BABEȘ BOLYAI UNIVERSITY

FACULTY OF PSYCHOLOGY AND EDUCATIONAL SCIENCES

DOCTORAL SCHOOL “EVIDENCE-BASED

ASSESSMENT AND PSYCHOLOGICAL INTERVENTIONS”

Ph.D. THESIS

Efficacy and Mechanisms of Change of Mobile Mental Health (mHealth) Interventions in Reducing Psychological Distress

SUMMARY

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CLUJ-NAPOCA 2025

ACKNOWLEDGMENTS

My thanks go first to the scientific advisor of this thesis, Professor Oana Alexandra David, to whom I am grateful for all her guidance efforts throughout this process. I thank her for the trust she gave me from the start, when she agreed to coordinate, as is often the case at the beginning, my initially slightly unrealistic doctoral proposal, and for the guidance she continued to provide in polishing and completing it. The constant support and considerable feedback were not only indispensable for writing this thesis, but also contributed to my professional development, instilling a strong work ethic. In short, it made me more responsible and I think it prepared me to be closer to the professional I want to become in the field.

A decisive role in writing this thesis was also played by the members of the advisory committee, Professor Anca Dobrean PhD, Professor Aurora Szentágotai-Tătar PhD and Assistant Professor Lia Oltean PhD, to whom I thank for the feedback provided over the years.

Much of my gratitude goes above all to my family. My parents were the pillars of emotional and financial support, who, although since the bachelor level they did not quite understand exactly what their son was studying, have admirably understood the role of education and have continuously supported me since the beginning of this path, more than 22 years now. During the writing of this thesis, I also had the chance of my life, meeting my future wife. She took over the firsthand emotional support and stood by me with love and understanding ever since. I can hardly imagine how I could have continued and completed this endeavor without the trust and meaning she gives me.

The Department also had great members and colleagues which made the journey a lot better. You all I thank you.

Notes. ____

(1) This is to certify by Sîrbu Vasile that:

(a) The thesis includes the original research work of Sîrbu Vasile (author) towards the Ph.D.;

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CHAPTER I: THEORETICAL BACKGROUND

1.1. Fundamentals of mHealth

Digital health is one of the terms that designates the integration of health applications into a digital format with the goal of increasing accessibility, economic feasibility, and augmentation of the current care system (Chan, 2021).

mHealth, according to World Health Organization definition represents the "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices" (Kay, Santos & Takane, 2011, pg. 6).

1.1.2. Clinical and Research Relevance of mHealth Apps

Given their accessibility and capabilities features, smartphones provide a unique opportunity to address some of the problems of mental health care and research. For example, compared with overreliance on retrospective, large number of items self-reports, smartphones' functionalities open the possibility of collecting continuous streams of passive, objective data regarding the user's behavior (e.g., screen usage, social-media use, sleep, physical activity, audio and video recording). Various neuropsychological cognitive and behavioral tests can be integrated as well as digital tasks or "games" apps (e.g., David, Tomoiagă & Fodor, 2024), offering behavioral measures about these processes. Whereas, the retrospective recall bias of self-reports can be mitigated through in-the-moment, multiple times, and embedded in the occurring context measures of mood, symptoms and other psychological phenomena. A paradigm called Ecological Momentary Assessments (EMA), for which smartphones are particularly well-suited (Myin-Germeys et al., 2018).

The data obtained in this manner can then be used by the individual themselves, or shared with health specialists, to monitor and gain insight into the patterns and dynamics of the mechanisms of their mental health. These insights can also be used to alert when the mental health status is aggravating and there is need to intervene before the situation becomes more severe. In this regard, another promising potential of mHealth is its ability to address another key limitation of traditional mental health service, namely, the need for timely, personalized, and scalable interventions. Capabilities of mHealth apps captured by terms like just-in-time interventions (JTI, Nahum-Shami et al., 2018) and ecological momentary interventions (EMI, Proudfoot, 2013).

1.1.3. Types of mHealth Apps, Content, Features, and User Experience

A broader distinction is made by the American Psychiatric Association (APA, 2022)'s clinician guideline towards mHealth and include general wellness products (GWPs), apps as medical devices, and apps with the American regulation body approval for public health, Food and Drugs Administration (FDA).

Created by both research groups and organizations stemming from the continued need to identify qualitive and evidence-based apps, app evaluation frameworks offer a more grained and practical guideline for the app's characterization. Among these the APA App Evaluation Model is one of the most comprehensive frameworks, and the five levels of the revised version by which the quality of an app is evaluated (Lagan et al., 2021) represent important benchmarks to characterize a mental health app's quality: accessibility and background, privacy and security, clinical foundation, engagement style, and therapeutic goal.

1.1.4. Psychological Distress and Risk and Protective Mechanisms. The Role of mHealth Apps in Offering Just in Time Support

Depression and anxiety conditions have the highest prevalence among mental disorders across the world (World Health Organization, 2022; World Health Organization, 2023a; World Health Organization, 2023b).

Mental health is shaped by a complex interplay of personal, familial, community, and societal influences, which can either support well-being or contribute to its deterioration. To some degree, these influences can be linked to external or internal stressors, such as traumatic experiences, difficult life situations, or physical illnesses. This connection is why these conditions are broadly classified as stress-related disorders (Kalisch et al., 2015). At their core, they share common vulnerabilities and are often preceded by generalized psychological distress stemming from prolonged maladaptive responses to stress (Bystritsky & Kronemyer, 2014).

Representing the individual's propensity toward negative stimuli from internal and external environments to the detriment of positive information and possible available resources, negative cognitive biases are at the fore front of many conceptual accounts of risk factors for the development of psychological distress disorders. The associated negative affect response then represents the building block of stress.

It follows that the opposite tendency, of attending to positive stimuli and positively evaluating the information available, is the key protective factor and together with the positive emotions elicited, represent the common mechanisms by which the beneficial roles of other factors contribute to the well-being of the individual.

A further more deliberate and sustained effort is necessary to flexibly attend to new positive available information or to adjust the negative experience, while resisting the interferences of more negative appraisals, in the context of more hostile and challenging situations. This process is known as the reappraisal, an emotion regulation (ER) strategy that is another major mechanism in the vulnerability and resilience interplay of psychological distress (Kalisch et al., 2015).

A compelling usage case of mHealth has been made in the literature for the increasing awareness and preventive self-management of the psychological distress in the general population, targeting the mechanisms responsible for the protection against and the risk of distress (Bakker, Kazantzis, Rickwood, & Rickard, 2018).

1.2. Relevant Issues to be Addressed in mHealth Apps for Managing Psychological Distress

Despite the increasing interest in psychological mhealth apps from both the market and professional and research communities, the claims of many apps available still need to be substantiated empirically (Torous et al., 2019). The already available meta-analytical systematic reviews on this topic have shown that mhealth app are efficacious in reducing the symptoms of stress-related disorders like depression, anxiety, and stress (Firth et al., 2017a; Firth et al., 2017b; Linardon et al., 2019; Lu et al., 2022; Weisel et al., 2019).

But the main objective of these reviews was on studies including either indiscriminately both clinical and nonclinical populations or focusing on specific disorders. While not primarily focusing on studies investigating psychological stress/distress in the general population, one of the main predilected usage of mHealth apps, precludes the clear investigation of the apps' content and features especially designed for stress management.

And given the multiple dimensions of the stress response, with both psychological and physiological outcomes, the investigation of both outcomes generally lacks in the mHealth literature (Epel et al., 2018).

Also, the mechanisms that are vehiculated as responsible for the vulnerability and resilience of psychological distress need to be investigated in more interrelated models. Taking into account the multitude of factors involved as mechanisms of change (i.e., emotions, cognitive biases, beliefs, ER strategies) will allow to explore which factors are the most relevant targets of the app interventions and to select their content accordingly (Troy et al., 2023).

In the meantime, there is need for more primary studies to consolidate the quality and strength of the results for the efficacy of mHealth apps in the reduction of psychological distress in the general population.

The investigation of mechanisms of change are of high interest not only for the specific mHealth literature but for the broader clinical psychology as well, because of the potential to better tailor the current interventions and to enhance the efficiency.

CHAPTER II: RESEARCH OBJECTIVES AND OVERALL METHODOLOGY

The present thesis's main aim was to contribute to the mental health mHealth app literature by following four main objectives addressed in four studies, examined through different methodological approaches. The first objective was to test the efficacy claim of mHealth smartphone apps primarily targeted at psychological stress/distress management and to investigate in a meta-analysis if the results are moderated by specific study, population, intervention, apps characteristics, and types of stress outcomes and response. The second objective of the thesis was to explore the interplay of key risk and protective mechanisms in the psychological distress in general population, using a network analysis model. For the third objective, we conducted a randomized control trial (RCT) to compare the efficacy of two mobile interventions against an active placebo control group, to test the efficacy of reducing psychological distress in a general population sample, both at post and follow-up. Following the results of the above RCT we looked for the last objective of this thesis to test the different pathways by which PsyPills and OCAT exert their therapeutic effects in reducing distress, thereby contributing to expanding knowledge about the mechanisms of change in mHealth app interventions.

Figure 1 illustrates graphically the structure of the thesis with its four studies.

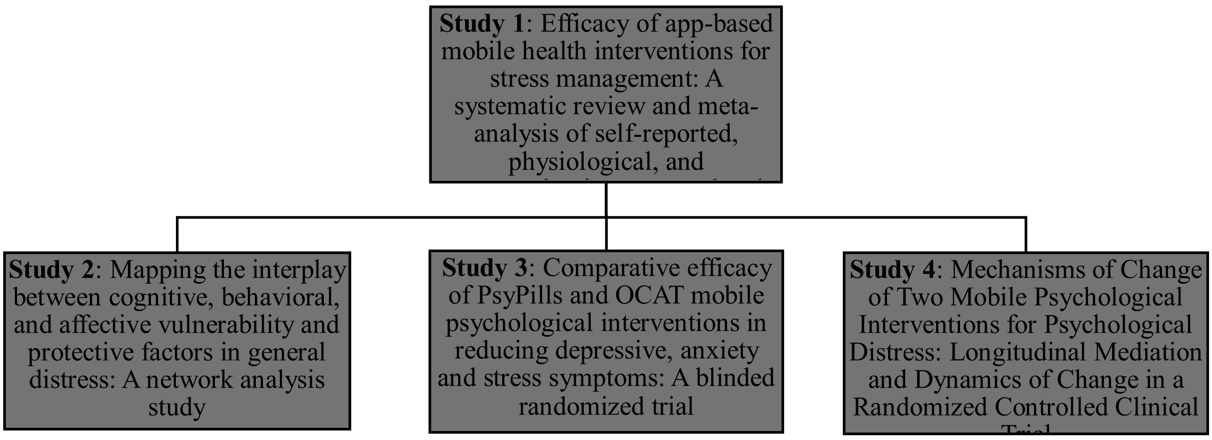

Figure 1. The structure of the thesis

CHAPTER III: ORIGINAL RESEARCH

3.1. Efficacy of App-based Mobile Health Interventions for Stress Management: A Systematic Review and Meta-Analysis of Self-Reported, Physiological, and Neuroendocrine Stress-Related Outcomes

3.1.1. Introduction

Previous meta-analyses (Firth et al., 2017a, 2017b; Linardon et al., 2019; Lu et al., 2022; Weisel et al., 2019) have primarily focused on specific mental health disorders when evaluating the efficacy of mHealth smartphone apps. While some of these analyses included stress as an outcome, it was not the primary focus of their studies, and they often included only those studies where stress was not the main target of intervention. As such, including studies not primarily targeting stress prevent a clear investigation of the effect of apps designed for stress reduction. On the other hand, focusing on a broad area of mental conditions has the disadvantage of not being able to focus on the relevant characteristics of a particular outcome. Likewise, the latest and most comprehensive meta-review study so far, which synthesized results from 14 meta-analyses on mHealth intervention for mental health (Goldberg et al., 2022) highlighted among others the role of the relevant moderators in trying to explain the variance in the results of a particular outcome and increase thus the confidence in the obtained results.

While other meta-analyses and systematic reviews investigated the physiological outcomes of stress (e.g., de Witte, Spruit, van Hooren, Moonen, & Stams, 2020; Pascoe, Thompson, Jenkins, & Ski, 2017), none were examining the effects in the context of mHealth app interventions. To our knowledge, this is the first meta-analysis with the primary focus on the effects of mHealth apps specifically designed for stress management, and which statistically analyzed the results of both psychological and physiological outcomes. Thus, our objectives were to investigate the efficiency of mental health apps in stress reduction for the general population, and to explore the difference in efficiency depending on various types of stress outcomes, characteristics of the studies, samples, and interventions.

3.1.2. Methods

Selection of Studies and Data Extraction

We included randomized controlled trials that investigated the effects of a psychological intervention delivered via a standalone smartphone application primarily aimed at the reductions of stress/distress in non-clinical populations. A systematic literature search was conducted on the following online databases: Web of Science, PsycInfo, PubMed, and Cochrane Central Register of Controlled Trials. Searches were restricted to peer-reviewed journal articles, available in English, and published from 2007 onward.

The following data were extracted: citation, year of publication; data on the characteristics of the sample, such as number, age, percentage of female gender, type of population; study design such as: inclusion criteria (healthy status, risk factors, unselected), naturalistic setting vs. lab-based environment and the type of control (inactive, nonspecific active, and specific active); data on the intervention characteristics: CBT-based; meditation/mindfulness; muscle and respiratory relaxation; multimodal; and other; data related to the functions of the applications: Monitoring, Participant engagement, Tailoring, Gamification, Reminders, Social component, Personalization, Guidance, Simulation of situations, option for Wearable devices; other data related to the intervention were also coded: the duration of the intervention (in weeks), the duration of the session (in minutes), the prescribed use (daily, weekly, at discretion, experimental occasion), the level of guidance (reminder, unguided, feedback), adherence to the use of the intervention, reported satisfaction and adverse effects.

For the outcomes, we extracted the self-report measurements of psychological stress, where this construct was specifically measured, or those of psychological distress, where only this measurement was offered. In the case of physiological measurements, we coded the different biomarkers of stress in several overarching groups: cardiac (heart rate and breathing rate), hemodynamic (systolic blood pressure [SBP] and diastolic blood pressure [DBP]), HPA axis (cortisol, dehydroepiandrosterone sulfate (DHEAS), DHEAS/cortisol ratio), autonomic (heart rate variability [HRV], salivary alpha amylase [sAA], and skin conductance), and others (immunity and inflammation markers). Physiological outcomes were also grouped into acute and chronic depending on the time-measured effect of the reaction to stress (during the intervention or after an acute stress manipulation task, and after the intervention, respectively). Risk of Bias Assessment was measured using RoB 2.

3.1.3. Results

Characteristics of Included Studies

As seen from the PRISMA flow diagram in Figure 1, 80 studies were included, representing 16,097 participants, and 102 comparisons. The average age across all studies was 31.93 years, and the average percentage of female participants was 69.03 %.

Self-Reported Stress/Distress Outcomes

Stress symptoms were assessed as an outcome in 72 trials, with a significant polled effect size for the post time point of g = 0.33 (95 % CI 0.26–0.40, p = 0.000), with moderate to high heterogeneity (I^2 = 72.87 %, see Table 1 for all of the reported outcomes and Figure 2 for the forest plot).

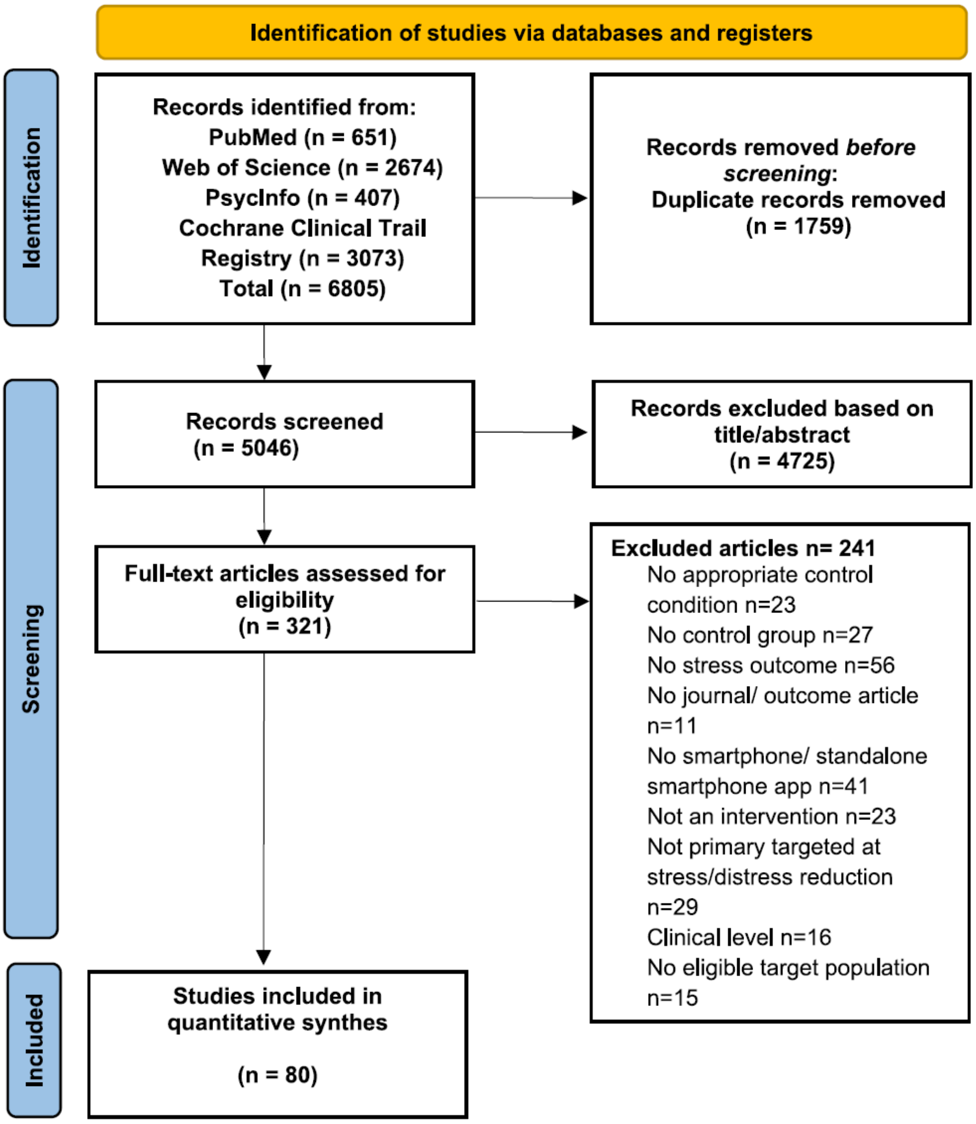

Figure 1. PRISMA Flow diagram of the study selection process.

When accounting for the for missing studies, the Duval and Tweedie trim-and-fill analysis estimated the effect size to change to be somewhat smaller (g = 0.19, 95 % CI 0.12–0.28, p = 0.000), although still significant and of the same interpretation of magnitude. The Egger's regression intercept was significant ($t_{(70)} = 3.74$, $p < 0.000$), suggesting a potential risk for publication bias. The polled effect size was higher when only inactive comparisons conditions were analyzed (k = 49, g = 0.41, 95 % CI 0.32–0.50, p = 0.000, $I^2 = 70.11$), and smaller but still significant when compared with nonspecific active conditions (k = 15, g = 0.23, 95 % CI 0.10–0.36, p = 0.000, $I^2 = 63.83$), and specific active conditions (k =16, g =

0.16, 95 % CI 0.03–0.29, $p = 0.014$, $I^2 = 57.67$). The Egger's regression intercept was significant only for this last control condition ($t_{(14)} = 3.16$, $p = 0.007$), but not for the inactive ($t_{(47)} = 1.59$, $p < 0.118$) or nonspecific comparisons analyses ($t_{(13)} = 1.37$, $p < 0.194$), indicating a potential for the risk for publication bias for this type of comparison.

There also have been 20 studies with various follow-up time points, with a polled effect of $g = 0.27$ (95 % CI 0.15–0.39, $p = 0.000$), with moderate heterogeneity ($I^2 = 68.23$).

Subgroups Comparisons and Meta-Regression Analyses

Of the continuous characteristics (drop-out rate per group, age, gender distribution, duration of intervention, session duration, adherence, and satisfaction) significant results were found for total usage time ($b = 0.0006$, $SE = 0.0002$, 95 % CI 0.0003–0.001, $p < 0.001$), drop-out IG ($b = 0.0147$, $SE = 0.0042$, 95 % CI 0.0065–0.0229, $p < 0.001$), and drop-out CG ($b = -0.0187$, $SE = 0.0046$, 95 % CI -0.0276;-0.0097, $p < 0.001$). The model including all these predictors explained the variance in proportion of $R^2 = 0.45$.

Table 1. Psychological and Physiological outcomes

	Self-reported outcomes				Physiological outcomes			
	N	*g* (95 % CI)	I^2	*Q* (*p*)	*N*	*g* (95 % CI)	I^2	*Q* (*p*)
Overall post effect	72	0.329 (0.257–0.400)***	72.869	-	18	0.261 (0.122–0.400)***	52.235	-
Adjusted for publication bias	90	0.198 (0.121–0.275)	-	-	25	0.081 (-0.067–0.228)	-	-
Type of control				**11.704 (0.003)**				0.496 (0.780)
Inactive	49	0.410 (0.321–0.500)***	70.105		12	0.259 (0.080–0.437)**	47.151	
Nonspecific AC	15	0.231 (0.102–0.362)***	63.833		4	0.328 (0.097–0.559)**	0.000	
Specific AC	16	0.158 (0.031-0.285)*	57.670		9	0.221 (0.029–0.413)*	54.487	
Intervention strategy				1.120 (0.891)				**8.639 (0.034)**
CBT-based	16	0.327 (0.168–0.487)***	66.014		2	-0.010 (-0.291–0.270)	NA	
Meditation	37	0.341 (0.241–0.440)***	74.797		7	0.320 (0.163–0.478)***	0.000	
Muscle and breathing relaxation	6	0.393 (0.013–0.773)*	85.180		8	0.370 (0.095–0.644)**	72.613	
Multimodal	13	0.316 (0.207–0.425)***	22.677		2	-0.111 (-0.463–0.242)	NA	
Other	1	0.176 (-0.135–0.487)	NA		-	-	-	
Study Inclusion				5.268 (0.072)				3.700 (0.157)
Healthy	13	0.342 (0.105–0.579)**	81.729		5	0.445 (0.211–0.678)***	28.349	
Risk factors	21	0.431 (0.310–0.553)***	51.768		7	0.167 (0.007–0.328)*	0.000	
Unselected	38	0.262 (0.182–0.342)***	66.062		6	0.235 (-0.057–0.527)*	64.598	
Population type				0.600 (0.741)				1.276 (0.528)
Employees	28	0.319 (0.224–0.414)***	65.084		5	0.320 (0.015–0.624)*	54.043	
General population	21	0.382 (0.216–0.549)***	84.215		7	0.172 (-0.027–0.372)	51.016	
University students	23	0.302 (0.174–0.429)***	60.691		6	0.327 (0.116–0.539)**	16.173	
Prescribed usage				4.342 (0.227)				**12.193 (0.007)**
At discretion	10	0.247 (0.105–0.389)**	60.415		2	-0.082 (-0.378–0.214)	N.A	
Daily	51	0.343 (0.253–0.433)***	76.538		10	0.176 (0.031–0.321)*	34.661	
Weekly	10	0.342 (0.164–0.519)***	54.048		2	0.287 (-0.043–0.616)	N.A	
Experiment occasion	1	0.828 (0.259–1.397)***	NA		4	0.645 (0.390–0.901)***	0.000	
Guidance				5.316 (0.070)				**9.148 (0.010)**
Feedback	7	0.601 (0.210–0.993)**	82.512		6	0.520 (0.318–0.721)***	0.000	
Reminders	33	0.246 (0.154–0.339)***	68.539		4	0.124 (-0.084–0.332)	52.864	

Unguided	32	0.371 (0.268–0.474)***	67.021		8	0.146 (-0.022–0.314)	4.356	
Type of stress response				0.658 (0.417)				**8.023 (0.005)**
Acute	6	0.222 (-0.042–0.486)*	66.627		11	0.482 (0.209–0.754)**	79.312	
Chronic	68	0.335 (0.265–0.406)***	68.632		12	0.065 (-0.026–0.157)	0.000	
Laboratory context				**4.392 (0.036)**				**11.680 (0.001)**
No	70	0.321 (0.249–0.393)***	73.013		13	0.136 (0.017–0.254)*	24.432	
Yes	2	0.838 (0.360–1.316)***	NA		5	0.588 (0.357–0.819)***	0.000	
Risk of bias				**18.311 (0.000)**				2.500 (0.286)
High	6	0.243 (0.111–0.375)***	0.000		4	0.165 (-0.024–0.354)	0.000	
Low	21	0.137 (0.052–0.223)**	44.805		14	0.275 (0.092–0.457)**	63.657	
Some concerns	49	0.413 (0.320–0.506)***	71.488		4	0.414 (0.169–0.660)**	0.000	
Overall follow-up	20	0.266 (0.150–0.383)***	68.233	NA	-	-	-	-
1 month or less	11	0.331 (0.144–0.518)**	77.336					
3 months	8	0.213 (0.058–0.367)**	52.127					
6 months	2	0.010 (-0.268–0.289)	NA					

Notes: AC = active control; N = number of comparisons; CBT = cognitive behavior therapy; *p<0.05, **p<0.01, ***p<0.001. Bold prints indicate significant differences

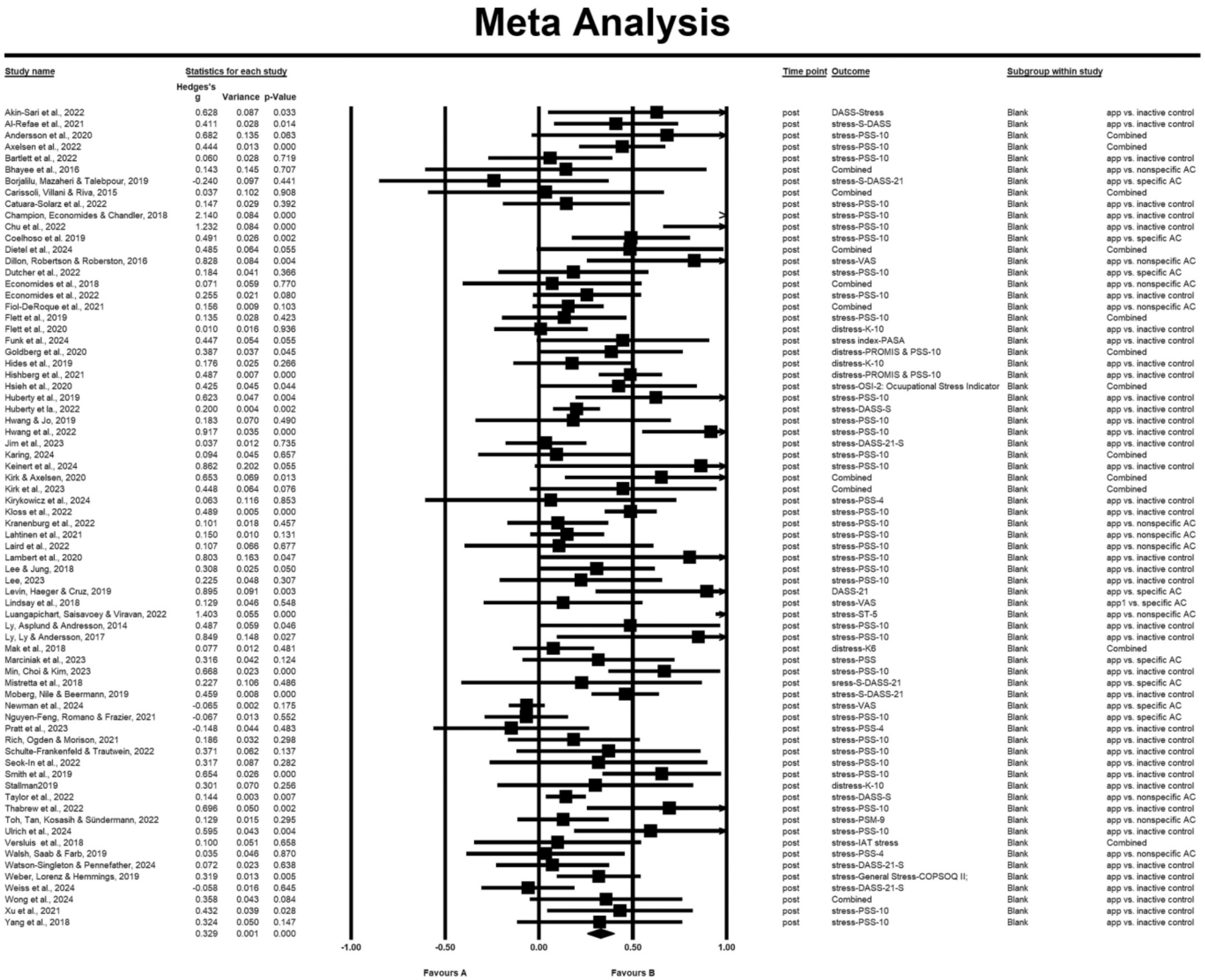

Figure 2. Forest plot of self-reported stress outcomes

In the case of the categorical characteristics, the comparisons inside the type of control moderator were significantly associated with the polled effect size, with larger effects and high heterogeneity found in the inactive controls group (k = 45, g = 0.41, 95 % CI 0.32–0.50, I^2 = 70.11). Another moderator that was found significant was the laboratory context, in which the two studies had an effect size of large magnitude (g = 0.84, 95 % CI 0.36–1.32) compared with the majority of studies conducted outside of the laboratory (k = 70, g = 0.32, 95 % CI 0.25–0.39, I^2 = 73.01). And the last significant moderator found was overall risk of bias assessment, coded per study, with studies receiving a judgment of low risk obtaining lower effect sizes (k = 21; g = 0.14, 95 % CI 0.05-0.22, I^2 = 44.81).

Physiological Stress-related Outcomes

As can be seen in the Table 1 and Figure 3 for the forest plot, there were 18 studies which assessed a physiological stress-related outcome and the analyzes indicate a significant small polled effect size (g = 0.26, 95 % CI 0.12–0.40), with medium heterogeneity (I^2 = 52.24). The trim and fill procedure did indicate a potential for publication bias, as there were 7 imputed effect sizes estimated to the sides of the funnel plot, as well as the Egger's intercept regression test being significant ($t_{(16)}$ = 3.88, p = 0.001). When inspected separately for the type of control, the publication bias was suspected only for the specific active comparison studies ($t_{(7)}$ = 3.88, p = 0.011), while no significant results were obtained for the inactive ($t_{(10)}$ = 1.07, p = 0.309), or nonspecific comparisons ($t_{(2)}$ = 0.23, p = 0.840). Only one study included a follow-up period for a physiological outcome, with a non-significant result (g = -0.03, 95 % CI -0.39–0.33, p = 0.886).

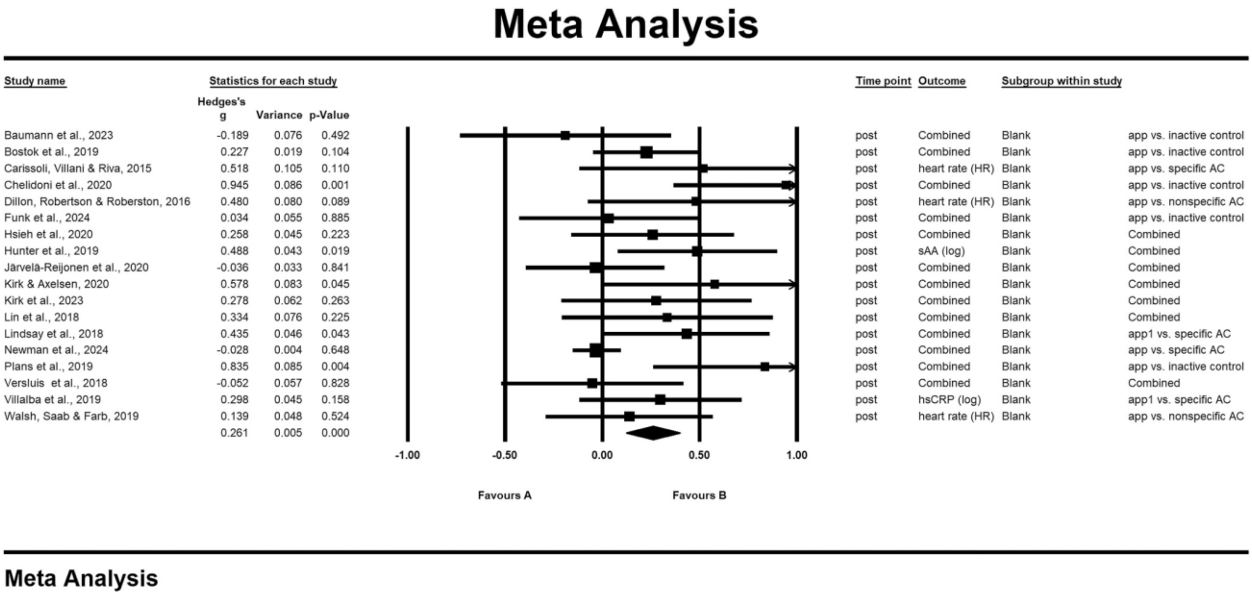

Figure 3. Forest plot of physiological stress-related outcomes

Subgroups Comparisons and Meta-Regression Analyses

The meta-regression analyses found significant results only for age (b = -0.0165, SE = 0.006, 95 % CI -0.0284; -0.0047, $p < 0.01$), and total usage time (b = 0.0007, SE = 0.0003, 95 % CI 0.0002–0.0012, $p < 0.01$).

Significant results were obtained also for the subgroup analyses within the following categorical moderators. In the case of the intervention strategy, apps based on muscle and breathing relaxation strategies and mediation ones obtained the largest and sole significant effect sizes compared to the other strategies (k = 8, g = 0.37, 95 % CI 0.09-0.64, I^2 = 72.61 and k = 7, g = 0.32, 95 % CI 0.16-0.48, I^2 = 0.00, respectively). Comparisons within the type of stress response criteria showed larger and significant effect sizes only for the acute stress response (k = 11, g = 0.48, 95 % CI 0.21-0.75, I^2 = 79.31). Also, studies whose prescribed usage was done on the experiment occasion (k = 4, g = 0.65, 95 % CI 0.39-0.90, I^2 = 0.00), offered feedback as the guidance strategy (k = 6, g = 0.52, 95 % CI 0.32-0.72, I^2 = 0.00), and were conducted in a laboratory context (k = 5, g = 0.59, 95 % CI 0.36-0.82, I^2 = 0.00) produced larger effect sizes and made a significant comparison.

Further analysis of specific physiological systems revealed small effect sizes for autonomic (g = 0.32) and cardiac outcomes (g = 0.36)

3.1.4. Discussions

Overall, statistically significant effect sizes were observed in both self-reported and physiological outcomes. There were signs of risk for publication bias, with indication that the source of this bias came from studies adopting a specific active comparison.

In the case of self-reported stress outcomes, the small-to-medium effect size obtained (g =0.33) corresponds with the results founded in the other meta-analyses to date that reported stress between the outcomes included (Goldberg et al., 2022; Linardon et al., 2019). Among the continuous moderators analyzed, dropout rates in both the intervention and control groups were significant predictors of effect size. Specifically, a higher dropout rate in the intervention group was associated with a higher effect size, whereas a higher dropout rate in the control group was associated with a smaller effect size.

The type of control, laboratory context, and the risk of bias assessment were the sole moderators significantly associated with differences in effect sizes. The apps investigated in comparison with inactive controls, like waiting list and treatment as usual, obtained significantly larger effect size (g = 0.41), compared with nonspecific and specific controls (g = 0.23 and g = 0.16, respectively). A similar trend of diminishing effect size as control conditions became more rigorous was somewhat observed for the physiological outcomes as well (Goyal et al., 2014).

The effect size was significantly smaller in the case of low risk of bias studies (*g* = 0.14), compared with those with high and some concerns for bias (*g* = 0.24 and *g* = 0.41, respectively), being in accordance with the findings in the general psychotherapeutic literature in which low risk studies give a more conservative effect (Cuijpers, van Straten, Bohlmeijer, Hollon, & Andersson, 2010).

Physiological Stress Findings

For physiological outcomes, a small effect size on psychological stress-related outcomes (*g* = 0.26) was obtained. Significant moderation for the physiological outcomes was obtained by intervention strategy, prescribed usage, guidance, type of stress response, and laboratory context categories. In the case of intervention strategy, the muscle and breathing relaxation and meditation had the largest and the sole significant effects.

Further, when we investigated the effects separately per different physiological systems, significant results were found only for the autonomic and cardiac outcomes, both with a small effect size of *g* = 0.32, and *g* = 0.36, respectively. Within the autonomic category, two indices for time domain HRV with medium effect sizes (RMSSD, *g* = 0.46 and pNN50, *g* = 0.69) were further found to be significant. The interpretation of such results seems to converge with the resonance frequency theory according to which slow and diaphragmatic breathing partly causes dominance of the PNS and increases in HRV, through the improved homeostasis of the baroreflex activation and the stimulation of vagal afferent pathways, with such beneficial effects as stress and mood recovery (Lehrer & Gevirtz, 2014).

Limitations and Implications for Research and Practice

The following limitations should be considered when interpreting the findings of this study: substantial heterogeneity unexplained for most of the results; many of the subgroup categories in the moderation and separate analyses for the physiological outcomes contained too few studies, which reduces statistical power and thus the results should be considered preliminary; the inclusion of follow-up assessments continues to remain a necessity for the synthesis of the long-term effects.

Despite these limitations, this study can have important directions for future research and clinical practice. Although with a modest effect for the psychological symptoms, and preliminary findings of efficiency for the physiological reactions, the findings resulted in this study supports the suggestion that smartphone app interventions represent a viable platform for stress management in the larger population. In particular, muscle relaxation and breathing and meditation seem to be requisite strategies for inclusion in any such intervention that aims to effectively reduce stress. CBT based strategies were found to have comparable efficiency for psychological stress. More studies should include CBT-based intervention for stress management in an app format, especially assessing physiological effects. Following shortly in the results obtained by the strategies above, mediation approaches had long been appreciated for their stress reduction efficiency (Pascoe et al., 2017), with recent applications in the format of mHealth showing moderate effect size on stress reduction (Gál, Ștefan, & Cristea, 2021).

In summary, we found evidence for the efficacy of mHealth apps in stress reduction for non-clinical populations. Both the significant effects recorded among the psychological outcomes and the physiological ones, with important points of convergence and mutual support, give credence in the efficacy of this scalable intervention format for the self-management of stress responses in a broad general population to recommend its utility.

3.2. Mapping the Interplay Between Psychological Vulnerability and Protective Factors in Mental Health: A Network Analysis Study

3.2.1. Introduction

Although findings from different research programs have separately brought significant knowledge progress regarding the risk and protective factors in psyhcologicla distress, recent integrative models link such research approaches (i.e., cognitive biases, emotions and ER). The Affect-Regulation Framework (Troy et al., 2023) has highlighted future common directions to advance our understanding of emotional psychopathology. These include among others the need for more research to cover a wider array of ER strategies besides reappraisal and rumination (e.g., acceptance, Troy et al., 2023); the differentiation between as well as within strategies (e.g., different types of reappraisal, Cristea et al., 2012); the integration of behavioral assessments with self-reported ones (Bernstein et al., 2017); the focus on the study of positive emotions beyond negative ones, and on different types of emotional states (Boemo et al., 2022); consider other constructs that may shape affect-regulation processes and their downstream outcomes (e.g., beliefs, Ford & Gross, 2019); broader and more representative samples; examining long-term consequences like mental health outcomes as well (e.g., Socastro et al., 2022); and, finally, broaden the scope of analysis, testing how these multiple factors and outcomes interrelate in multivariate models (e.g., network analysis - Hoorelbeke et al., 2016, 2019).

Current Study

As part of the attempt to address as many of the issues signaled above, the aim of the current study was to assess, through network analysis approach (Epskamp et al., 2018), the interrelation between cognitive biases, ER strategies, affect, beliefs, and psychopathology variables in a moderately large general population sample.

Objectives of the current study were then the network estimation of interactions between the included variables; identifying the most influential network nodes; identifying the strongest links in the network; and identifying those variables the most central bridge roles.

3.2.2. Methods

Participants and Procedure

The sample consisted of 489 final participants from the general population of various regions from Romania that were recruited for a mobile health randomized control trial, and which offered data at the baseline.

3.2.3. Results

Initially, Figure 1.B illustrates the statistically significant differences in the expected influence among the nodes. It was observed that dysfunctional negative emotions exhibited the highest expected influence, surpassing all other nodes significantly. This was followed by functional negative emotions, which held a significantly higher expected influence than 78.57 % of all nodes. Both positive reappraisal and stress symptoms also showed a significantly higher expected influence than 64.29 % of the nodes in terms of their expected influence. Secondly, Figure 1.A details the statistically significant differences in edge weights across the network. The strongest positive edges were those between the functional and dysfunctional negative emotions (stronger than all the other edges), acceptance and positive reappraisal (stronger than 98.1 % of the other edges), stress symptoms and functional negative emotions (stronger than 79.63 % of the other edges), anxiety and stress symptoms (stronger than 77.78 % of the other edges), depression symptoms and dysfunctional negative emotions (stronger than 75.93 % of the other edges), catastrophizing and rumination (stronger than 74.07 % of the other edges), anxiety symptoms and dysfunctional negative emotions (stronger than 68.52 % of the other edges), irrational beliefs and catastrophizing (stronger than 66.67 % of the other edges), depression symptoms and irrational beliefs (stronger than 61.11 % of the other edges), positive emotions and positive reappraisal, and between positive reappraisal and putting into perspective (each stronger than 55.56 % of the other edges), and between positive interpretation bias and positive emotions (stronger than 46.30 % of the other edges). On the other end, the strongest negative edges were those between rational and irrational beliefs (stronger than 90.74 % of the other edges), depression symptoms and positive emotions, and between positive emotions and functional negative emotions (each stronger than 88.89 % of the other edges), positive interpretation bias and depressive symptoms (stronger than 72.22 % of the other edges), positive attentional bias and anxiety symptoms, rational beliefs and catastrophizing, and between positive reappraisal and catastrophizing (each stronger than 68.52 % of the other edges).

Finally, the results of the bridge centrality analysis can be seen in Figure 2 for the top 20 % scoring nodes on the bridge expected influence centrality index. Accordingly, stress has the highest value as the bridge value in our network, followed by dysfunctional and functional negative emotions.

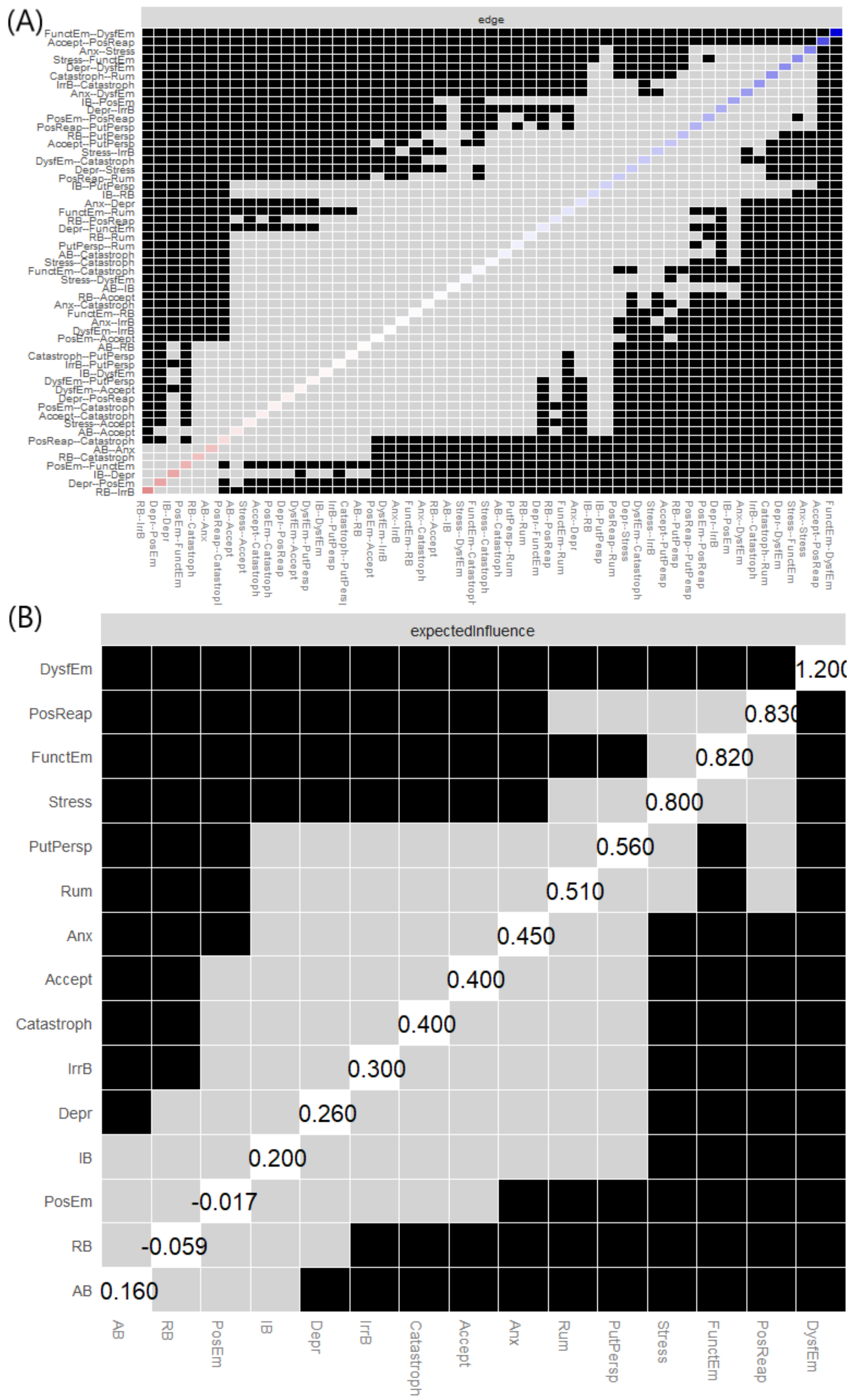

Figure 1. (A) Edge and (B) expected influence bootstrapped difference tests plot (a black cells represent a significant difference at 0.5% level of significance)

Note. AB – Attention Bias index; IB – Interpretation Bias index; Anx – Anxiety subscale, DASS-21; Depr – Depression subscale, DASS-21; PosEm – Positive Emotions, PAD; FunctEm – negative Functional Emotions, PAD; DysfEm – negative Dysfunctional Emotions; RB – Rational Beliefs, HABS-AV; IrrB – Irrational Beliefs, HABS-AV; Accept – Acceptance subscale, CERQ-9; PosReap – positive Reappraisal subscale, CERQ-9; Catastroph – Catastrophizing subscale, CERQ-9; PuPersp – Putting into Perspective subscale, CERQ-9; Rum – focus on thought/Rumination susbcale, CERQ-9.

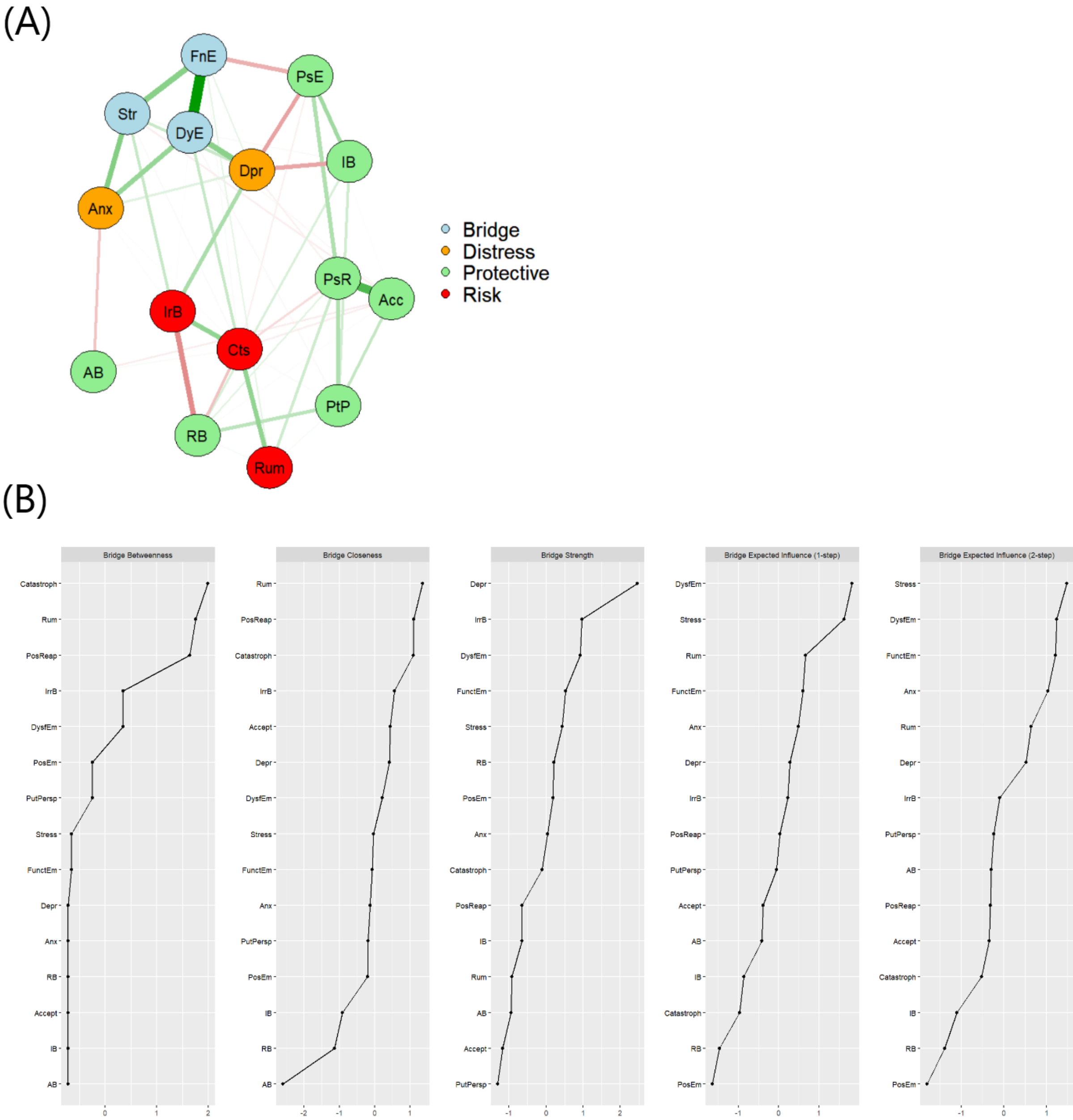

Figure 2. (A) A graphical model of protective factors, risk factors, and distress symptoms, with nodes identified as bridge variables colored in blue. (B) Bridge centrality estimates for each node in the network (in standardized z-scores)

Note. AB – Attention Bias index; IB – Interpretation Bias index; Anx – Anxiety subscale, DASS-21; Depr/Dpr – Depression subscale, DASS-21; PosEm/PsE – Positive Emotions, PAD; FunctEm/FnE – negative Functional Emotions, PAD; DysfEm/DyE – negative Dysfunctional Emotions; RB – Rational Beliefs, HABS-AV; IrrB/IrB – Irrational Beliefs, HABS-AV; Accept/Acc – Acceptance subscale, CERQ-9; PosReap/PsR – positive Reappraisal subscale, CERQ-9; Catastroph/Cts – Catastrophizing subscale, CERQ-9; PuPersp/PtP – Putting into Perspective subscale, CERQ-9; Rum – focus on thought/Rumination susbcale, CERQ-9.

3.2.4. Discussion

Our results showed that negative emotions, both dysfunctional and functional, resulted as the most central factors of the network according to the strength and expected influence indicators. They have also most of the strongest edges with the dimensions of psychological distress. This aligns with a substantial body of literature showing the contributing role of negative affect in mood and anxiety disorders (Barlow, et., 2014), and with recent studies incorporating network models

Findings indicate that negative emotions, stress, and positive reappraisal are the most influential variables. Bridge analyses suggest that stress mediates between functional and dysfunctional negative emotions and their effects on mental health factors. Additionally, positive emotions, interpretation bias, and rational beliefs are key in this interplay.

We consider there are important research and clinical implications for the current findings. Our results suggest that reducing negative emotions and stress symptoms, while improving strategies like positive reappraisal might represent priority intervention objectives for protecting against exacerbation of psychological distress and fostering resilience. Together with the strongest edges from the network discussed above, these results also indicate important mechanisms by which intended outcomes may occur.

We conclude a central role for stress symptoms and negative emotions as risk factors in mental health, along with positive reappraisal as an important protective factor. Additionally, positive emotions, interpretation bias and rational beliefs play further key roles in this interplay. These strengthen and complement past findings while opening venues for future confirmatory research.

3.3. Comparative Efficacy of PsyPills and OCAT Mobile Psychological Interventions in Reducing Depressive, Anxiety and Stress Symptoms: A Blinded Randomized Trial

3.3.1. Introduction

PsyPills is the first mental health mobile application that integrates Rational Emotive Behavior Therapy strategies (REBT, Ellis, 2013), a distinct approach of Cognitive Behavioral Therapy (CBT). The REBT approach is mainly focused on challenging the irrational/dysfunctional beliefs (illogical, unrealistic, and contribute to emotional distress and maladaptive behavior) and strengthening the rational/functional ones (i.e., logical, flexible, and based on evidence and reason) to address mental disorders and promote emotional well-being (David et al., 2018). In PsyPills, users track their emotional distress and identify the cognitive processes involved in it.

Another promising and innovative smartphone app is OCAT. More specifically, OCAT is grounded in the cognitive bias modification paradigm (CBM; MacLeod et al., 2009). CBM posits that a core risk factor underlying the onset and further persistence of stress-related disorders is the presence of negative cognitive biases. The app works by facilitating attentional disengagement from negative content and positive engagement of personally relevant information, providing instruction and performance feedback to facilitate top-down cognitive control and to improve the generation of adaptive interpretations.

Overall, both PsyPills and OCAT have been previously validated as promising mobile-phone psychological interventions to reduce general distress in the general population, yet further steps are required to test their efficacy under rigorously controlled designs.

Thus, we aimed to test the efficacy of both PsyPills and OCAT in a community sample against a placebo active control condition, at both ten days post-intervention and one-month follow-up and tested their effects on the reduction of psychological distress symptoms.

3.3.2. Methods

Study Design, Procedure and Participants

The research design of the present study is a multi-arm parallel-group randomized trial, with four waves of data collection (at baseline, mid, post, and follow-up)

A total of 493 participants completed the eligibility questionnaire, of which 229 were randomly allocated into the three groups (PsyPills n = 80; OCAT n = 70; shamOCAT n = 79) Measurements were collected before intervention allocation (baseline), five days during (mid), at the end of the ten-days intervention (post), and at one month after the intervention (follow-up). All measurement phases were collected online.

3.3.3. Results

General Psychological Distress

We obtained a significant Group x Time interaction, $F(6, 225.65) = 225.65$, $p < 0.05$. Thus, there was a change in the participants' psychological distress symptoms across the four time points, different for the three intervention groups (as illustrated in Figure 2). Following pairwise tests (as shown in Table 1), participants in both the PsyPills (MD = -5.22; 95 % CI = -10.00 to -0.44; adjusted p = 0.03) and active OCAT (MD = -6.30; 95 % CI = -11.39 to -1.21; adjusted p = 0.02) conditions showed a significantly greater reduction in the psychological distress levels compared with the control group at the follow-up. Although the second Sidak adjusted p-value was marginally non-significant for the PsyPills condition (p = 0.09), both interventions effects were of medium size (PsyPills, d = -0.48; OCAT, d = -0.58).

Table 3. Contrasts and between-group effect size calculations from LMMs[a]

Outcome	*MD*[b] (*SE*; 95% CI)	*P* value		Cohen's *d*
		LSD[c]	Sidak[d]	
DASS-21[e]				
Follow up				
PsyPills	-5.22 (2.43; -10.00 to -0.44)	**0.03***	0.09	-0.48
OCAT	-6.30 (2.59; -11.39 to -1.21)	**0.02***	**0.04***	-0.58
Post				
Psypills	-1.20 (2.13; -5.38 to 2.98)	0.57	0.92	-0.11
OCAT	0.76 (2.25; -3.68 to 5.19)	0.74	0.98	0.07
Mid				
PsyPills	-1.17 (1.87; -4.85 to 2.51)	0.53	0.90	-0.11
OCAT	0.22 (2.01; -3.73 to 4.16)	0.91	0.99	0.02
Depression				
Follow up				
PsyPills	-0.67 (0.98; -2.60 to 1.26)	0.49	0.87	-0.15
OCAT	-1.50 (1.03; -3.53 to 0.54)	0.15	0.38	-0.34
Post				
Psypills	-0.21 (0.85; -1.88 to 1.47)	0.81	0.99	-0.04
OCAT	0.27 (0.90; -1.50 to 2.05)	0.76	0.99	0.06
Mid				
PsyPills	-0.80 (0.75; -2.26 to 0.67)	0.29	0.63	-0.18
OCAT	0.24 (0.80; -1.32 to 1.81)	0.76	0.99	0.05
Anxiety				
Follow up				
PsyPills	-2.17 (0.85; -3.83 to -0.50)	**0.01***	**0.03***	-0.60
OCAT	-1.55 (0.90; -3.31 to 0.212)	0.085	0.23	-0.43
Post				
Psypills	-0.80 (0.74; -2.25 to 0.66)	0.28	0.63	-0.22
OCAT	0.46 (0.79; -1.08 to 2.01)	0.56	0.91	0.13
Mid				
PsyPills	0.27 (0.65; -1.01 to 1.54)	0.68	0.97	0.07
OCAT	0.13 (0.70; -1.25 to 1.51)	0.85	0.99	0.04
Stress				
Follow up				
PsyPills	-2.64 (1.06; -4.72 to -0.56)	**0.01***	**0.04***	-0.59
OCAT	-2.62 (1.12; -4.83 to -0.41)	**0.02***	0.06	-0.58
Post				
Psypills	-0.16 (0.92; -1.97 to 1.65)	0.86	0.99	-.04
OCAT	0.36 (0.98; -1.55 to 2.28)	0.71	0.98	0.08
Mid				
PsyPills	-0.45 (0.80; -2.02 to 1.12)	0.57	0.92	-0.10
OCAT	-.01 (0.86; -1.70 to 1.68)	0.98	0.99	0.00

Note: significant results are bolded and superscripted with *
[a] linear mixed-effects models
[b] Pairwise mean differences from LMMs
[c] *P* value following least significant difference (LSD) adjustment for all pairwise comparisons
[d] *P* value following Sidak adjustment for all pairwise comparisons
[e] DASS-21: Depression, Anxiety, and Stress Scale - 21 items form

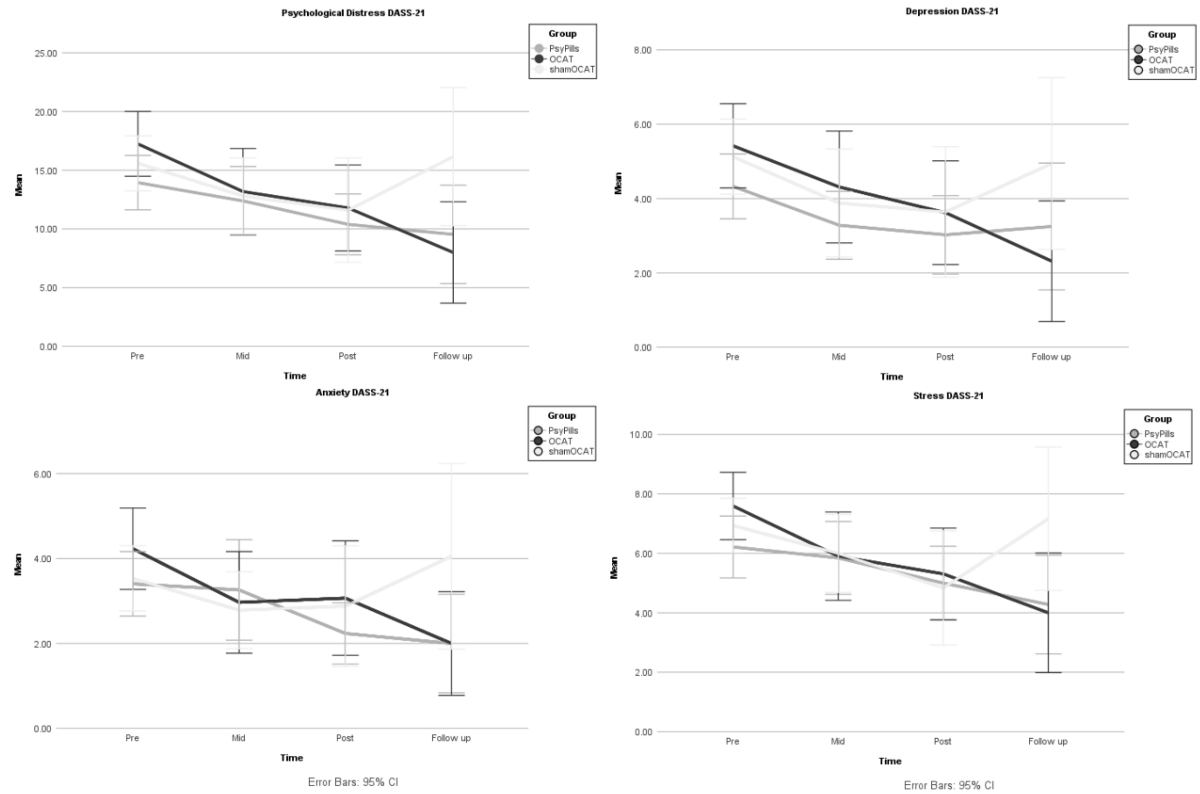

Figure 1. Scores on the Pyschological distress, Depression, Anxiety, and Stress during the study

Depression, Anxiety, and Stress

For the separate depression outcome, we did not obtain a significant Group x Time interaction, $F(6, 184.253) = 1.20$, $p > 0.05$ (Figure a), although the active OCAT intervention demonstrated a small effect size ($d = -0.34$). Further examining changes within each group, there was also a significant decrease in depression for those in the active OCAT condition ($MD = -2.98$; 95 % CI = -4.31 to -1.66; adjusted $p < 0.001$) across time, which was not found in either of the other two groups (PysPills, $MD = -1.06$; 95 % CI = -2.23 to 0.11; adjusted $p = 0.07$; control group, $MD = -1.20$; 95 % CI = -2.55 to 0.14; adjusted $p = 0.08$).

For the anxiety outcome, there was a significant Group x Time interaction, $F(6, 227.45) = 2.41$, $p = 0.03$ (Figure 1), and following pairwise comparisons, only participants in the PsyPills group significantly decreased their anxiety symptoms, with a medium effect size at follow-up in comparison with the control group ($MD = -2.17$; 95 % CI = -3.83 to -0.50; adjusted $p = 0.01$; $d = -0.60$).

As for the stress outcome, analyses also supported a significant Group x Time interaction, $F(6, 186.45) = 2.42$, $p = 0.03$ (Figure 2). Looking at the pairwise comparisons, both PsyPills and active OCAT apps significantly decreased the stress symptoms with medium effects size at the follow-up period (PsyPills, $MD = -2.64$; 95 % CI = -4.72 to -0.56; adjusted $p = 0.01$; $d = -0.59$; and OCAT, $MD = -2.62$; 95 % CI = -4.83 to -0.41; adjusted $p = 0.02$; $d = -0.58$).

3.3.4. Discussion

The results confirm the similar effectiveness of both interventions to target the symptomatology of psychological distress, with a medium effect size, and indices of specificity in the mechanisms involved (PsyPills with a larger effect size on Anxiety, and OCAT in Depression, although with a non-significant difference). The present findings are congruent with those observed in the meta-analytical literature (Goldberg et al., 2022), where small to medium magnitude effects (*d*s = 0.32 to 0.47) were obtained for smartphone interventions compared to inactive controls on the reduction of common psychological symptoms (anxiety, depression, stress) in the general population.

The finding that PsyPills was the only effective specifically for anxiety symptoms, might suggest a predilection usage and a particularly efficient way of targeting anxious symptoms, by addressing the irrational beliefs that sustain them, in an easy and interactive format.

The reduction in depression, although non-significant for the between comparisons, but with a small effect, and significant within reduction trends from pre to both post, and follow-up in active OCAT users is a promising finding too.

The main limitations were that we registered high attrition and low adherence rates. Also, lower-than-planned effects might have been statistically underpowered to detect.

In conclusion, the results support the high potential of both apps as scalable tools to provide low-intensity self-guided interventions for common psychological problems in the general population and expand opportunities for further research (e.g., confirm and capitulate on the differential effects).

3.4. Mechanisms of Change in Two Mobile Psychological Interventions for Psychological Distress: Longitudinal Mediation and Dynamic of Change in a Randomized Controlled Clinical Trial

3.4.1. Introduction

Digital psychological interventions have been advanced in recent years to respond to the problem of accessibility given their features that allow dissemination on a population scale, anonymity, constant access, and reduced costs (Linardon et al. 2019). Moreover, digital interventions also hold considerable methodological opportunities for psychotherapy process research in active ingredients and mechanisms of change due to high technical standardization of their intervention format (Domhardt, Cuijpers, et al. 2021).

Importantly, smartphones are particularly well-suited for incorporating Ecological Momentary Assessments (EMA), which involve the collection of fine-grained, real-time data on psychological states and behaviors in naturalistic settings (Myin-Germeys et al. 2018). This capability allows for nuanced temporal evaluations which can be used to test more dynamically the change processes that are happening during or after an intervention (Tomoiagă, Gheorghiu, and David, 2024).

Current Study

The study focuses on two psychological apps recently shown to be effective in reducing general distress—PsyPills and OCAT (Sîrbu et al. 2025)—both of which employ distinct therapeutic strategies targeting general distress.

Mediation Hypothesis 1: The efficacy of PsyPills intervention in decreasing psychological distress at 1-month follow-up is mediated by the indirect effect on irrational beliefs, functional reappraisal (represented by acceptance, putting into perspective, and catastrophizing emotional regulation strategies), and negative emotions at post intervention in comparison with the control group.

Mediation Hypothesis 2: The efficacy of OCAT intervention in decreasing psychological distress at 1-month follow-up is mediated by the indirect effect on positive reappraisal, positive emotions and rumination at post intervention in comparison with the control group.

For investigating how pairs of variables measured daily are influenced during the 10-day intervention and how this dynamic is influenced differently by the 2 active app groups compared with the control, we generated the following dynamic of change hypotheses:

Dynamic Hypothesis 1: Changes in functional reappraisal determine changes in irrational beliefs and changes in negative emotions, which are influenced by PsyPills group in comparison with the control group.

Dynamic Hypothesis 2: Changes in interpretation bias determine changes in positive reappraisal and changes in positive emotions, which are influenced by OCAT group in comparison with the control.

3.4.2. Method

Study Design and Participants

The current study tested multiple proposed mediators within the context of a rigorously designed randomized controlled trial (RCT), using standard self-reported questionnaires at four study key time points (baseline, mid-intervention, post-intervention, and one-month follow-up), and EMA data collected daily over the 10-day intervention period. 450 eligible participants from 718 total participants were randomized into the three groups

(PsyPills n =154; OCAT n =136; shamOCAT n =160) and included in the intention-to-treat analyses (see Figure 2).

3.4.3. Results

Mediation Results

We found that catastrophizing was the single mediator variable that registered changes due to both active app interventions temporarily preceding the outcome (PsyPills: $\beta = -0.21$, $SE = 0.28$, 95 % CI [-1.37 to -0.29], $p < 0.01$; OCAT: $\beta = -0.16$, $SE = 0.32$, 95 % CI [-1.28 to 0.04], $p = 0.04$). The further effect from catastrophizing at post to psychological distress at follow-up was not significant, $\beta = -0.03$, $SE = 0.49$, 95 % CI [-1.15 to 0.77], $p = 0.70$, while the direct effects of both groups were still significant, $\beta = -0.18$, $SE = 1.66$, 95 % CI [-7.33 to -0.83], $p = 0.01$ for PsyPills, and $\beta = -0.27$, $SE = 1.42$, 95 % CI [-8.90 to -3.33], $p < 0.001$ for OCAT, respectively. These results indicate that the mediation effect was not hold.

Figure 1 illustrates the model specification of the Dynamic Panel Model used for mediation together with β coefficients for the paths between groups, catastrophizing mediator at post intervention and pychological distress at follow-up.

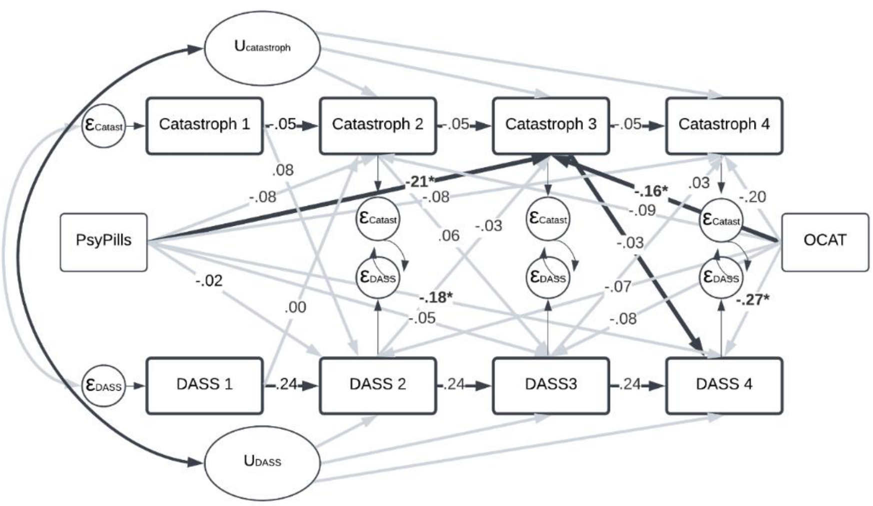

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Figure 1. DPM for the indirect effect of catastrophizing

Note: DPM – mediation Dynamic Panel Model; U – between-person random terms; ε – error terms; Catastroph – catastrophizing mediator; DASS – psychological distress outcome; values represent standardized beta coefficients; ellipses represent latent variables, rectangles represent manifest variables; dark lines represent the mediation relations of interest between active groups, mediator at post and outcome at a later follow-up time; * - represent significant effects

The Dynamic of Mechanisms during the Intervention

There were significant results of the composite functional reappraisal score from previous day to the next occasion of irrational beliefs (β = -0.17, 95 % CI -0.32 to -0.04) and negative emotions (β = -0.16, 95 % CI -0.30 to -0.03), and only PsyPills influenced this dynamic (β = 0.43, 95 % CI 0.08 to 0.76). Interpretation bias also conducted to changes in the next moment positive reappraisal (β = 0.18, 95 % CI 0.06 to 0.33), and only OCAT (β = 0.24, 95 % CI 0.06 to 0.42) was found to increase the overall level of the interpretation bias. Both app interventions influenced the changes in the stability to which positive reappraisal and positive emotions levels predicted themselves in the next day.

Figure 2 illustrate the model specification for the Dynamic Structural Equation Model used to study the dynamics of change variables.

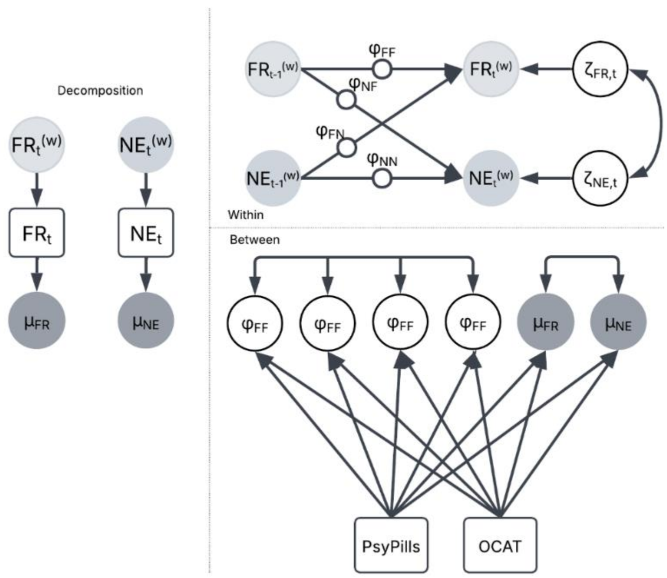

*Figure 2***.** DSEM specification between functional reappraisal and negative emotions

Note: DSEM – multilevel Dynamic Structural Equation Model; FR – functional reappraisal; NE – negative emotions; $^{(w)}$ - within-person variation from the latent mean of the variable; μ – laten mean across the measurements; φ_{FF} / φ_{NN} – autoregressive terms; φ_{NF} / φ_{FN} – cross-lagged terms; ς – random components a current time

3.4.4. Discussion

The results showed a significant negative effect of both groups on the mediator, while there was no significant effect of catastrophizing on the last measure of psychological distress. Also, both groups still retained their significant effect on psychological distress, implying that there was no mediation effect, contradicting the mediation hypothesis in the case of both apps. When looking at the results of the more time-grained analysis of the dynamics of change during the interventions, we found that in the case of PsyPills hypothesized mechanisms, momentary changes in functional reappraisal significantly reduced the levels of irrational beliefs and negative emotions in the next day. While the significant finding that OCAT app influence the change in the stability of positive emotions and positive reappraisal and that only in the case of OCAT the overall level of interpretation bias increases during the treatment and the momentary changes in interpretation bias conduced to increase next occasion positive reappraisal, confirm as well one pathway by which OCAT is supposed to transmit its therapeutic effect.

Related to this, a similar probable explanation is the difference between retrospective and EMA measurement methods. While retrospective questionnaires cover a broad time span, they may be too coarse and insufficiently sensitive to detect some changes. In contrast, EMA enables more frequent repeated measurements, also capturing experiences within a timeframe that minimizes recall bias. For example, Moore et al. (2016) found that for the same variables, significant changes went undetected when using retrospective questionnaires, whereas EMA measures revealed meaningful variations for the effect of a mindfulness intervention. Similarly, the dynamic analysis part of our study using the EMA daily measures uncovered significant changes that were not discovered by the overall treatment effects.

Limitations

Many of the limitations of the current study are inherited from the primary study already published (Sîrbu et al. 2025): i.e., high missing data, low engagement rates, use of a convenience sample, a female majority sample. Furthermore, among the shortcomings for the current approach of the study, single items for many of the EMA measures might pose a problem for the reliability of the construct thus measured, despite the reduced participant's burden in intensive repeated measures and common use in the EMA literature.

In conclusion, these results reinforce the evidence supporting the role of reappraisal strategies, as key mechanisms behind effective psychological interventions in enhancing psychological resilience to stress. Notably, our findings suggest that even when delivered through a brief, cost-effective, and scalable app-based format, these strategies can have a meaningful impact.

CHAPTER IV: GENERAL CONCLUSIONS AND IMPLICATIONS

4.1. Overview of the Main Findings of the Present Thesis

The results of the meta-analysis showed that stress management mHealth apps have a small but significant aggregate effect for reducing both self-reported psychological distress and its physiological indicators in the general non-clinical population. Looking more specifically, we additionally observed significant results for improving self-reported sleep problems, as well as autonomic (e.g., heart rate variability) and cardiac (e.g., heart rate and respiratory) outcomes. Among the significant moderators, we observed that apps that offer techniques based on muscle and breathing relaxation and meditation, present personalized guidance features, have a greater effect, as do studies that are carried out in experimental laboratory conditions and measure acute, as immediate versus chronic, over time stress response. These effects were found at post the intervention, but in the case of self-reported measures, it was also possible to investigate the follow-up periods of one and three months, where it was found that the significant beneficial effect was maintained.

Findings of the network analysis study showed that negative emotions (both functional and dysfunctional) were the most central factors, showing the most and strongest links with all other variables in the estimated network. When considered separately, the type of dysfunctional negative emotions was found to hold among the strongest relationships with anxiety and depression symptoms, while functional negative emotions showed the strongest relationships with stress. The latter also represented the next most central factor in the network, and further bridge analyses showed that stress plays a bridge role between functional and dysfunctional negative emotions' relations to the rest of risk and protective factors in the network. Positive reappraisal also obtained one of the most influential roles in the network, and together with positive emotions and interpretation bias, on the resilience pole, and catastrophizing, and irrational beliefs on the vulnerability side, were found in one of the strongest relations.

From the RCT study we obtained that both PsyPills and OCAT apps significantly reduced psychological distress one month after the end of the intervention, with a medium effect, compared to the placebo active control group. And when we looked separately at the three subscales of distress, depression, anxiety and stress, we observed that only PsyPills significantly reduced anxiety levels, while OCAT registered a small effect size for reducing depressive symptoms.

Lastly, the results of the mediation and dynamic of change study showed that in the case of the mediation analysis, catastrophizing ER strategy was the only variable that could be investigated in the longitudinal mediation model, being the only one that met the temporal criterion, with a significant difference between groups before the last moment of time. However, we could only observe the effect of both mobile interventions, PsyPills and OCAT, for decreasing the levels of catastrophizing, without this result mediating the effect that the interventions had further on, one month after the intervention, for reducing psychological distress (no mediation effect found, only the direct effects were significant). Moving to the dynamics of change model, we found that previous higher functional reappraisal ER strategies (a composite variable of the Acceptance, Catastrophizing, and Putting into Perpesctive scales items) lead to both significantly lower irrational beliefs and negative emotions in the next day. Furthermore, only PsyPills in comparison with the control groups significantly influenced the dynamic between functional reappraisal and negative emotions, in the sense that for the users of PsyPills, more frequent functional reappraisal leads to less negative emotions in a subsequent day. A significant positive dynamic was found also between the increasing levels of interpretation bias at a previous moment and next day more frequent positive reappraisal. This time, as expected, only OCAT has a significant role determining the levels of interpretation levels to increase during the interventions.

4.2. Implications

The findings of the present thesis have several important theoretical, practical and methodological implications. The systematic review and meta-analysis study showed that smartphone mental health apps are effective in reducing distress in the absence of any other treatment (inactive control), the effect is not only due to the factors of time, attention and waiting (non-specific control), and have a comparative advantage over other interventions that were known to be effective (specific control) in the general population. The utility of such mental health apps can be found in their inclusion in preventive programs, within a stepped-care approach for treatment, or as adjuvant tool to more intensive treatment protocols. The consistently higher effect of muscle and breathing relaxation and meditation in both types of outcomes additionally indicates that this content should be implemented for an increased efficacy on stress reduction.

Next, the network analysis study contributes to the current scientific knowledge by showing that, independent of the other variable simultaneously taken into account, negative emotions represent the most significant vulnerability factor in psychological distress, while stress mediates between the dysfunctional and functional poles of negative emotions and their subsequent effect on psychological distress. Positive reappraisal, on the other hand, was found as the resilience factor with the most beneficial influence for the psychological distress. Thus, these findings are particularly valuable insights for preventive interventions, aimed at addressing the vulnerable factors before negative consequences worsen.

The results of the RCT study confirm the equal efficacy of the two interventions in the symptomatology of psychological distress, with an average effect and the indication of specificity in the mechanisms involved. Such results provide empirical support for the efficacy of two interventions that are able to play this preventive role in mental health by reducing psychological distress in a general population, non-clinical sample. The results also showed that PsyPills app was found to be especially effective in reducing anxiety symptoms, while OCAT in reducing depressive ones.

Study four showed that both functional and positive reappraisal emerged as significant mechanisms for the dynamics of change during app intervention along with factors such as negative emotions, irrational beliefs and interpretive bias. Thus, these findings imply the role these processes play in reducing distress and their importance in being included in intervention protocols. Also, these findings indicate that these mechanisms conduce to beneficial outcome even as techniques in the content of brief, low-intensity, and self-guided interventions, emphasizing their scalability potential.

4.3. Limitations

The main limitations can be summarized as: predominant characteristics of the recruited sample, which reduced the power of generalization to other population categories: high percentage of female participants, with higher education, professionally active and with a normal to mild level of psychological distress; high dropout and low app engagement rates; insufficient statistical power for smaller effects.

4.4. Conclusion

The incremental contribution to the literature of the present thesis by its original and innovative study components allows the following main conclusions regarding the efficacy and mechanisms of change of mobile health app interventions. mHealth apps for stress management demonstrate small but significant effects in reducing psychological distress, as evidenced by both self-reported and physiological outcomes when compared to various control conditions. Among available strategies, muscle relaxation, breathing techniques, and meditation are among the most effective.

Key psychological factors in distress regulation include negative emotions, stress, and positive reappraisal, with stress acting as a bridge symptom linking functional and dysfunctional negative emotions to worsening mental health. Two apps, PsyPills (REBT-based functional reappraisal) and OCAT (CBM-based attention and interpretation bias training), both effectively reduced psychological distress compared to a placebo group. PsyPills was particularly beneficial for anxiety symptoms, while OCAT showed promise in reducing depressive symptoms. Their efficacy is driven by reappraisal processes, irrational belief modification, and emotion regulation mechanisms.

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