Towards Heuristics for AI-Based Eating Disorder Apps

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Despite the societal impact of eating disorders, the exploration of mobile apps for eating disorders and in particular their AI-based features has been limited. We report a functionality review of 4 apps for eating disorders which claim to leverage AI. Findings indicate that apps provide functionalities such as tracking of thoughts and moods, provision of interventions, including conversational agents designed by using ML and NLP, albeit the specific use of AI lacks clarity. We advance some heuristics for AI-based mobile apps for eating disorders which, by drawing from previous work, we grouped under four themes of heuristics for decision-making, personalization, productivity, and security.

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

Additional Key Words and Phrases: eating disorders, AI, artificial intelligence, heuristics, mobile apps, chatbots, conversational agents, explainable AI

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1 INTRODUCTION

In recent years there has been an increased HCI interest in food [22] given its potential to impact user experience [20, 25] and in particular emotions [21] and memories [23, 24]. There has been also a significant growth in HCI research for wellbeing and affective health [41] including a focus on eating disorders (EDs). The latter pose a significant health concern due to their expensive treatment, widespread occurrence, and associated health dangers, making them one of the mental illnesses with the highest mortality rates [44]. The prevalent mobile devices and smartphones could support ED symptom monitoring [19, 30, 47], increase patients' treatment adherence, and alleviate feelings of stigma associated with in-person psychological treatment [29]. When adequately designed, mHealth (mobile health) interventions can contribute to behaviour change by allowing users to self-monitor personal data by reflecting on moods, thoughts, physical activities, and eating patterns (e.g., portion size, caloric intake) [47]; facilitating patients to share progress with therapists without time and location constraints, or by providing psychoeducational materials [18, 19].

Technological advancements specifically in artificial intelligence (AI) and machine learning (ML) methods hold promise to reshape mental health treatment from early detection or diagnosis of mental health symptoms [10, 11, 28], and predictions of mental health risks [2, 3, 37], to understanding mental health-related behaviours on online communities [33, 40], and recommendation of personalized interventions [46]. Besides, AI and ML, chatbots or conversational agents are developed for healthcare assistance to communicate with humans by using natural language processing (NLP) [6] to support text or voice-based conversations [6] for a range of applications including mobile apps for mental health [5]. With respect to EDs, most HCI research has focused on the impact of social platforms [9, 35, 36, 48], and mobile app interventions [14–16]. Given the prevalence of the latter, emerging work has explored their functionalities, but limited work has focused on AI-based functionalities of EDs apps, and in particular how these can be explored through tailored heuristic.

From Nielsen's seminal work [1], heuristics have gained large acceptance for rapid, expert evaluation of technologies, with specific heuristics being developed different classes of technologies such as mobile apps on health and wellbeing [42], fitness [43], VR [45], and games [38]. However, heuristics for AI-based technologies have been limitedly explored. A noticeable exception is work of Jin and colleagues [27] on heuristics derived from AI patents, and validated through case studies to aid the generation of innovative AI-powered solutions in early design stages. These heuristics serve as prompts for exploring design opportunities, and enhancing UX ideation. Authors organized heuristics into four categories namely decision making, personalization, productivity, and security [27]. However, heuristics for AI-based mental health apps particularly EDs apps have not been explored. To address this gap, we report a functionality review of 4 AI-based apps for EDs, complemented with autoethnography, and review of apps' Terms and Conditions, and Privacy Policies. The main contribution of this work is advancing heuristics for AI-based mobile apps for health and in particular for EDs. We build on similar approaches to the exploration of commercial apps such as functionalities review for digital wellbeing apps [4], or for apps for depression [7, 39], and autoethnography for mindfulness eating apps [26].

2 METHOD

This section describes the two stage-process for identifying the apps, and their analysis. To identify the apps we searched the two main app stores in the UK: Apple App Store and Google Play Store using the following keywords "*binge eating*", "*binge eating disorder*", "*eating disorders*", "*anorexia*", "*anorexia nervosa*", "*bulimia*", "*bulimia nervosa*", "*obesity*", "*stress eating*" and "*emotional eating*". From the initial 586 apps, we included those which met the following criteria: highly rated free apps, scoring 4 out of 5, having at least 20 user reviews, belonging to the Health and Fitness category, and whose title or description on the marketplace mentioned at least one of our keywords. From these, we excluded apps which focused mostly on aspects like "*diet*", "*fasting*", and "*fitness*" as mentioned in their title and description which led to 32 apps. We have also considered additional criteria to focus specifically on AI features, therefore within these 32 apps, we searched their descriptions using the keywords: "*artificial intelligence*", "*AI*", "*machine learning*", "*ML*", and "*chatbot*" which led to a small set of 4 apps from Apple App and Google Play Stores: Reflectly, Meditopia, VOS, and Holly Health.

The first author, with expertise in HCI and design, has used the 4 apps for minimum 10 days to understand how AI is leveraged for the provision of interventions. For this, we adapted the autoethnography method by providing data reflecting symptoms of EDs, such as low mood and urge to eat. For apps' analysis, we also developed a codebook to capture their functionalities, inspired from previous work on review of healthy eating, and mindfulness eating apps [26], which we extended with codes such as mental health condition, therapy intervention, micro interventions, AI based intervention, AI-based intervention outcome, AI-based techniques (Table 2), and ethical aspects including apps' cost, medical disclaimer, age rating, user age restriction, data safety and apps' external documents (Table 1). The codes were discussed and iterated until agreement was reached.

We also analysed apps' descriptions on marketplace, their Terms and Conditions, and Privacy Policies. For this, we searched these resources for keywords: "*artificial intelligence*", "*AI*", "*machine learning*", "*ML*", "*chatbot*", "*conversational agent*", "*NLP*", and "*automated*".

App name	ETHICS									
	App cost (marketplace)	Medical disclaimer	Age rating (marketplace)	User age restriction	Data safety	App's external documents (mentioning AI)				
						Website	Description	Title	Privacy Policy	Terms of Conditions
Holly Health	offers in-app purchases	Yes, available	12+	N/A	share data with 3rd parties (GP practices)	x	x			
VOS	offers in-app purchases	Yes, available	4+	Yes, they recommend that children under the age of 15 ask for their parent's or guardian's permission before using the app	share data with 3rd parties (advertisers)	x	x	x	x	
Reftlectly	offers in-app purchases	Yes, available	4+	Yes, they do not collect, maintain, or use personal information from children under 13 years of age, and no part of the services are directed to children under 13.	share data with 3rd parties (advertisers)	x	x	x		
Meditopia	offers in-app purchases	Yes, available	4+	N/A	share data with 3rd parties (advertisers)		x	x	x	x

Table 1. Ethical concerns of apps regarding AI

App name	POBLEMATIC EATING BEHAVIOR											
	Mental health condition	Therapy intervention	Micro-interventions (guided meditations)	AI-based intervention	AI-based intervention outcome	AI-based techniques	What is captured	How is captured	When is captured	Psycho-education	Motivational quotes	Relationship with body
Holly Health	Wellbeing	ACT CBT Mindfulness Self compassion	Mantra Walking Breathing Body scan Mindfulness Yoga/ relaxation Loving/ kindness	Recommendation Conversational agent	To analyze habit patterns based on user's entries and provide daily challenges, nudges and reminders	NLP (standard chabot - without AI)	Mood Sleep Habits	Journal entry - chatbot (text)	Custom (self entry)	x		x
VOS	Wellbeing	CBT Psychology Mindfulness	Sleep Walking Gratitude Focusing Letting go Breathing Awareness Mindfulness Loving/ kindness	Recommendation Conversational agent	To analyze emotion patterns in journal entries and provide personalized recommendations to track mood correlations with sleep, activity level, and calorie intake	NLP (free text conversation)	Thoughts	Journal entry - chatbot (text + photo + voice record)	Custom (self entry)	x	x	x
Reftlectly	Wellbeing	CBT Mindfulness Positive Psychology					Mood Thoughts	Journal entry (text + photo + voice record)	Custom (self entry)		x	
Meditopia	Wellbeing	ACT CBT	Sleep Walking Breathing Gratitude Body scan Mindfulness Yoga/ relaxation Loving/ kindness Mindfulness eating	Coversational agent	To analyze/ recognize emotion and thought patterns in journal entries and provide personalized recommendations to meditate	NLP (free text conversation) ML (ChatGPT model)	Mood Thoughts	Journal entry - chatbot (text)	Custom (self entry)	x	x	

Table 2. AI- functionalities of top-rated eating disorders apps

3 FINDINGS

This section includes a description of the main functionalities of apps for EDs, and in particular those which may be AI-based.

3.1 Functionalities of Apps for Eating Disorders

Findings indicate four main functionalities namely journaling, tracking, conversational agents, and recommending personalized interventions. All 4 apps provide *journaling functionality* usually in text (4 apps: Holly Health, Meditopia, Reflectly, VOS); photos (2 apps: Reflectly, VOS) or voice notes (2 apps: Reflectly, VOS). Some apps (2 apps: VOS, Reflectly) also support reflection on such content for instance by prompting users with questions such as *"what do you do to take care of your mental health?")*.

Tracking functionality was also supported by all 4 apps to target emotions and moods (Meditopia, Reflectly, VOS, Holly Health), physical activity (VOS), and bodily sensations of hunger/fullness cues (Holly Health). Emotions and moods are captured mostly through emojis (Meditopia, Holly Health), and 5-point Likert scales (Reftlectly, VOS). In contrast to emotions, physical and bodily aspects are less captured, and apps which do such as the VOS app uses health kits consisting of steps, sleep, average burned calories or Holly Health app uses hunger scale for bodily sensations. All apps also track biodata such as heart rate, collected with user's consent through Apple Health and Google Fit. For visualizing such tracked content, for emotions and moods, apps use mostly charts, calendar views integrated with line graphs and emojis (1 app: VOS), calendar views with emojis (2 apps: Meditopia, Holly Health), and bar charts with emojis (1 app: Reflectly). For physical activity, visualizations are in the form of bar charts (VOS).

An interesting outcome is the limited vizualizations integrating both emotions/moods and phsyical activity. For instance, only VOS app provides graphs showing the correlations of mood and other tracked behaviours (e.g., sleep, physical activity) which arguably can better support users to self-monitor and regulate. Apps provide no visualisations, neither for bodily sensations nor biodata.

Chatbots functionality, is supported by 3 apps (Meditopia, VOS, Holly Health). While VOS and Meditopia apps allow free text entry, most likely to leverage NLP, Holly Health app provides standard, rule-based chatbot with predefined answers for eating behaviour (e.g., *"I have strong cravings"*) and mood (e.g., *"I feel stressed"*) (Fig. 3). This app offers also pre-defined menu options for reflecting on mood by providing emoticons, and hunger scale (Fig. 2). For instance, when we selected one of the pre-defined answers such as *"I have strong cravings"*, the app suggested generic interventions (Table 3) such as going for a walk or journaling about feelings rather than more specific ones such as guided mindfulness eating meditation.

All 4 apps supported the functionality of providing *personalised interventions*, and apps' descriptions specify three main therapeutic approaches: CBT (4 apps: Holly Health, VOS, Reflectly, Meditopia), Mindfulness (3 apps: Holly Health, VOS, Meditopia), and holistic approaches (3 apps: Holly Health, VOS, Meditopia), as well as a range of micro-interventions: mantras (Holly Health), walking (3 apps: VOS, Meditopia, Holly Health), breathing exercises (3 apps: VOS, Meditopia, Holly Health), body scan (2 apps: Meditopia, Holly Health), mindfulness practices (3 apps: VOS, Meditopia, Holly Health), yoga/relaxation (2 apps: Holly Health, Meditopia), and loving-kindness exercises (3 apps: VOS, Meditopia, Holly Health). Additionally, the apps provide psychoeducation materials on wellbeing (3 apps: VOS, Meditopia, Holly Health), calming sounds (2 apps: Meditopia, VOS), and further breathing exercises (3 apps: VOS, Meditopia, Holly Health). However, except for the Meditopia app (1000 meditations), the number of different micro-interventions remains ambiguous (Table 2, column on micro-interventions).

	User data (input- free text entry)	Suggestive micro-interventions		
		VOS	**Meditopia**	**Holly Health**
1	I have strong cravings	Suggests calming breathing	Suggest considering mindfulness eating practices to recognize hunger cues from emotional cravings	Suggests to identify associated emotions and how they feel in the body and recommends interventions (e.g., going for a walk, journaling about feelings)
2	I feel stressed	Suggests calming breathing	Suggests meditations related to stress	Suggest pre-defined interventions with different durations (min. 10 sec - max. 5 min.) such as body stretch, gratitude practice, physical exercises (e.g., running)
3	I feel numb or empty	Suggests meditation	Suggests meditations (e.g., self-compassion, chakra meditations)	Suggests text-based breath exercise
4	I feel anxious or panicked	Suggests breathing animation to calm down (no duration)	Suggests meditations (relaxation with whole body)	Suggests text-based grounding exercise
5	I am not sure how I feel right now	Suggests to practise meditation, yoga, journaling	Suggests meditations and calm sounds	Suggests to talk with a close friend or family.
6	I feel angry	Suggests guided calming meditation (7 min.)	Suggests meditations (e.g., acceptance, understanding emotions, connecting with emotions)	Suggests to practice breath exercise
7	I am not happy with my body shape	Suggests practising yoga and provides in-moment mood check-in. Do not offer follow-up intervention	Suggests body positivity meditations	-
8	I am feeling low and urged to eat	Suggests guided calming meditation (7 min.)	Suggests guided meditations (e.g., releasing stress, loving/kindness)	-
9	I am restricting my food intake	-	Suggests guided meditations (e.g., eating with joy) and articles on eating behaviours	-
10	I have an intense fear of weight gain	Suggests breathing animation to calm down (no duration)	-	-
11	I ate a lot, and I purged by vomiting	Suggests guided calming meditation (7 min.)	Suggests meditations related to stress	-
12	I overeat and feel guilty. I will practice some exercise to burn calories	Suggests gentle movements but does not recommend specific intervention	Suggests starting to engage in mindfulness eating daily for at least one meal and journaling to reflect on feelings - but does not offer follow-up intervention (e.g., guided mindfulness eating meditation)	-

Table 3. Autoethnography findings from interacting with chatbots that are available in 3 apps (Holly Health, VOS, and Meditopia). Prompts between 1 and 6 are predefined inputs in the Holly Health app, which we used as free text entries on the VOS and Meditopia apps' chatbots.

3.2 AI-based Functionalities of EDs Apps

In this section, we investigated resoruces such as apps' Terms and Conditions, and Privacy Policies to understand how app developers provide information regarding the AI models used, the types of data collected, their purposes, and the AI-based functionalities offered. We also report on our findings from autoethnography.

An important outcome is that AI-based functionalities are not clearly signposted across these resources. While journaling and tracking are less likely to leverage AI, both chatbots and personalized interventions functionalities are suitable candidates to use AI. In this respect, findings indicate that Meditopia app specifies in its Terms and Conditions, and Privacy Policies that it is powered by OpenAI's ChatGPT, albeit without mentioning its purpose such as for recommending interventions, the other 3 apps do not mention whether they use specific ML models or ChatGPT/NLP, neither for what purposes. The VOS app mentions in the app's description that uses AI-powered contextual chatbot - "*personalization is powered by smart AI*" and "*online AI chat therapy*".

In their Privacy Policies, apps also specify that collected data will be used only for research (Meditopia), especially in the field of AI (VOS), for statistical purposes (Meditopia), or to recommend better personalized information and interventions (e.g., articles, videos, activity challenges) for sleep, nutrition, exercise and mental health (3 apps: Meditopia, Holly Health).

However in Terms and Conditions, and Privacy Policies no app specified how AI is used to recommend personalized interventions. In order to explore how interventions are suggested, through autoethnography, we provided into apps' chatbots (2 apps: VOS, Meditopia) free entry text reflecting EDs symptoms such as *"I am restricting my food intake" or "I ate a lot, and I purged by vomiting"* as informed by previous research [31], or selected predefined answers reflecting such symptoms such as *"I have strong cravings"* (Holly Health) (Table 3). As a result of such entries, VOS and Meditopia suggested guided mindfulness interventions, while the Holly Health provides only text based interventions such as going for a walk or journaling about feelings. While apps (3 apps: Holly Health, VOS, Meditopia) may offer interventions including meditations or calming breathing exercises for low severity symptoms (e.g., *craving for food*), some apps (2 apps: VOS, Meditopia) provide the same micro-interventions irrespectively of the severity of symptoms we entered (e.g., *purged by vomiting*) (Table 3).

Furthermore, except for the Meditopia app, other apps do not explicitly specify that these features are AI-based and limited explanation of AI was provided to support users understand the recommendation of a specific micro-interventions.

4 DISCUSSION

We now discuss how our findings inform a set of heuristics for the design and evaluation of AI-based functionalities of apps for eating disorders. We organise them under four groups namely decision making, personalization, productivity, and security as categories of AI-related heuristics previously suggested [27].

4.0.1 Decision-Making Heuristics. Heuristics in this group target the decision making informed by AI technologies and their explainability. Findings show limited clarity about the specific data, specific ML models using such data, or AI-based decision-making models, as well as how these decisions are informed by AI and communicated to the user Instead of merely tracking data or journal entries, apps offer personalized interventions through chatbot conversations (Table 3). Our entries related to EDs symptoms indicated that the recommended interventions are not sufficiently tailored, for instance to reflect the severity of the sympotms.

4.0.2 Personalization Heuristics. These group of heuristic target personalization, in particular of recommended interventions. If a personalized intervention is AI-based, or if interactions with the app more broadly rely on AI, users should be informed of this aspect and provided with an explanation. In particular, explanations should be provided regarding how the AI algorithms function, how they analyze user data, and how they generate personalized interventions. This transparency could help users understand the decision-making process behind the interventions and fosters a sense of control and trust in the app's recommendations. In order to cultivate awareness of bodily sensations, Holly Healthy app stands out as it allows users to report their hunger and satiety levels before, during, and after meals (Fig. 2). This finding emphasizes the value of being aware of one's bodily cues in mindfulness eating practices to prevent problematic eating behaviour. However, we have seen limited indication of such important data is used to recommend personalized interventions. For instance, personalization can be supported by capturing bodily sensations based on user's selection of hunger level, using a validated scale and prompting specific questions related to problematic eating behaviour, as shown in recent review on mindfulness eating apps [26]. Such data can then be leverage to recommend personalized micro interventions such as guided mindfulness eating meditation. Food diaries play a significant role in CBT for EDs due to its value for increasing awareness of eating behaviours, patterns, and triggers [17]. By recording what, and when they eat, as well as thoughts and feelings, users can identify problematic eating patterns and gain insight into the relationship between their emotions and their eating behaviours. Our findings show that none of the apps track eating

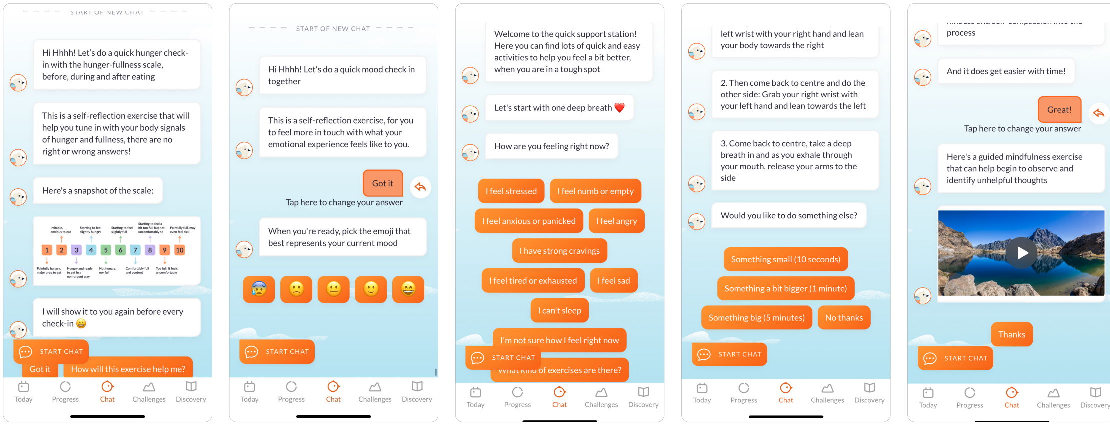

Fig. 1. The Holly Health app implements rule-based chatbot and provides hunger scale (left image) and mood check-in (left-middle image) features; interventions of varying durations , in text and video modalities (min. 10 seconds - max. 5 minutes) (right-middle and right images) based on user's choice (e.g., stress, cravings) (middle image). © Copyright held by the developer(s) and used with permission.

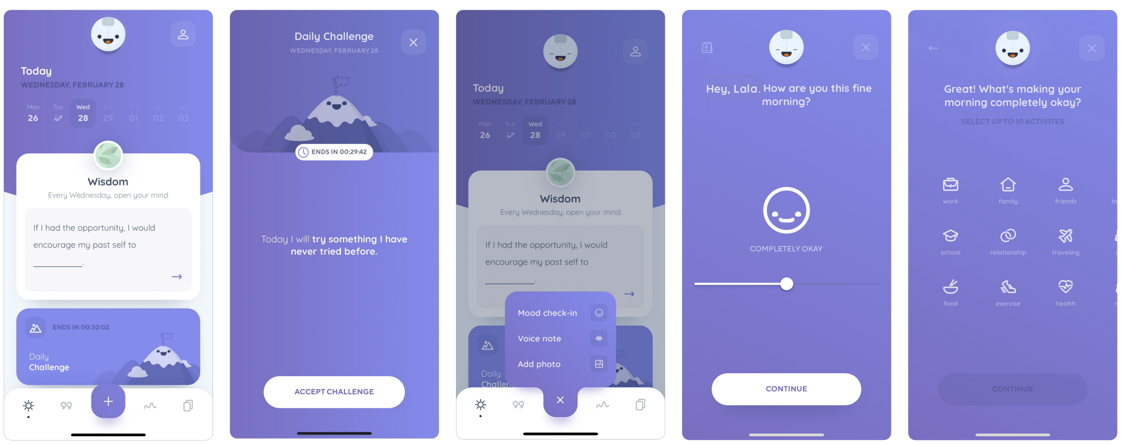

Fig. 2. The Reflectly app provides daily journal prompts (left image), and based on the user's mood input (middle image) it suggests daily challenges (left-middle image). The app captures mood on a 5-point Likert scale (right-middle image) and captures it with related factors (right image). © Copyright held by the developer(s) and used with permission.

pattern or provides food journal. Future apps can allow users to reflect on their eating patterns and based on these provide interventions such as healthy food preparation. While apps (3 apps: Meditopia, Reflectly, Holly Health) use avatars to differentiate conversation between user and chatbots, future apps might dynamically manipulate avatars within the app, to express their emotions, experiences, or recovery progress which may allow users' self-expression and reflection, and enhanced engagement.

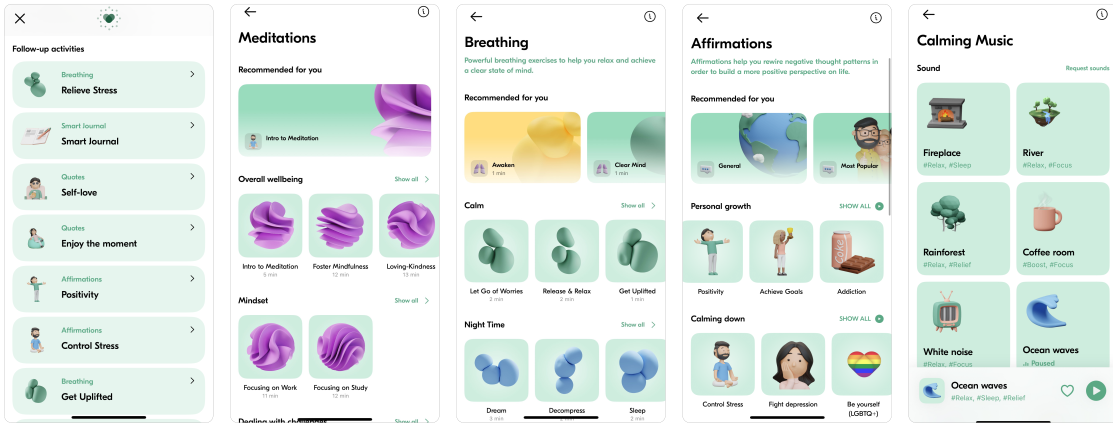

Fig. 3. The VOS app provides interventions based on user's chat input (left image), respectively guided mindfulness meditations (left-middle image), breathing exercises (middle image), affirmations (right-middle image), and calming sounds (right image). © Copyright held by the developer(s) and used with permission.

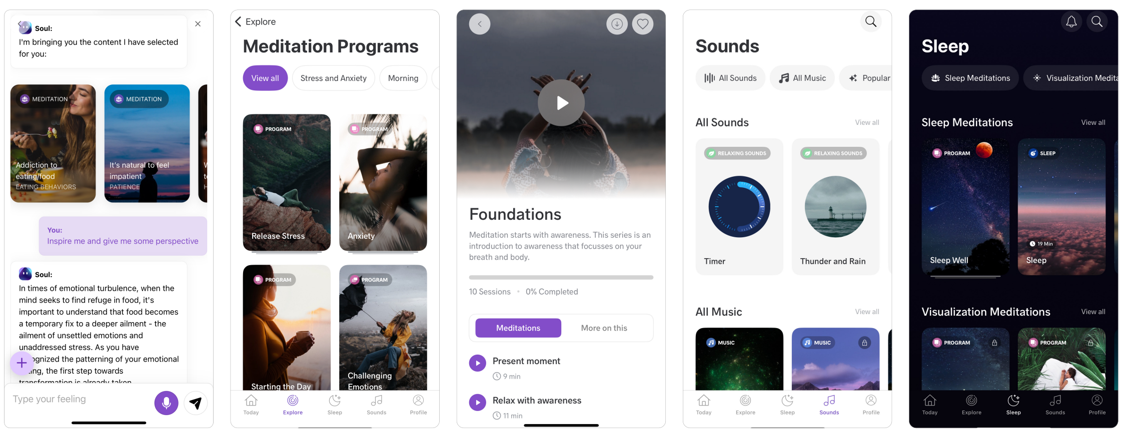

Fig. 4. The Meditopia app provides interventions based on user's chat input (left image), respectively guided mindfulness meditations (left image), calming sounds (right-middle image) and sleep meditations (right image). © Copyright held by the developer(s) and used with permission.

4.0.3 Productivity Heuristics. Heuristics within this group are concerned with improved usability and user experience leveraging tracking and classification for better symptom identification, and prediction. Our findings show that none of the apps provides pscyhoeducation on EDs symptoms. We can think of design and evaluation heuristics about functionalities for analyzing user input (e.g., journaling, mood tracking) to identify potential EDs symptoms, and categorize them based on severity or type (e.g., restrictive eating, binge eating, purging). Furthermore, apps could classify meals based on nutritional content (e.g., calories, macronutrients) and provide feedback on balance and adherence to a personalized meal plan.

4.0.4 Security Heuristics. Heuristics within this group are concerned with improved security regarding data, and safeguarding users from harm. With regard to latter, an important finding is that a few apps (2 apps: VOS, Meditopia) analyze user input (e.g., chatbot conversations) for signs of self-harm or suicidal thoughts in order to offer emergency resources, or real-time support options (e.g., crisis helpline) which is only provided by the VOS app Concern for clients' privacy is a crucial requirement for all mental healthcare interventions, therefore is vital that systems must be secure, and also perceived to be secure [13]. All apps specify that users' data will be shared with third parties and more details are needed about on data management, i.e., what data will be shared and for what purposes. Out of the 4 apps, only the Meditopia app, informs users of the Terms and Conditions regarding the accuracy of generated responses through ML algorithms and ChatGBT model. Data accuracy is important in terms of fostering user trust, and increasing acceptance, so heuristics supporting data accuracy are much needed.

Findings show that apps (3 apps: Meditopia, Reflectly, VOS) mention on the Privacy Policies that with user consent, they make use of wearable devices to collect health data (Apple Health, Google Fit) (heart rate, physical activity). The aim is to monitor overall well-being to provide better personalized interventions (e.g., guided meditations) and progress visualizations. An important outcome is that while all apps mention AI in the app's title or description they provide limited information to support users' AI literacy, and transparency of how AI is used.

We have built on groups of heuristics for AI technologies such as those for decision making, personalization, productivity, and security [27] to tailor them to mobile apps for EDs. AI technology is developing rapidly and can complement the strengths of diagnosis and treatment [10, 11, 28]. AI chatbots leverage NLP and ML [34] to understand users inputs and recognize patterns in order to provide personalized interventions [32]. These chatbots use sentiment analysis to provide treatment analysis for a user by analyzing their responses [12].

Future interfaces should consider the incorporation of explainable AI (XAI) which is crucial for transparency, trust, and accountability in AI systems, particularly those for mental health [8]. It provides insights into how AI algorithms make decisions, fostering users' understanding. XAI helps detect and mitigate biases, ensuring fair and unbiased results. Besides, it aids in adherence to regulations and promotes user adoption by enhancing user understanding of AI systems.

5 CONCLUSION

Considering the significant societal impact of EDs, there has been limited exploration into mobile apps designed to address them, especially in terms of their AI-based functionalities. Our study reported 4 ED apps that claim to utilize AI. Findings extend those on functionalities of mobile apps for healthy and mindfulness eating, indicating insufficient clarity on how AI is used by apps that claim using it. limited apps support AI literacy and its explainability. We advanced conversations about heuristics for AI-based mobile apps tailored to apps for eating disorders.

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