaimer, peer feedback, technical support, therapeutic support, and trust.

While some users (12/1248) mentioned their satisfaction with the free app content, others (15/1248) expressed frustration that most content was restricted which forced them to seek alternative apps that meet their needs without subscription costs. A related issue raised by users (33/1248) was excessive advertisements which led some users to discontinue the app's use.

Regarding apps' prices and billing methods, some users (17/1248) complained that despite canceling subscriptions before the end of free trials, they were still charged without their permission or information. The limited transparency of such pricing practices, coupled with limited support from developers to address such issues, negatively impacted users' adoption of apps. The presence of in-app purchases has negative implications. In-app purchases are at risk of being perceived as deceptive, especially if not clearly communicated, since users have already invested time in using the app and tracking their data. In turn, this can potentially exacerbate the stressors for already vulnerable users who also face financial challenges. Premium features behind paywalls may exacerbate disparities in accessing support services, favoring individuals with financial means and widening existing gaps in healthcare accessibility.

Findings show that while 11 apps provide content in *multiple languages*, 16 apps support only English. Surprisingly, only 2 apps (A2, A5) have Privacy Policies in multiple languages, matching those supported within the app. Ethical concerns arise from the lack of language preferences in Privacy Policies of mobile health apps, particularly in terms of accessibility, informed consent, equity, trust, transparency, and legal compliance. Failing to provide Privacy Policies in multiple languages may compromise users' understanding of their rights, exacerbate healthcare disparities, undermine trust, and potentially breach legal requirements. Addressing these concerns necessitates commitment to inclusivity, transparency, and respect for users' rights and preferences.

4.4.3 Privacy of Users' Personal and Sensitive Data. Findings also highlight privacy concerns regarding users' personal and often sensitive data, data sharing with third parties, data storage, and ownership. We found that 22 apps mentioned in their Privacy Policies that users' information will be captured through cookies, and could be shared with *third parties* such as advertisers or analytics providers. Only 4 apps informed users that their data will not be collected nor shared (A5, A6, A7, A13). Surprisingly, a low number of users' reviews (16/1248) mentioned data safety. While a few users' reviews (2/1248) indicated their appreciation of understandable Privacy Policies, others expressed concerns about the protection and *safety of their data*, especially concerning third parties (12/1248) (Table 5 and 6). The *sensitivity of data* pertains to fingerprint authentication, and tracking functionality for emotions, moods, and thoughts: "*ignoring data privacy and lacking proactive security measures makes sharing personal journal entries unsafe*".

Users (2/1248) also emphasized the importance of having *control over their data*, including what gets collected, how it is *stored*, and whom is *shared with*. While some users prioritized enhanced data protection, others were more willing to overlook potential privacy concerns in using cloud storage to protect against data loss: "*I recommend not allowing the app to access all data when uploading food images. This app is very risky because it scans all the files on my device and backs them up in its cloud. If you don't give any consent, it won't be able to access any photos even if you're running it from cloud storage, which doesn't make sense and seems suspicious*".

4.4.4 Users' Limited Trust in Apps and Developers. Trust was one of the themes that emerged in 82/1248 user reviews, with mostly negative experiences being reported about limited costing details, and reduced trust in apps and developers. Several users outlined insufficient information regarding app costs and billing practices. Regarding costs, users' primary concerns included hidden costs (16/1248), paywalls (14/1248), and unexpected charges (27/1248). This also involved misleading advertisements regarding apps' content (20/1248) and details regarding treatment and benefits after treatment. Some reviews (5/1248) also reflected users' disappointment that despite their trust and payment for their apps, these did not meet expectations: "*I subscribed to this app after seeing an Instagram ad promising help with EDs and focus through features like boldening the initial letters of words in text. However, upon payment, I realized that the app lacks this specific feature as advertised*".

Our functionality and users' reviews indicate that users are mostly satisfied with the content diversity that improves their overall health and well-being. They also expressed the desire to improve such apps due to having limited support for understanding factors associated with EDs, the limited interventions that are tailored to problematic eating behaviors, and the limited validity of self-monitoring tools.

5 DISCUSSION & DESIGN IMPLICATIONS

In this section we revisit the research questions, highlighting the key findings and their novelty, which we used to inform the design implications. We start by reflecting on the questions on the main functionalities of top-rated apps for mindfulness eating and EDs, and users' satisfaction with them.

5.1 Tracking Functionalities of Apps for Mindfulness Eating and Eating Disorders

An important outcome is the breadth of functionalities and sub-functionalities across our reviewed apps, albeit with limited integration of such functionalities in individual apps. With respect to tracking functionality, 6 apps track meals, 3 apps track bodily sensations, 4 apps track emotions, and 3 apps track thoughts, while only 3 apps track all of these aspects. These confirm previous outcomes on mobile apps tracking aspects such as nutrients, physical activities, or calorie intake, although the latter is problematic, particularly for people living with EDs [8].

Our findings also show that such data is tracked mostly through food diaries, free text, or photos of meals or eating practices which users appreciate, echoing previous outcomes [16]. Users also enjoy emojis and voice recordings for capturing emotions or moods, whose visualizations could be integrated with calendar views and charts for later reflection on mood changes over time, or AI-based food diaries for prompting reflection on emotions and thoughts.

Users' reviews of these apps also indicate their appreciation for the Likert scale for self-reporting bodily sensations such as levels of hunger and satiety. While users appreciate the richness of such captured content, a trade-off is needed to limit users' burden for self-tracking data. Our outcomes confirm previous ones highlighting the tracking of emotions, and thoughts for mental health conditions such as depression [83], or tracking of emotions, thoughts, and meals for EDs [22]. In addition, we extend previous work by emphasizing also the value of tracking additional types of data, namely bodily sensations.

Another key finding is the limited support for tracking EDs symptoms, triggers, and behaviors (6 apps), and for supporting users' reflection on them, although when available, users felt empowered to explore the relationship between their behaviors and triggers or symptoms of EDs. However, only 1 app employs validated scales for symptoms' identification, namely Eating Pathology Symptoms Inventory (EPSI) [35], and Eating Disorder Examination Questionnaire (EDE-Q) [70]. Given the relationship between food and emotion [39, 40], it is not trivial for people living with EDs to differentiate emotions and bodily experiences, therefore sensitive scaffolding may be needed to support such users [72]. For EDs, one app (A20) also supported the tracking of dysfunctional thoughts through multiple options which can be particularly useful to support self-reflection.

5.1.1 Design implications: Tracking and Reflecting on Multiple Aspects of Mindfulness & Healthy Eating. We argue that mobile apps aimed to support mindfulness eating, and healthy eating practices for people living with EDs could benefit from tracking all key aspects of such practices such as eating behaviors, associated emotions, bodily sensations, and thoughts. Eating behaviors could also track aspects such as macro or micro-nutrients, water intake, physical activity, sleep, or energy level, albeit less so calorie intake. Such rich content could be tracked through a range of modalities, users preferring text, media, or voice recordings, as well as brief digitized scales for ecological momentary assessment of dysfunctional thoughts, and levels of hunger and satiety before, during, and after meals. Together, these aspects, and in particular emotions and bodily sensations are essential as also highlighted in the MB-EAT interventions which aim to bring attention to the food intake and cultivate non-judgmental awareness of internal bodily sensations and external triggers for automatic eating patterns [61]. For apps targeting users living with EDs, we also argue for the value of leveraging digitized valid scales for symptom identification. While self-reporting is key, complementing it with automatic data tracking is recommended, to lessen users' burden for self-tracking. Moreover, as shown in our findings, we also argue for the value of AI to prompt reflection through questions based on identified changes or patterns in tracked data. Such AI-based reflection extends previous design suggestions for supporting reflection on tracked data merely through text, icons, charts, or media [22].

5.2 Providing Interventions within Apps for Mindfulness Eating & Eating Disorders

Our findings indicate the limited provision of interventions, with 7 apps providing no intervention despite tracking aspects of eating behaviors, 5 apps providing interventions without tracking such aspects, and only 14 apps both tracking aspects of eating behaviors and providing interventions. Among the latter, most apps support a range of interventions namely mindfulness meditation (12 apps), followed by goal setting for healthy eating (10 apps), psychoeducation (9 apps), CBT-based interventions (8 apps), mindfulness eating meditation (8 apps), and holistic approaches (7 apps). However, although users appreciated the options of multiple available interventions, only 11 apps support more than one intervention, common pairs being mindfulness eating and CBT (6 apps), mindfulness eating and mindfulness meditation (5 apps), and mindfulness eating and goal setting (1 app).

Another significant outcome is users' dissatisfaction with the limited provision of tailored interventions for people living with EDs, namely mindfulness meditation interventions (5 apps), CBT-based interventions (2 apps), mindfulness eating meditation (1 app), goal setting for EDs recovery (1 app), and psychoeducation (0 apps). Apps A1 is an exception, providing a good illustration for integrating psychoeducational videos, mindfulness interventions for body awareness, and for problematic eating. Our outcomes confirm previous ones on the limitations of commercial apps for EDs with respect to tailoring CBT-based interventions to the complexity of the condition, and for supporting users to reflect and make sense of their tracked data [22].

5.2.1 Design Implication: Supporting Personalized Interventions, particularly for EDs. We suggest providing a range of available interventions, and given the specific focus on mindfulness eating meditation, integrating at least MB-EAT based interventions [37, 47, 50, 62, 67, 71] alongside CBT [72] and holistic approaches [84, 100] and tailoring them based on tracked data on eating behaviors and associated aspects. Such integration can be beneficial for both healthy eating and, more importantly for users living with EDs for whom CBT-based interventions have been much explored and empirically validated [29, 95].

Personalization is particularly important given the limitations of insufficiently tailored content in app-based mental health interventions [23, 74], and users' preference for personalization [21, 42]. This is even more important for people living with EDs given the significant impact of these conditions on wellbeing. While our study explored mobile apps, research on Human-Food interaction has also focused on other classes of technologies such as wearables [58] and smart tableware [54, 102, 103] to support slow eating. We suggest the value of integrating smart tableware with mobile apps for richer interventions that can be better embodied in eating practices.

5.2.2 Design Implication: Supporting AI-based Interventions. A surprising outcome is the limited use of AI for the provision of interventions, despite emerging HCI research showing both ethical challenges as well as the potential of AI for mental health technologies which range from the detection of symptoms and diagnosis of conditions to recommendation of interventions [93], including personalizing app-based interventions for conditions such as depression [5]. We highlight the feature of the A20 app providing a range of microinterventions as coping skills from which users could choose the one they prefer. We can imagine future interfaces that integrate AI to identify problematic eating behaviors and predict EDs triggers or symptoms by analyzing patterns of users' tracked data such as meal logs, moods, thoughts, and bodily sensations. Such interfaces could also leverage AI to provide recommendations for the most suitable in-time interventions from various therapeutic approaches, given the value of complementary interventions [52].

Despite such potential, AI technologies in this space also raise ethical concerns [5, 93] such as algorithmic biases due to incomplete, underrepresented, or inaccurate data which can undermine the accuracy of detected patterns or recommended interventions. There is also the risk of over-reliance on AI, potentially undermining the role of human therapists or healthcare professionals [5, 94]. Therefore, we support the view of developing AI-powered apps whose predictions and recommended interventions are subject to review and validation by healthcare professionals to prevent unintended harm when diagnosing or treating problematic eating.

5.3 Addressing Challenges of Apps for Mindfulness Eating and Eating Disorders

The third research question focused on the challenges of these apps and how can they be addressed. Findings from users' reviews highlighted over 10 times more negative than positive user experiences due to apps' inconsistent performance caused by bugs, and often limited technical support from developers to address them, extending those on usability of commercial apps for mental health [6, 9, 76]. In turn, such issues may lead to loss of, or inaccurate tracked data, hindering users' reflection. Particularly problematic experiences relate to perceived judgmental tracking and monitoring of food, calories, and weight which can harm more vulnerable users living with EDs by triggering them. Moreover, our users' reviews indicate that users with EDs become overwhelmed by rich visualizations with complex color schemes and charts, confirming findings on the comorbidity of EDs and attention deficit disorders [55].

While a substantial number of reviews (>44%) acknowledged the benefits of these apps for improving eating practices and wellbeing, and for better management of EDs (552/1248), about 19% of users' reviews also highlighted ethical concerns (284/1248) which we grouped under the principles of biomedical ethics [7] previously used in a HCI review of technologies for mental health [86]. These principles consist of beneficence (i.e., providing benefits, ensuring interventions' validity), non-maleficence (i.e., preventing harm), autonomy (i.e., respecting the privacy of users' personal and sensitive data), and justice (i.e., fair distribution of apps' benefits and costs).

With respect to beneficence, users' reviews indicate the importance of the validity of the provided interventions and their scientific underpinnings, mentioned only in the descriptions of 8 apps. Despite users' satisfaction with interventions, their limited validity reflected in limited evidence-base or clinical grounding can potentially harm users [46]. Also related to non-maleficence, findings showed that only 11 apps provide medical disclaimers. We argue for the importance of providing such disclaimers, as without them, apps could be used by people living with different EDs or mental health conditions, albeit such apps may not have been tailored to the specific needs of these vulnerable users.

Non-maleficence principle also requires protecting the most vulnerable younger users. Findings showed that according to their Privacy Policies, most apps (21/27) could be used by people older than 13 years of age, information which for some apps is also inconsistent with the specified users' age rating on the marketplace. To address these, we urge developers to limit access of vulnerable users, if their specific needs are not particularly addressed by the app. These outcomes extend similar ones on younger users' vulnerability when using apps for depression [10, 83] to apps for mindfulness eating and EDs.

In terms of the autonomy principle, our findings show that 22 apps share users' data with third parties, although a limited number of users' reviews expressed concerns regarding users' control over their data, possibly stemming from the complex language, lengthy documents, and lack of transparency in Privacy Policies [104]. This finding shows limited alignment with previous work where users' concerns with the security and confidentiality of their health data impacted their decisions to not use mHealth apps [56, 60]. We argue for the value of increasing the accessibility and transparency of these Policies, and of supporting users' privacy literacy, while future work should explore the rationale for these users' limited concerns with their data privacy.

Concerning justice and fair access, key findings relate to apps' costs; despite their initial free download, the presence of premium features behind paywalls could exacerbate disparities in accessing such apps, thus further widening the gaps in healthcare accessibility. Users' reviews also indicated that problematic costing practices impacted their trust and apps' adoption, extending similar findings from users' reviews of apps for depression [10].

5.3.1 Design Implication: Supporting Sensitive Design for Diagnosis. Non-maleficence is reflected also in the need to limit the risk of misdiagnosis due to inaccurate tracked data, as well as that of automatic diagnosis. The potentially harmful impact of in-app self-diagnosis when delivered without therapeutic support has been previously reported for apps targeting people living with mental health conditions [86] and is also relevant for people living with EDs. Similarly, we argue for the value of supporting therapists' efforts for diagnosis, so that it can be sensitively communicated within a therapeutic context.

5.3.2 Design Implications: Supporting Sensitive Co-Design for Tracking & Monitoring of Problematic Data. Findings indicate the challenges of tracking and monitoring problematic data such as negative emotions, thoughts or behaviors, peer feedback, as well as judgemental food or bodily data which can negatively impact users, or act as triggers for EDs. These outcomes extend those on the impact of negative content [83] or peer review on users of apps for mental health [3, 9] to apps for mindfulness eating and EDs. They also confirm previous outcomes on the negative impact of caloric intake, weight data, or food labeling as triggers for EDs [8, 27, 43]. To address these challenges, we strongly recommend limiting such problematic, triggering data being explicitly tracked and monitored, and for monitoring and curating peer feedback on online communities. For this, it is crucial to engage people living with EDs and their therapists in the apps' design process. We can imagine tracking such data less frequently over time, if possible through the system's input rather than explicit user input, and leveraging ambiguous representations in a range of modalities, but also more embodied and less representational such as haptic ones [19].

6 CONCLUSIONS

This work reports functionality review of 27 apps on mindfulness eating and EDs and content analysis of 1248 of their users' reviews. Findings showed the rich set of data being tracked and reflected on, and various interventions provided by these apps, along with key usability and ethical challenges. These outcomes led to five design implications namely tracking and reflecting on multiple aspects of mindfulness and healthy eating, supporting personalized interventions and AI-based ones, as well as the sensitive design for diagnosis, and for tracking and monitoring problematic data.

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A APPENDICES

A.1 Supplementary Tables and Figures

ID	App name	Users' rating (/5)		Number of user ratings		Word counts		Type of user ratings		
		Apple App Store	Google Play Store	Apple App Store	Google Play Store	Apple App Store	Google Play Store	Low (1)	Ambivalent (2,3,4)	High (5)
A1	Eat Right Now	4.8	4.8	4	33	231	1722	7	8	22
A2	Headspace	4.8	4.5	49	72	4795	2831	34	42	45
A3	Yuka	4.8	-	54	-	2951	-	2	12	40
A4	Meditopia	4.8	-	13	-	647	-	3	6	4
A5	Mindshine	4.8	-	8	-	643	-	1	2	5
A6	VOS	4.7	4.5	10	49	562	2757	12	20	27
A7	Mindful Chef	4.7	-	43	-	1734	-	10	9	24
A8	Mindfulness Guided Meditations	4.7	-	1	-	42	-		1	
A9	Pactive	4.7	-	1	-	67	-			1
A10	My Possible Self	4.6	4.6	36	59	1822	2200	4	29	62
A11	Feelsy	4.6	4.2	50	50	3456	2610	53	35	12
A12	Remente	4.6	4.2	12	49	240	2594	14	22	25
A13	Eating Disorder Recovery	4.6	-	3	-	92	-		2	1
A14	Reftlectly	4.5	4.3	52	50	3713	2652	9	40	53
A15	BMI Calculator	4.5	-	13	-	608	-	4	1	8
A16	Holly Health	4.5	-	13	-	862	-	1	3	9
A17	Fabulous	4.4	-	62	-	3556	-	11	22	29
A18	Tellmi	4.4	-	27	-	1682	-	3	11	13
A19	Habio	4.0	-	25	-	1440	-	15	4	6
A20	RR Eating Disorder Recovery	-	4.8	-	71	-	2833	2	13	56
A21	Insight Timer	-	4.8	-	64	-	2808	18	16	30
A22	Mood Symptom Tracker	-	4.7	-	60	-	2830	4	23	33
A23	Shutterbite	-	4.4	-	11	-	611	1	5	5
A24	Food View	-	4.3	-	65	-	1003	1	39	25
A25	My Symptoms Food Diary	-	4.2	-	102	-	2872	12	42	48
A26	Commonality	-	4.2	-	12	-	394	1	3	8
A27	Endive	-	4.1	-	25	-	648	2	18	5

Table 4: List of 27 apps included in our analysis which focused on mindfulness eating, healthy eating, or eating disorders.

App name	App cost (marketplace)	Medical disclaimer	Age rating (marketplace)	User age restriction	Clinical involvement (while using the app)	Privacy policy (available/ or not)	Data safety
A1	offers in-app purchases	Yes, available	12+	Parental permission is recommended for teens 13-18 years old.		Yes, available as a medium page	3rd party data sharing (e.g., advertisers)
A2	offers in-app purchases	N/A	4+	Parental permission is recommended for teens 13-18 years old.		Yes	3rd party data sharing (e.g., advertisers)
A3	offers in-app purchases	N/A	4+	N/A		Yes	3rd party data sharing (e.g., advertisers)
A4	offers in-app purchases	Yes, available	4+	N/A		Yes	3rd party data sharing (e.g., advertisers)
A5	offers in-app purchases	N/A	17+	No data from under 13 years old. Parental permission is recommended.		Yes	3rd party data sharing (e.g., advertisers)
A6	offers in-app purchases	Yes, available	4+	No data from under 15 years old. Parental permission is recommended.	Users can activate standby health practitioners in the app	Yes	
A7	free	N/A	4+	The app explicitly states it's not for children and does not knowingly collect data on them.		Yes	
A8	offers in-app purchases	not available in English	4+	not available in English	not available in English	not available in English	not available in english
A9	free	N/A	18+	N/A		Yes, available as a medium page	3rd party data sharing (e.g., advertisers)
A10	free	N/A	12+	N/A		Yes	3rd party data sharing (e.g., advertisers)
A11	offers in-app purchases	N/A	4+	No data from under 18 years old. Parental permission is recommended.		Yes	3rd party data sharing (e.g., advertisers)
A12	offers in-app purchases	Yes, available	12+	No data from under 13 years old. Parental permission is recommended.		Yes	3rd party data sharing (e.g., advertisers)
A13	offers in-app purchases	Yes, available	12+	No data from under 13 years old. Parental permission is recommended.	Users can generate report to show clinicians	Yes	
A14	offers in-app purchases	Yes, available	4+	No data from under 13 years old. Parental permission is recommended.		Yes	3rd party data sharing (e.g., advertisers)

Table 5: Descriptive characteristics of the apps including app name, app cost, medical disclaimer, age rating, user age restriction, clinical involvement, privacy policy, and data safety.

App name	App cost (marketplace)	Medical disclaimer	Age rating (marketplace)	User age restriction	Clinical involvement (while using the app)	Privacy policy (available/ or not)	Data safety
A15	offers in-app purchases	N/A	12+	N/A		Yes	3rd party data sharing (e.g., advertisers)
A16	offers in-app purchases	Yes, available	12+	N/A		Yes	3rd party data sharing (e.g., GP)
A17	offers in-app purchases	Yes, available	4+	Parental permission is recommended for teens 13-18 years old.		Yes	3rd party data sharing (e.g., advertisers)
A18	free	N/A	12+	The app, being a preventative service, is exempt from requiring parental consent for children of any age.	Users can activate standby health practitioners in the app	Yes	3rd party data sharing (e.g., advertisers)
A19	offers in-app purchases	N/A	4+	No data from under 13 years old. Parental permission is recommended.		Yes	3rd party data sharing (e.g., advertisers)
A20	free	Yes, available	12+	No data from under 13 years old. Parental permission is recommended.	Users can generate reports to show clinicians Users can activate standby health practitioners in the app	Yes	3rd party data sharing (e.g., advertisers)
A21	offers in-app purchases	Yes, available	12+	No data from under 13 years old. Parental permission is recommended.		Yes	3rd party data sharing (e.g., advertisers)
A22	offers in-app purchases	N/A	4+	No data from under 16 years old. Parental permission is recommended.		Yes	3rd party data sharing (e.g., advertisers)
A23	offers in-app purchases	N/A	4+	No data from under 13 years old. Parental permission is recommended.	Users can generate report to show clinicians	Yes	3rd party data sharing (e.g., advertisers)
A24	free	N/A	4+	No data from under 13 years old. Parental permission is recommended.		Yes	3rd party data sharing (e.g., advertisers)
A25	offers in-app purchases	Yes, available	17+	No data from under 14 years old. Parental permission is recommended.	Users can generate report to show clinicians	Yes, available as a medium page	3rd party data sharing (e.g., GP)
A26	offers in-app purchases	N/A	N/A	N/A		Yes	3rd party data sharing (e.g., advertisers)
A27	free	N/A	12+	No data from under 16 years old. Parental permission is recommended.	Users can generate report to show clinicians	Yes	3rd party data sharing (e.g., advertisers)

Table 6: Descriptive characteristics of the apps including app name, app cost, medical disclaimer, age rating, user age restriction, clinical involvement, privacy policy, and data safety.

Apple App Store

```
https://colab.research.google.com/

/New line
!pip install app-store-scraper

/New line
from app_store_scraper import AppStore
from pprint import pprint
import pandas as pd
import numpy as np
import json
slack = AppStore(country='gb', app_name='APP NAME',
app_id=000000000)
slack .review(how_many=100)

/New line
slack.reviews

/New line
df= pd.DataFrame(np.array(slack.reviews),columns=['review'])
df2 = df.join(pd.DataFrame(df.pop('review').tolist()))
df2.head()

/New line
df2.to_csv('App name.csv')
```

Google Play Store

```
https://colab.research.google.com/

/New line
pip install google-play-scraper

/New line
import pandas as pd
import numpy as np

/New line
from google_play_scraper import Sort, reviews_all
uk_reviews = reviews_all(
    'com.appname',
    sleep_milliseconds=0, # defaults to 0
    lang='en', # defaults to 'en'
    country='gb', # defaults to 'gb'
    sort=Sort.NEWEST, # defaults to Sort.MOST_RELEVANT)

/New line
df_busu = pd.DataFrame(np.array(uk_reviews),columns=['review'])
df_busu = df_busu.join(pd.DataFrame(df_busu.pop('review').tolist()))
df_busu.head()

/New line
df_busu.to_csv('App name.csv')
```

Figure 5: Codes used for scraping users' reviews from the Apple App Store and Google Play Store.