Personalization and Persuasive Strategies in Digital Mental Health Applications for Depression: A Systematic Review

Hyunjin Kim, Boyoung Kang, Juhee Choi, Eunbyeol Lee, Kyu-Man Han, Kee-Hong Choi

Submitted to: Journal of Medical Internet Research
on: May 29, 2024

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Hyunjin Kim[1*] BA; Boyoung Kang[1*] BA; Juhee Choi[1] BA; Eunbyeol Lee[1] PhD; Kyu-Man Han[2] MD, PhD; Kee-Hong Choi[3] PhD

[1]Department of Psychiatry Samsung Medical Center Seoul KR
[2]Department of Psychiatry Korea University Anam Hospital Korea University College of Medicine Seoul KR
[3]School of Psychology Korea University Seoul KR
[*]these authors contributed equally

Corresponding Author:
Kee-Hong Choi PhD
School of Psychology
Korea University
145 Anam-ro, Seongbuk-gu
Seoul
KR

Abstract

Background: Depression is a common mental health disorder worldwide. With advances in technology, digital mental health applications and technologies for depression have been in the spotlight. However, more personalization and in situ support for digital mental health interventions are necessary as tailoring strategies can improve adherence and engagement with interventions delivered through apps. Personalization, a persuasive strategy, is crucial for user-friendly and effective digital mental health applications.

Objective: Despite the necessity and importance of personalization in digital mental health interventions, few systematic reviews of personalization strategies have been employed in depression intervention apps. We review existing mobile and web-based applications for depression, along with personalization and other features.

Methods: We systematically searched Google Scholar, PubMed, and PsycInfo using the following key words: “Depression,” “Digital,” “Digital Therapeutics,” “Artificial Intelligence (AI),” “Machine Learning (ML),” and “Personalization” and “Tailored” and “Application” AND “Web-based.” Four independent reviewers selected studies for inclusion and extracted and reviewed the data.

Results: Among 54 studies identified for personalization strategies operationalized in depression intervention apps, nine of these 29 applications supported the customization functions, allowing a self-tailored environment to match users’ personal preferences. All reviewed digital interventions for depression except one collected active data; in particular, three utilized active and passive data from users to personalize digital interventions.
Notably, the ML model enhanced the sophistication of personalization by recognizing and predicting users’ emotional states (n = 7), recommending practical activities (n = 2), and directly providing evidence-based interventions (n = 4) to improve depressive symptoms. Additionally, 17 apps showed significantly better outcomes for depression in comparison with a control group not using them. Among the 17 studies that scrutinized the applications’ efficacy, 14 used a randomized controlled trial design. Three Food and Drug Administration-approved apps integrate therapist–client interaction based on cognitive behavioral therapy. Diverse strategies were implemented. In analyzing all apps, we found no discrepancy in specific strategy prevalence between validated apps showing efficacy and those not yet validated.

Conclusions: The current review suggests future development directions in the personalization elements of digital mental health apps for depression based on our findings to improve these apps’ effectiveness and user engagement and foster future research.

(JMIR Preprints 29/05/2024:62685)
DOI: https://doi.org/10.2196/preprints.62685

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Review

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Hyunjin Kim*[12]; Boyoung Kang*[12]; Juhee Choi[12]; Eunbyeol Lee[3], PhD; Kyu-Man Han[4], MD, PhD; Kee-Hong Choi[12]†, PhD

[1]School of Psychology, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul 02841, Republic of Korea. [2]KU Mind Health Institute, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul 02841, Republic of Korea. [3]Department of Psychiatry, Samsung Medical Center, 81, Irwon-ro, Gangnam-gu, Seoul 06351, Repulbic of Korea. [4]Department of Psychiatry, Korea University Anam Hospital, Korea University College of Medicine, 73, Goryeodae-ro, Seongbuk-gu, Seoul 02841, Repulbic of Korea

*These authors contributed equally.

Corresponding Author:
Kee-Hong Choi, PhD
School of Psychology and KU Mind Health Institute of Korea University
145 Anam-ro, Seongbuk-gu, Seoul
Republic of Korea
Email: kchoi1@korea.ac.kr

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applications' efficacy, 14 used a randomized controlled trial design. Three Food and Drug Administration-approved apps integrate therapist–client interaction based on cognitive behavioral therapy. Diverse strategies were implemented. In analyzing all apps, we found no discrepancy in specific strategy prevalence between validated apps showing efficacy and those not yet validated.
Conclusions: The current review suggests future development directions in the personalization elements of digital mental health apps for depression based on our findings to improve these apps' effectiveness and user engagement and foster future research.

Keywords: Personalization; Persuasive Strategies; Depression; Digital mental health applications; Digital Therapeutics; Artificial Intelligence; Machine Learning; Tailored; Application; Web-based

Introduction

Depression is a prevalent mental health disorder characterized by persistent feelings of sadness, hopelessness, and loss of interest or pleasure in daily activities [1]. According to the World Health Organization [2], depression is a leading cause of disability worldwide, affecting more than 264 million people. Medications and psychological interventions such as cognitive behavioral therapy are known to be effective for depression. However, barriers to traditional mental health interventions exist, such as stigma, time availability, and financial burdens [3]. To address these barriers, digital mental health interventions and technologies for depression have been in the spotlight. In particular, smartphone applications and other digital mental health applications are becoming more widely recognized as effective tools for mental health support and treatment owing to their growing popularity and expansion [4]. Their accessibility and features, such as anonymity, prompt feedback, cost-effectiveness, and applicability in real-life situations, contribute to effectively address depression [5]. A notable decrease in the severity of depression was observed in connection with the utilization of these app interventions in a systematic review and meta-analysis that evaluated the effectiveness of app-based interventions for moderate to severe depression [6]. Persuasive strategies for optimizing the development and use of digital mental health applications have received substantial attention. Persuasive technology can be defined as an interactive computerized system designed to change people's attitudes and promote behaviors [7,8]. Four categories of persuasive strategies exist: primary task, dialogue, system credibility, and social support. Table 1 illustrates these and other informative strategies.

Table 1. Definitions of persuasive strategies and other informative strategies.

Persuasive and Other Informative Strategy			Definition
Primary Task Support	Self-monitoring		Enable users to monitor and track their progress, performance, or status in attaining their goals.
	Personalization	Customization	Offer users a chance to modify app environment features to match their preferences, giving users more control over their in-app experience.

		Data Collection & Usage	**[Active Data]** Data that require the active involvement of users in its creation, collection, and application. **[Passive Data]** Data from sensors on devices such as smartphones that are collected automatically at regular intervals and transmitted without requiring the user's active participation.
	Tunneling		Assist users by guiding them through a structured process that offers encouragement and motivation along the way.
Dialogue Support	Rewards/Praise		Offer virtual incentives or rewards to users upon successfully accomplishing their desired behaviors.
	Reminder		Send reminders to users to help them stay on track and achieve their goals.
	Social Role		Adopt a social role by facilitating communication between users and specialized professionals within the system.
Social Support			Provide a supportive and interactive community for users to connect and engage with peers or individuals in their target population.
System Credibility Support	Privacy		Inform the application users of privacy policy and protect users' privacy.
	Real-World Feel		Present information about the individuals or organizations responsible for the content or services offered within the application.
Other Informative Strategy	Pricing		Provide access to the app through any associated costs or payment requirements such as free, freemium, paid, or in-app purchase options.
	Accessibility		Provide information on whether the application is released on the market.

	FDA	Offer information on FDA approval.

Primary task support aids users in performing their primary tasks using persuasive strategies. One example is self-monitoring, which allows users to track their progress, performance, and achievement status. Dialogue support provides systematic feedback to users persuasively, and the reward strategy is one such strategy. Applications provide virtual rewards, such as points, to users when they complete their specific desired behaviors. System credibility support encourages persuasive and credible application design, exemplified by a real-world feel strategy that displays information on professionals or organizations alongside the contents or services. Social support prompts users to engage with others [7]. This review illustrates whether applications offer a supportive and interactive community for users to connect with others within their target population.

Among these strategies, personalization is the most common, and the need for personalization and in situ support for digital mental health interventions is growing. Personalization plays a crucial role in tailoring interventions to provide the right strategy at the right time based on individualized data [9,10]. It refers to the process of using personal, behavioral, and real-time data to develop tailored and adaptive messages and educational materials (such as videos, text, and literature) that align with individuals' evolving needs with the goal of optimizing behavioral change. Personalized interventions aim to enhance engagement and treatment adherence [11]; additionally, they can enhance adherence to and engagement with digital therapeutics [12,13]. Despite the necessity and importance of personalization in digital mental health applications, the systematic review of personalization strategies employed in depression intervention apps is currently limited.

Additionally, machine learning (ML) and algorithms have emerged as powerful tools that can contribute to the personalization of digital mental health interventions for depression. Artificial intelligence (AI) and ML enable systems to autonomously acquire knowledge from new experiences, adapt their responses, and execute tasks that resemble human actions without requiring direct programming [14]. AI can be harnessed in the decision-making process, and it has practical applications in evaluating and delivering treatment. ML, which is a subset of AI, allows computers to acquire knowledge through extensive data training, eliminating the requirement for explicit programming [15,16].

ML methods offer numerous advantages in terms of diagnosis, treatment, support, research, and clinical administration, enabling personalized and timely interventions for depression [17]. Many smartphone applications that use ML techniques detect changes related to mental health conditions and provide personalized feedback [18]. By leveraging ML algorithms, digital mental health applications can continuously learn and improve user data, enabling a more precise and tailored approach to treatment.

Despite the potential benefits, the application of ML and algorithms in personalization for depression within digital mental health interventions remains an emerging field. We review and analyze 34 existing mobile and web-based applications designed to treat depression. Additionally, we examine personalization strategies in digital mental health applications for depression, including persuasive strategies and the use of ML and algorithms.

Methods

This review focuses on the personalization of digital interventions for depression. We searched all relevant databases from 2010 to 2022 for reviews in the titles and abstracts on Google Scholar, PubMed, and PsycINFO. The main search terms were (Depression) AND (Digital) AND (Digital

Therapeutics) AND (Machine Learning) AND (Artificial Intelligence) AND (Personalization) AND (Tailored) AND (Application) AND (Web-based) OR (Digital intervention) OR (Digital CBT) OR (Depression prevention) OR (Smartphone apps) OR (Web-based) OR (Depression treatment) OR (FDA) OR (Customization) OR (Active Data) AND (Passive Data).

The inclusion criteria were as follows: (a) published in peer-reviewed journals, (b) targeting depression, (c) personalization elements in digital interventions, (d) intervention effectiveness assessment as study design, and (e) written in English or Korean. Articles were excluded if they met any of the following criteria: (a) lack of intervention, (b) meta-review papers, (c) absence of personalization, or (d) overlapping content with prior applications.

Four authors independently extracted the following data: type of research, design of studies in the review, mental health condition(s), population description (age groups), type of digital health interventions, type of interventions, personalization (self-monitoring and customization), type of data collection, aim to use data, ML method, algorithm, tunneling, dialogue support, social support, privacy, real-world contact, and accessibility, as well as FDA information.

Results

Selection and Inclusion of Studies

The following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines summarize our search results. The systematic search yielded 1,786 results, of which 2,010 were excluded based on the screening of titles, abstracts, and other reasons. We performed a thorough evaluation of 233 full-text articles to determine their eligibility for inclusion. Among these, we excluded 198 articles, which resulted in a final selection of 34 mental health applications for the systematic review. **Figure 1** presents a detailed overview of the results at each stage and the specific reasons for exclusion.

[Figure 1 here]

Target Population, Target Issues, Intervention Types, and Food and Drug Administration (FDA) Approval

The target population of the 34 digital mental health applications reviewed is diverse. Ten of them specifically cater to children and adolescents, whereas two are designed for college students and two for perinatal women. One application focuses on individuals experiencing antidepressant-refractory conditions; another one targets those facing long waiting times for face-to-face psychotherapy, and 17 applications do not specify a particular target population. In terms of the mental health conditions addressed, 23 applications solely target depression; six address both depression and anxiety (with one also including stress and another addressing sleep and eating disorders), and five aim to improve overall mental health as well as depression. A wide range of intervention theories is implemented across these applications, with cognitive behavioral therapy (CBT) being the most prevalent at 63%. Other theories utilized include psychoeducation, positive psychology, interpersonal psychotherapy, behavioral activation, mindfulness, acceptance, and commitment therapy (ACT), motivational interviewing, dialectical behavior therapy, problem-solving therapy, psychosocial interventions, and other intervention techniques or approaches such as self-management and behavioral correction. Many of these interventions are combined and used in conjunction with each other. Regarding the digital technologies employed, 11 applications follow a structured and modular approach, whereas 11 offer interactive and personalized interventions. Seven applications utilize conversational AI agents or chatbots; three incorporate gamification elements; one utilizes virtual reality (VR) technology, and one integrates social media and messaging features. Among the 34 applications, 16 are either not yet available on the market or have not been released; Out of 18 released applications, 14 are available for free, and four are paid applications. Most of these applications are not FDA-approved, although three have received FDA certification. **Table 2** summarizes the target populations, target issues, and intervention types in the reviewed applications.

Table 2. Summary of target population, target issues, and intervention types.

Name of Application	Target population	Target Issue	Intervention Type
MoodHwb [23]	Adolescents	Depression	Psychoeducation, CBT, Positive psychology, Interpersonal, Behavioral change theories
CATCH-IT [32]	Adolescents	Depression	CBT
SPARX [19]	Adolescents	Depression	CBT
Rebound [47]	Young people	Depression	Positive psychology, Mindfulness
The VR Personality Project [30]	Adolescents	Depression	Psychoeducation
Smartteen [21]	Adolescents	Depression	CBT
Think Feel Do [49]	children and adolescents	Depression and Anxiety	CBT
The Journey [20]	Adolescents	Depression	CBT
Stressbuster [41]	Adolescents	Depression	CBT

MUBS [18]	Not specified	Depression	BA
MOSS [27]	Not specified	Depression	CBT
Woebot [45]	Not specified	Depression	CBT
Tess [42]	Not specified	Depression and Anxiety	CBT, Mindfulness, ACT, Motivational interviewing, Interpersonal psychotherapy
Wysa [43]	Not specified	Well-being	CBT, DBT, Motivational interviewing, Positive behavior support, Behavior reinforcement, Mindfulness
Deprexis [44]	Not specified	Depression	CBT
Thrive [48]	Not specified	Depression	CBT
Mobilyze! [25]	Not specified	Depression	BA, Psychoeducation
Sanvello (formerly known as Pacifica) [24]	Not specified	Depression, Anxiety, and Stress	CBT, Mindfulness
Youper [36]	Not specified	Depression and Anxiety	BA, Problem solving, Mindfulness, Cognitive restructuring
7 Cups [29]	Perinatal women	Depression	Psychosocial intervention

Circadian Rhythm for Mood (CRM) [26]	Not specified	Mood disorders including MDD and BDI	Not specified
Healthy Moms [33]	Perinatal women	Depression	CBT, Mindfulness
XiaoNan [46]	Not specified	Depression	CBT
MindDoc [34]	Not specified	Depression, Anxiety, Sleep disorders, and Eating disorders	Not specified
ACT Daily [9]	Not specified	Well-being	ACT
ACT-DL [40]	Not specified	Psychological flexibility	ACT
Ajivar [38]	College students	Self-esteem, Social and emotional awareness	Positive psychology, Mindfulness
Kokoro-app [52]	Antidepressant-refractory	Depression	CBT, BA
SELFPASS [35]	Those who waited for a long period of time for a face-to-face psychotherapy	Depression	Psychoeducation, CBT, BA
MoodHacker [31]	Not specified	Depression	CBT. Positive Psychology, Mindful self-awareness
Clemson AirHeart [22]	College students	Depression	CBT

Happify [37]	Not specified	Depression and Anxiety	CBT, Positive psychology, Mindfulness-based stress reduction
App-Based Prevention Program for Perinatal Depression [39]	Perinatal women	Depression	CBT
Cue [28]	Psychiatric outpatients	Depression and Anxiety	Psychoeducation and other micro-interventions to promote social rhythm regularity

Abbreviations: ACT, acceptance and commitment therapy; BA, behavioral activation; CBT, cognitive behavioral therapy; DBT, Dialectical behavioral therapy.

Use of Persuasive Strategies

The use of persuasive strategies in digital mental health applications also varies and includes self-monitoring, tunneling, rewards/praise, reminders, social roles, social support, privacy, and real-world experience. Among the 34 digital mental health applications analyzed, 27 incorporate self-monitoring, making this feature the most common digital intervention offered (79% of applications). Within these interventions, self-monitoring typically encompasses four main themes: mood monitoring, CBT elements, tracking daily activity patterns, and displaying program progress. Mood monitoring involves asking questions about mood and saving the responses in the app, such as a mood diary or mood tracking feature. CBT elements for self-monitoring often revolve around setting goals, monitoring thoughts, and engaging in problem-solving activities. Daily activity patterns focus on tracking various aspects, including time and location information, physical activities such as exercise or walking, social interactions such as call duration, and activities related to positive emotions. Program progress features aim to highlight the user's treatment progress and review the lessons learned. Additionally, 12 of the 34 applications implement tunneling, providing users with step-by-step or module pathways. A module pathway allows users to complete any module at any time, whereas a step-by-step pathway allows users to perform tasks based on their level of achievement in the application. Moreover, eight applications incorporate customization features with options such as adjusting avatars, setting goals, changing backgrounds, and other functions such as setting prompt times, saving quotes, and creating lists of personal preferences (e.g., what I like). Of the 34 digital mental health applications analyzed, six incorporate rewards or praise features, offering positive affirmation, feedback, or badges to app users. In addition, 15 applications provide reminders to prompt users to regularly engage with the app. Five applications with social roles include two that utilize AI to support users in discussing suicide or emergencies by referring them to counselors or mental assistance hotlines. Five applications offer social support features such as peer support communities, flagging systems, and the ability to share future goals and experiences of overcoming barriers with other users. Privacy policies are explicitly communicated through the 18 applications to ensure user confidentiality. Furthermore, 13 applications provide a real-world feel by offering crisis line information and resource lists for emergency assistance, as well as psychoeducational content. **Figure 2** shows the number of interventions that implement persuasive and other strategies in the reviewed applications.

Figure 2. The number of interventions implementing persuasive strategies in the persuasive systems design framework and other strategies.

[Figure 2 here]

Personalization Strategies and Their Implementation

Customization

The customization strategy, which offers users the chance to modify app environment features to match their preferences, was found in eight of the analyzed mental health applications. In the analyzed apps, customization is implemented in three ways: (1) avatar or character setting within the app, (2) background settings, and (3) other settings. One of the most common ways of customization is to allow users to set their own avatars or characters; five apps have this feature. This is a popular strategy, particularly among apps targeting adolescents or college students. For example, SPARX [19] and The Journey [20] offer fantasy game-style app environments where users can select their own avatars. Clemson AirHeart also allows users to customize their avatar's skin tone, eye and hair color, and clothing. Another way in which customization is implemented in the analyzed apps is to allow users to modify design elements, such as the app's background, to suit their preferences. For example, Smartteen [21] enables users to choose themes and colors for the cover and pages of their diary, intending to strengthen users' positive ownership of their diary. In Clemson AirHeart [22], users can modify the color of the hot-air balloon their avatar rides in while learning various techniques for managing depression symptoms within the app. Other apps employ various methods to customize their in-app experiences. For instance, MoodHwb [23] and Sanvello (formerly known as Pacifica) [24] allow users to save their favorite songs, images, quotes, and video links within the app. Smarteen enables users to create a list of enjoyable activities to include in their diary entries. In addition, Mobilyze! enhances users' sense of agency by allowing them to set a time for receiving app prompts [25].

Data Collection

To enable a personalized user experience within the app, two types of user data, active and passive, are collected and utilized. **Figure 3** illustrates the number of apps that collect each data type.

[Figure 3 here]

Of the 34 analyzed apps, most only collect active data and do not collect passive data (n = 29). Only one app, CRM [26], collects passive data without gathering active data, whereas four—MUBS [18], MOSS [27], Mobilyze! [25], and Cue [28]—collect active and passive data. In digital mental health applications for depression, four types of active data are collected from users: (1) the user's demographic information (n=2) [29][30], (2) self-reported ratings on symptoms or mood (n = 21) [9,18–23,25,28,31–41], (3) feedback on the user's experience within the app (such as star rating; n = 8) [18,27–29,42,43,37,39], and (4) information detected from the user's activities within the app (n = 15) [29,31,33–35,37,38,42–49]. Passive data are collected by monitoring users unobtrusively through sensors in their smartphones or other wearable devices. These data included activity level, walking time, pedometer, GPS location, geographical distance traveled, phone unlock time, calendar activity count, mobile app usage, sleep and heart rate information, and light exposure. Four apps—MUBS [18], MOSS [27], Mobilyze! [25], and Cue [28]—collect both active and passive data from users, leveraging this information for personalization. Only one app, CRM [26], gathers passive data.

Data Usage

The apps designed to alleviate depression symptoms use the gathered active and passive data for personalization in two ways: first, to track personal progress, including changes in symptoms, and second, to adjust and improve the therapeutic intervention process. **Figure 3** illustrates the number of apps that utilize active or passive data to monitor an individual's status or adjust the intervention process.

Active data usage for individual monitoring

Twenty apps utilize active data to monitor an individual's progress or current state. The purpose of collecting active data for monitoring is as follows:

1. Detecting risks such as self-harm or suicide to prompt users to seek help [20,33–35,41,47]
2. Enabling users to periodically observe changes in their overall condition, including mood and symptoms [22,24,25,28,31,33,34,37,38,44,46,48]
3. Tracking progress within the app [18,29,37].

First, certain apps use active data provided by users to detect signs of self-harm or suicide threats with the aim of guiding users toward seeking additional professional help. For example, apps such as The Journey [20] and SELFPASS [35] would display messages or emergency contact information to users if they detected risks such as self-harm or suicide during mood monitoring at the start of therapeutic modules or app sessions. Additionally, Healthy Moms [33] has a feature by which AI conversations transition to chat sessions with a human counselor if discussions about self-harm or crisis topics arise.

Second, some apps use active data to visually show trends in the user's overall mental health status, including their levels of mood changes. For instance, Sanvello [24] uses the user's daily mood ratings and their responses to health-related questions such as sleep, caffeine intake, and exercise, which they provide once a day. This function helps users identify their daily patterns and pinpoint mood triggers. Additionally, Happify [37] utilizes user responses about overall happiness, life satisfaction, and positive emotions to create graphs that depict how each measure changed for the individual over time. Clemson AirHeart [22] takes the emotional assessment data collected right after app login and presents them in a graph with two lines, allowing users to see the trends in their positive and negative emotions. Moreover, the app Cue [28] incorporates user self-reports on mood and gathers other behavioral biomarkers to offer quantitative measurements of the user's daily routines and social rhythms. These features enable users to track their progress.

Finally, certain apps have a feature that shows users how far they have progressed through the different stages of content provided by the app. For instance, in Happify [37], users can track their progress within their chosen goal track based on their objectives, such as improving stress management or enhancing romantic relationships. Similarly, in 7 Cups [29], users can monitor their progress within the app using various indicators on the "my path" page, with feedback such as "Your cup is half full," "167 growth points," or "0 compassion hearts." These features encourage users to keep using the app consistently.

Active data usage for adjusting intervention to individuals

Twenty-eight apps have utilized active data to adjust interventions for individuals. Gathering active data to tailor interventions serves the goals of

1) Suggesting appropriate activities that users are more likely to rate positively [e.g., 18,27,28,42].
2) Providing personalized therapeutic content based on the data on the user's mood or symptoms [e.g., 21,24,25,28,42,43,45,48].

Specific applications have developed a system to propose activities that individuals are more likely to find personally useful and beneficial. This feature is achieved by considering users' feedback on their past interactions within the app. For example, in the case of MUBS [18], the system customizes recommendations by suggesting 10 activities from a pool of approximately 400. This recommendation process is based on a content-based recommender model that considers users' feedback on activities in which they have previously engaged in the form of "thumbs up" or "thumbs down." Similarly, MOSS [27] also utilizes active feedback on past activity suggestions to learn about user preferences. These functionalities enable the system to suggest meaningful and contextually relevant interventions for users to incorporate into their daily lives.
Subsequently, a larger group of applications has focused on delivering personalized therapeutic content for individuals based on active data related to their emotions and depressive symptoms. For instance, a conversational AI called Tess [42] provides evidence-based interventions rooted in various orientations, such as CBT, Mindfulness, and ACT, all dependent on the emotions and moods conveyed by users during their conversations within the app. Similarly, Wysa [43] analyzes emotions expressed in user interactions with AI to suggest diverse, evidence-based psychological strategies. Another app, Smarteen [21], gathers information about users' symptoms, and if it detects specific symptoms such as depressive rumination, it offers specialized therapeutic content tailored to address those symptoms, supplementing the standard content options.

Passive data usage for individual monitoring or adjusting intervention to individuals

Five apps use the user's passive data to monitor an individual's state or adjust intervention. These apps include MUBS [18], MOSS [27], Mobilyze! [25], CRM [26], and Cue [28]. Among these, MUBS, MOSS, Mobilyze!, and Cue collect and use active and passive data, whereas CRM gathers passive data exclusively for personalization. MUBS gathers passive data, such as daily weather and step counts, and active data, including daily mood ratings, user-planned activities, and user assessments of activities in which they have already participated. By utilizing this combination of data, the app provides users with tailored recommendations for positive activities. Comparably, MOSS leverages a combination of passive data, such as accelerometer readings, time spent connected to Wi-Fi (indicating time spent at home), distances traveled, mobile phone unlock times, text message and call counts, and the number of activities stored in the calendar. It also incorporates active data—specifically, user-entered star ratings for each activity. By utilizing this diverse dataset, MOSS shows users their behavior patterns on the app's home screen and suggests personalized, evidence-based interventions with the aim of creating a more individualized user experience. Mobilyze! collects and utilizes various passive data, including smartphone sensing data such as GPS, accelerometers, Bluetooth, Wi-Fi connections, recent call logs, and active mobile apps. It also gathers active data through ecological momentary assessment (EMA), in which users self-report their mood, intensity of emotions, perceived control over current activities, physical movement, location, interactions with others, and relationships with people nearby. By incorporating this diverse range of data, the app's algorithms learn about the connections between users' social activities, situations, locations, and psychological states. Moreover, based on this learning, the app demonstrates shifts in the user's state and anticipates these changes ahead of time, delivering feedback that aligns with each user's values. Furthermore, Cue, grounded in social rhythm principles, combines data from smartphone sensors and user self-reports to create personalized micro-interventions for alleviating depressive symptoms. These tailored interventions focus on suggesting changes in behaviors that are prone to disturb a healthy social rhythm, thereby contributing to the persistence of a depressive state. Drawing insights from both passive behavior monitoring data collected over the last 3–4 days and mood ratings reported by the user, these interventions can offer a nuanced reflection of the individual's ongoing lifestyle.

Of the 34 apps examined, CRM is the only application that relies solely on passive data without utilizing any active data. This app also uses smartphone sensors to detect light exposure while gathering data on activities, sleep patterns, and heart rates through wearable devices. It collects passive information to create a personalized digital phenotype for users, enabling them to receive feedback regarding their daily routines and circadian rhythms. Furthermore, using the real-time data obtained, the app provides users with a "trend report" that predicts mood changes over the next three days. This feature highlights how past behavior can impact future moods, encouraging users to consider behavioral adjustments.

Machine-Learning Use for Personalization

Out of the 34 reviewed apps, 11 (31%) utilize ML techniques, as shown in **Figure 4**: MUBS [18], MOSS [27], Woebot [45], Tess [42], Wysa [43], Mobilyze! [25], Youper [36], CRM [26], Healthy Moms [33], XiaoNan [46], and Ajivar [38].

[Figure 4 here]

Upon examining the publication years of articles on apps that use ML, we observed that only one was published from 2010 to 2014; four were published from 201 to 2019, and six from 2020 to 2022. The ML technologies used in the 11 apps are listed in **Table 3**.

Table 3. Machine learning algorithms utilized in mental health applications for depression.

ML algorithms	*Digital Interventions*
Decision Tree	Woebot [45] Mobilyze! [25] Youper [36]
Random Forest	MOSS [27] CRM [26]
Deep Learning	Wysa [43]
Support Vector Machines	MOSS [27]
Multinomial Naïve Bayes	MUBS [18]

For some apps not listed in the table, we could only confirm approximate information that they utilize emotion recognition algorithms [33,42,46] and natural language processing [18,38,45,46].

Moreover, most ML apps use the supervised learning approach: decision trees, random forests, support vector machines, and Multinomial Naïve Bayes all belong to supervised learning algorithms. ML models are used for personalization, ranging from passive approaches such as identifying users' emotions [25,33,42,43,45,46] to more proactive approaches such as predicting changes in emotions [26], recommending activities to improve mood states [18,27], or providing direct therapeutic interventions (e.g., evidence-based intervention) [27,42,43,45,46] based on the data provided by the user.

Persuasive and Personalized Strategies in Applications with Verified Efficacy

We identified 17 applications that showed significantly better outcomes in depression compared to a control group not using the applications (**Multimedia Appendix 2**). Then, we conducted a more detailed examination of these apps' persuasive and personalized strategies. Additionally, **Multimedia Appendix 1** includes detailed descriptions and strategies of all reviewed apps, not just the 17 with proven effectiveness.

Among the 17 studies examining the efficacy of applications, 14 adhered to a randomized controlled trial (RCT) design, excluding Smartteen [21], Wysa [43], and CRM [26]. Of particular note, within the subset of apps validated through RCT are Woebot [45], Deprexis [44], and Thrive [48], all of which hold FDA approval as digital therapeutics. All three applications exhibit the shared characteristic of incorporating the interaction between therapists and clients as an interface within the app, rooted in the foundational principles of CBT. Woebot [45] employs natural language processing technology to discern a user's prevailing mood and circumstances during interactive conversations with AI, integrating these data into therapeutic interventions based on CBT principles. The interventions encompass providing targeted content and empathetic responses tailored to the user's mood. Notably, Woebot yields a statistically significant moderate effect size in ameliorating depressive symptoms, as assessed by the Patient Health Questionnaire (PHQ-9) [50] ($p = .017$, Cohen's $d = 0.44$). Deprexis [44], while not utilizing natural language processing or ML, is structured around modules rooted in CBT principles. This application introduces CBT-related concepts and techniques through text-based interactions. Subsequently, it personalizes the content based on the user's chosen response options among various reaction choices, facilitating the progression of CBT practice. This app exhibits a moderate-to-large effect size in the mitigation of depressive symptoms, as measured by the Beck Depression Inventory (BDI) [51] ($p < .001$, Cohen's $d = 0.64$). Thrive [48] is structured around three CBT-based modules: behavioral activation, cognitive restructuring, and social skills training. The personalized feedback of each module is tailored to individual users based on their usage patterns. The application demonstrates a moderate effect size in improving the severity of depression symptoms ($p < .001$, Cohen's $d = 0.63$).
From the standpoint of persuasive strategies, among the apps validated in comparison with the control group, four incorporate the customization strategy [19,20,21,24]; 13 feature self-monitoring functionalities [19,21,24,26,28,31,37,43–45,46,48,52]; three implement rewards/praise [20,26,45]; seven integrate reminders [24,28,31,37,40,42,45]; one adopts the social role approach [19], and six utilize the real-world feel strategy [20,24,26,42,45,46]. Considering the data utilization strategies for personalization, 15 apps exclusively gather and incorporate active data; one app solely utilizes passive data [26], and the remaining app [28] integrates both data types. When the aggregate frequency of each strategy across all apps is considered, the validated apps demonstrating efficacy relative to the control group show no discernible discrepancy when compared to their counterparts not yet validated with regard to either a heightened or diminished prevalence of specific strategies.

Discussion

The main goal of this review was to provide an overall picture of how mobile or web-based applications, developed up to 2022 and targeting individuals with depression, use persuasive and personalized strategies to increase user engagement and motivation. The second objective was to systematically analyze the personalization strategies implemented by each app among the various persuasive strategies. Specifically, regarding personalization strategies, we investigated the kind of data each program gathers from users, categorized as active and passive data, and how these collected data are used to create personalized user experiences. Furthermore, we investigated the specific purposes for which the ML models are employed to achieve personalization. To do so, we identified 34 studies on digital interventions for depression through a systematic search of peer-reviewed journals.

Persuasive Strategies

Our results revealed that self-monitoring (n = 27) is most employed, followed by reminders (n = 15), tunneling (n = 11), real-world feel (n = 11), and rewards or praise features (n = 6) among various persuasive strategies. Using a self-monitoring app can potentially decrease the symptoms of depression and anxiety while promoting overall well-being. Improving emotional self-awareness can mediate these positive changes [53,54]. In addition, the self-monitoring of depressive symptoms and mood positively affects user engagement in digital interventions for depression [55]. These reasons can be inferred as the underlying factors behind the common use of self-monitoring functionalities in diverse digital interventions to improve depression.

However, a meticulous examination concerning one of the attributes scrutinized—namely, the automated reminder function within the application seems imperative—seems imperative. Previous meta-analyses have consistently highlighted the positive influence of therapist-mediated reminders on the effectiveness of computerized psychological interventions [56,57]. An intriguing finding emerged in a recent meta-analysis that explored the feasibility of mobile app interventions for moderate to severe depression: interventions relying on in-app reminders show notably reduced therapeutic effects compared to interventions employing “more direct” reminders, such as those delivered through text messages or emails [6]. This underscores the notion that providing reminders through more direct channels in prescribing and utilizing mHealth apps may enhance user engagement and more effectively bolster motivational factors. Despite being digital-based notifications, reminders via text messages or emails may evoke a perception of more direct interpersonal support, in contrast to reminders within the application. Additional studies may thus be required to delve deeper into the effectiveness of in-app notifications.

Overall, the social support features are the least employed (n = 4). A systematic review of the association between loneliness, perceived social support, and outcomes of mental health problems demonstrated that individuals experiencing depression who perceived lower levels of social support tended to experience more severe symptoms, slower recovery, and impaired social functioning [58]. Given the research findings linking perceived social support with depressive symptoms, in the future development of applications for depression improvement, it is recommended to incorporate various social support strategies to enhance the sense of connection with peers or other users in the app environment, despite requiring careful attention from administrators to implement social connections among users online.

Last, from the efficacy perspective, a quantitative analysis of the frequency of each persuasive strategy revealed no significant quantitative difference between apps validated for effectiveness and those not yet proven or validated. Consequently, our research findings suggest that the meticulous implementation of persuasive strategies within the app—specifically, “how” they are implemented—holds greater importance than the specific selection of strategies. In essence, the degree to which the therapeutic process is intricately structured based on the app’s theoretical foundations appears to carry higher significance. This suggests that simply employing persuasive strategies may not be sufficient.

Personalization Strategies

Our results demonstrate that customization for personalization is extensively utilized in interventions targeting young populations with depression, including adolescents and young adults. Customization features allow users to adjust app settings based on their values and preferences and offer a straightforward method to personalize the app experience. However, relying solely on customization without incorporating other personalized strategies may lack substantial impact on digital interventions for depression [22]. Therefore, as researchers develop personalized digital interventions for depression, it is advised to carefully explore ways to effectively leverage user data for personalization while utilizing customization as an additional tool.

In addition, most interventions collect and use active data, which require active user engagement in data collection and generation. Digital interventions that collect both active and passive data to offer individually optimized and more refined interventions for each user are growing. Further, interesting attempts have been made to provide individual therapeutic feedback to users by utilizing passive digital phenotyping, which involves collecting and generating data through sensors embedded in wearable devices or smartphones while minimizing conscious user efforts [18,25,26–28]. This review focuses solely on digital interventions targeting the alleviation of depressive symptoms, and the use of passive data in such interventions is relatively limited. However, in predicting the onset of depression or other psychopathologies and conducting screening, the active utilization of passive data is already prominent [59–61]. We predict that passive data will be collected and used more extensively, not only for predicting and detecting depression but also for the treatment and development of interventions for depression.

Moreover, approximately one-third of the analyzed interventions used ML technology for personalized interventions, reflecting the growing trend of data science in the digital mental health intervention field. Our findings revealed that ML models have been employed to predict users' emotional changes and recommend specific activities or evidence-based interventions tailored to individuals based on collected active and passive data. One notable aspect is the utilization of the EMA in recent digital interventions for depression [25,34]. Through ecological momentary interventions (EMI), which utilize EMA to provide timely support to users, deeply personalized assistance for depression can be effectively delivered [62]. Progress in analytics, including data mining and ML, has enhanced the capacity to customize EMIs at the individual level [63]. Our finding that ML enhances the sophistication of personalization granularity in various ways aligns with prior review studies emphasizing the role of ML in bridging science and practice [64]. Furthermore, they are consistent with mental health research, and ML data science can facilitate the advancement of personalized treatments [65].

Strengths and Limitations

Many systematic reviews and meta-analyses have been conducted on the effectiveness or dropout rates of digital health interventions for improving depression [66–68]; however, our understanding of the overall scope of personalized strategies employed in such interventions shows a notable gap. Additionally, the current review takes a distinct approach by exploring personalization strategies for tailoring intervention and more general strategies to enhance user engagement through categorizing personalization and persuasive strategies. Despite the strengths of this review, there are substantial limitations. It is worth mentioning that we did not personally experience each app's strategies firsthand during our analysis. Our exploration of personalized and persuasive strategies relied exclusively on published findings and, when accessible, information available on the official websites of the respective apps or programs. As a result, specific programs may have incorporated features associated with personalized and persuasive strategies but were not accounted for in our analysis. Additionally, because our effectiveness analysis exclusively targeted apps utilizing personalized strategies, it is difficult to determine the importance of personalized strategies solely based on this analysis. Recognizing these limitations, future research should compare apps that employ personalized strategies with those that do not.

Future Work

Based on the findings of this review, we make the following suggestions regarding the future development of digital interventions to enhance the management of depressive symptoms. First, it is crucial to carefully consider ethical concerns, including safeguarding individual privacy. A rise in programs that combine the collection of passive and active data, enabling personalized intervention tailored to individuals, is expected. However, as the collected information becomes personalized, the risk of compromising information security and infringing on individuals' privacy increases. Notably, collecting passive data may evoke the sensation of being “tracked” in one's daily life, possibly causing discomfort to users [69]. Moreover, personal health-related data can be exploited for unforeseen secondary purposes that users do not expect [70]. Consequently, as the level of personalization in digital mental health interventions escalates, stringent management of the collected information and its usage becomes indispensable, necessitating policy discussions to prevent the excessive acquisition and exploitation of personal health data.

Second, it is essential to delve tangibly into the interplay between active and passive data. Smartphones are efficient and convenient tools for collecting hybrid active and passive data. Each type of data carries its unique information. Specifically, passive data provide precise and objective indicators of behaviors that cannot be captured through self-report measures, enabling users to continuously monitor their state in a non-intrusive manner. Actively collecting all information increases the burden on users; however, a passive data collection approach—if ethically considered—offers the advantage of user-centered interventions with little intrusion to users [71]. However, relying excessively on passive data utilization, despite its astonishing convenience and efficiency, may hinder the moments of insight that users can gain from actively providing information about themselves, such as daily monitoring of activities or mood, which is commonly used in behavioral activation treatment [72]. Therefore, in the future development of digital interventions for mental health, careful consideration should be given to appropriately leveraging active and passive data to achieve optimal results through personalized interventions. Future research on methods that facilitate the efficient interaction between active and passive data and their practical application during app development will contribute to more powerful personalized interventions.

Third, innovative methods are needed to enhance the diversity and depth of personalization techniques in digital interventions for alleviating depression. Owing to the rapid advancements in mobile and sensor technologies, smartphones and wearable devices are now widely used, gathering increasingly sophisticated data. To fully harness the potential of these technologies in mental health, it is crucial to explore various approaches for converting the data they collect into practical insights and using them to tailor interventions [73]. In the context of bipolar disorder treatment, Abdullah et al. [74] assessed the stability and regularity of daily routines through passive and active data by utilizing the Social Rhythm Metric. More recently, similar strategies have been applied in depression treatment, where behavioral markers and data reported by patients are employed to evaluate social rhythms. These insights are then used to offer timely interventions that assist patients in establishing more consistent routines through a digital monitoring platform [28]. Therefore, engaging in groundbreaking discussions on how to structure and process diverse user information for interventions is essential. Simultaneously, these discussions should focus on adjusting and enhancing these methods to make them more effective for interventions targeting mental disorders, including depression.

Fourthly, beyond the customization, active data collection, and passive data utilization strategies discussed in this paper, future research should identify and specify a diverse array of additional personalized strategies. While this study has primarily examined the effectiveness of apps utilizing personalized strategies, future research could delve more specifically into comparing and exploring the effects of apps that employ specific personalized strategies against those that do not. Through such research, it would be possible to quantify the importance of utilizing personalized strategies more accurately.

Conclusions

We conducted a comprehensive review of digital interventions in the mental health field targeting depression to explore the utilization of personalization and engagement strategies. The findings of this review provide insights into potential directions for future development, focusing on improving the effectiveness and user engagement of digital interventions for depression through personalized approaches.

Funding

The authors declare financial support was received for the publication of this article. This work received support from the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2023S1A5C2A0709598711). The funding source was not involved in the study design, analysis and interpretation, report writing, or decision to submit the article for publication.

Acknowledgements

We would like to thank Editage (www.editage.co.kr) for English language editing and some of the findings were presented at the 10th World Congress of Cognitive Behavioral Therapies and the 8th Asian CBT Congress.

Authors' Contributions

HK and BK contributed equally as co-first authors to the conception and design of the systematic review. Alongside JC and EL, they collectively conceptualized the study. HK, BK, and JC conducted the literature search and screening process, and participated in drafting the manuscript. Critical feedback on the methodology and interpretation of results was provided by EL, KH and the corresponding author, KC. All authors critically reviewed and approved the final version of the manuscript for submission.

Conflicts of Interest

None declared.

Abbreviations

ACT: acceptance and commitment therapy
AI: artificial intelligence
CBT: cognitive behavioral therapy
EMA: ecological momentary assessment
EMI: ecological momentary interventions
FDA: Food and Drug Administration

ML: machine learning
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT: randomized controlled trial
VR: virtual reality

Multimedia Appendix 1

Detailed Information on Persuasive Strategies and Personalization Strategies of Apps

Multimedia Appendix 2

Evaluation of Effective Apps: Outcomes and Strategic Approaches

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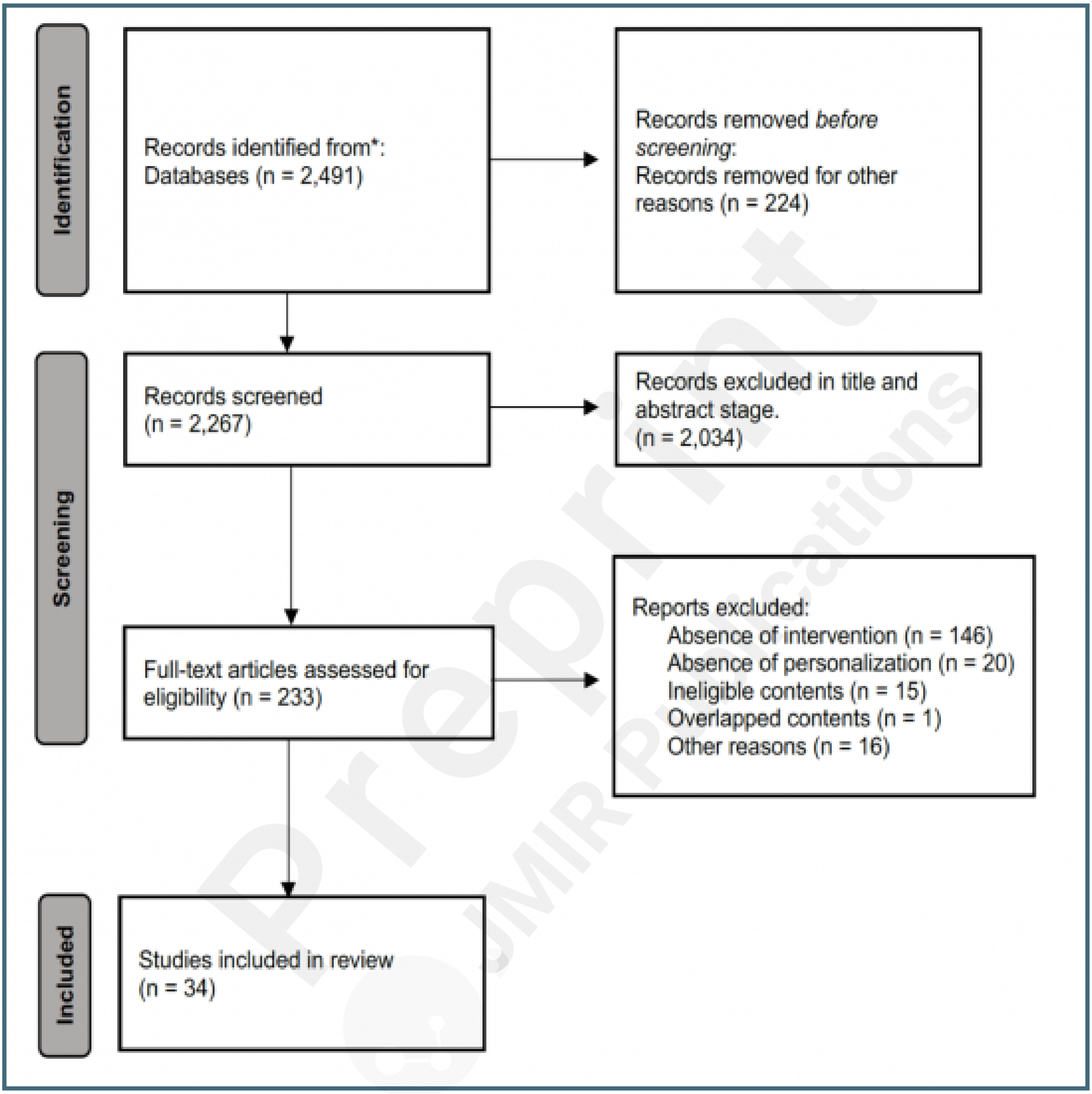
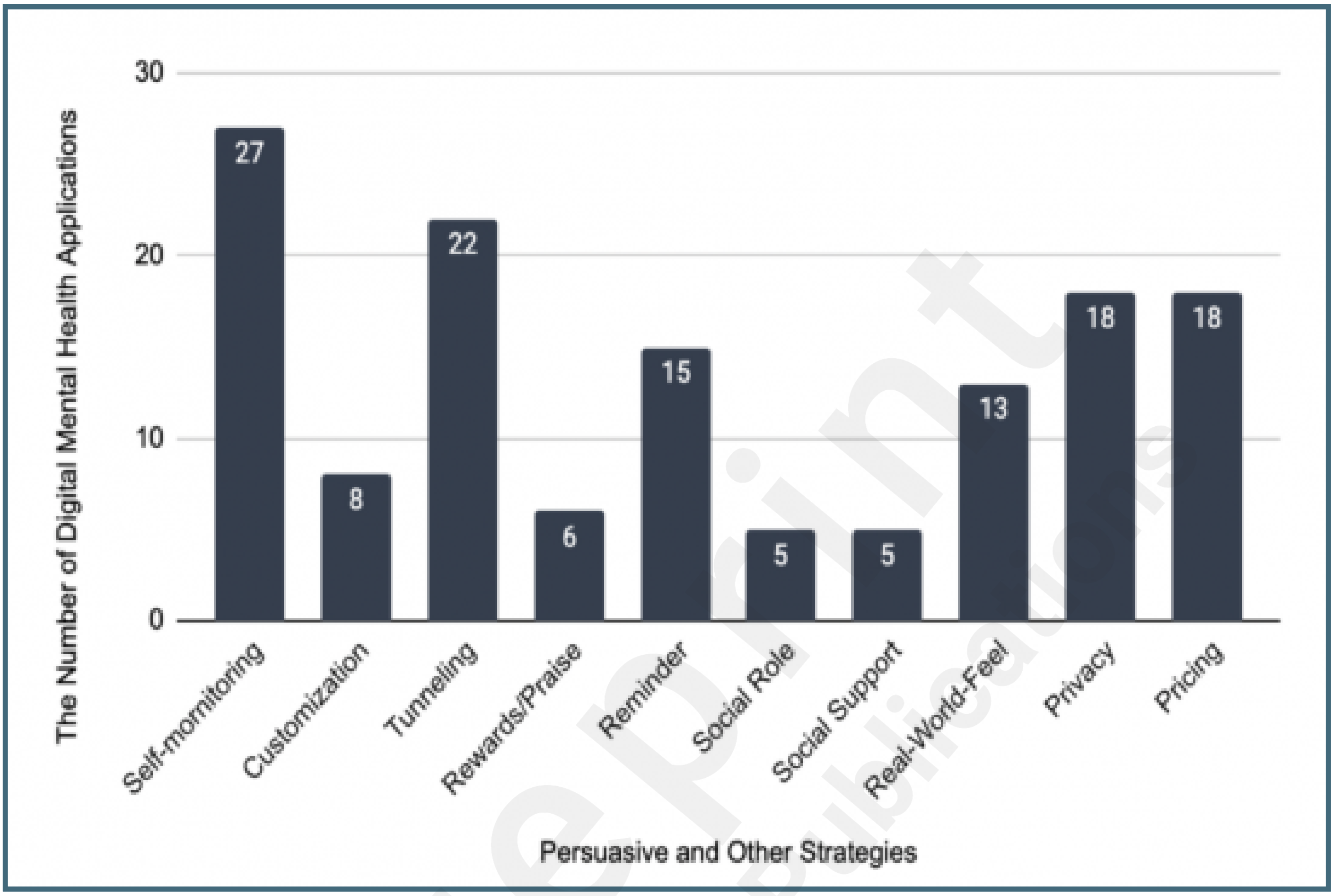
Supplementary Files

Figures

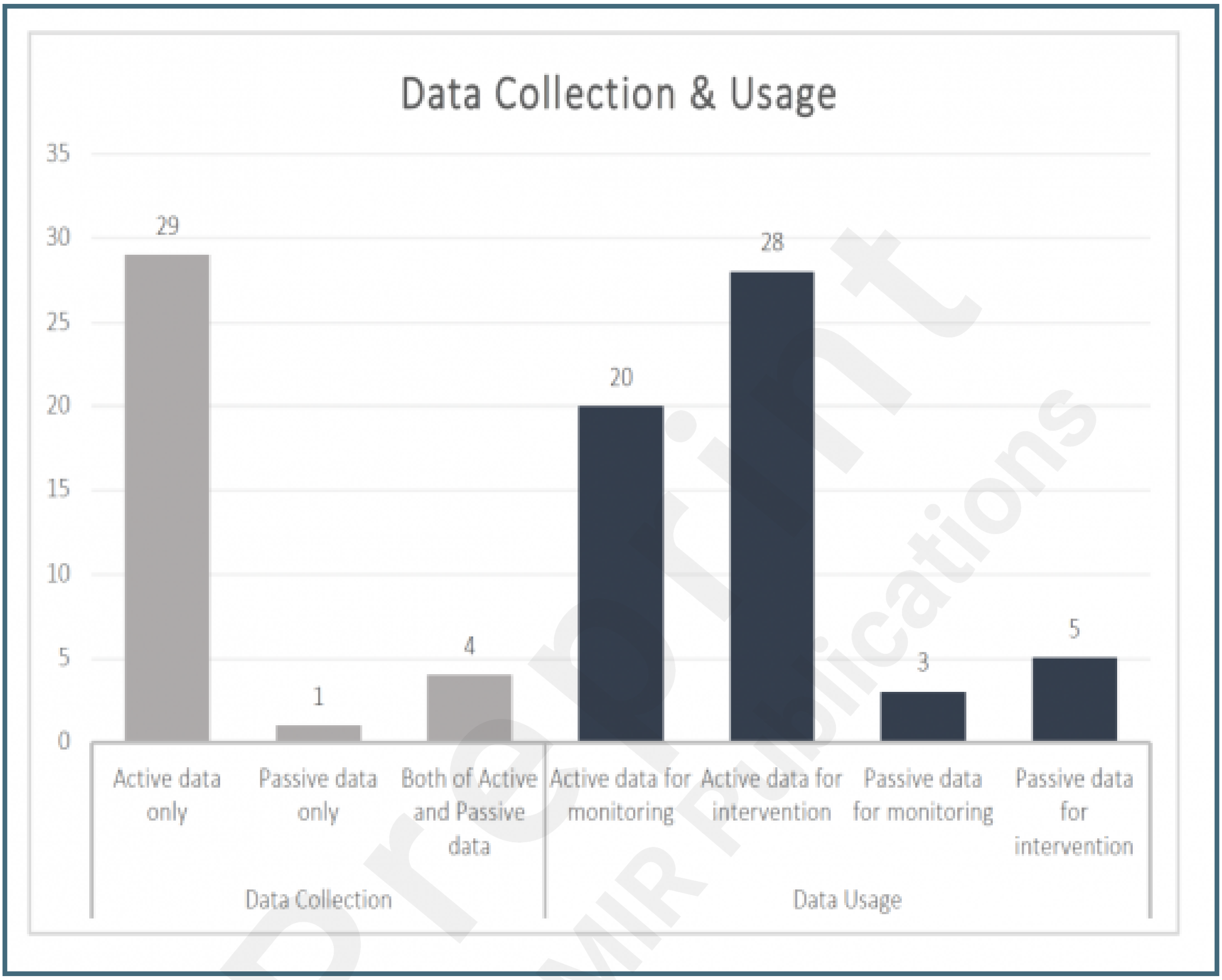
PRISMA flow diagram for systematic reviews.



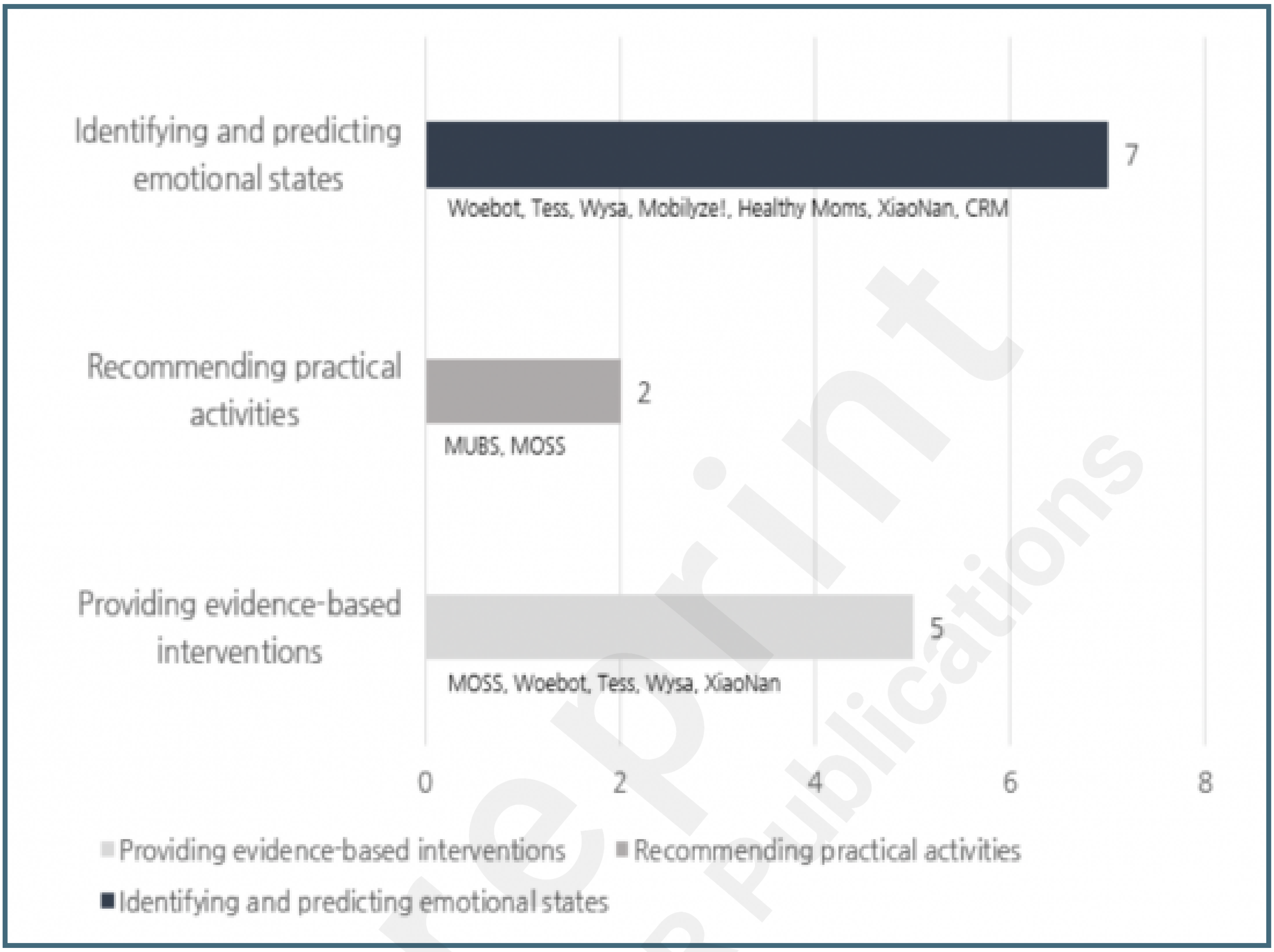
The number of interventions implementing persuasive strategies in the persuasive systems design framework and other strategies.



The number of interventions collecting and utilizing active or passive data for the purpose of personalization.



The way ML is used for personalization among 11 digital interventions.



Multimedia Appendixes

Detailed Information on Persuasive Strategies and Personalization Strategies of Apps.
URL: http://asset.jmir.pub/assets/7feda5ddcaeefbabf307a27725bb9e2a.xlsx

Evaluation of Effective Apps: Outcomes and Strategic Approaches.
URL: http://asset.jmir.pub/assets/c52563970cc7672840e2772672bbf84c.doc