



# Emotion regulation and insomnia as candidate processes of change in a digital mental health intervention

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## ARTICLE INFO

### Keywords:

Emotion regulation  
Insomnia  
Processes-based  
Mediation  
Digital intervention  
Well-being  
University students

## ABSTRACT

**Background:** Digital mental health interventions can improve distress and well-being, but the processes statistically accounting for these effects remain unclear. We examined emotion regulation and insomnia as candidate processes in university students.

**Methods:** Data came from a three-arm randomized trial of the ETUCARE program, an eight-week multicomponent program for French university students. The ITT dataset contained 1064 participants (online:  $n = 460$ ; hybrid:  $n = 235$ ; control:  $n = 369$ ); 947 contributed to FIML estimation. Parallel mediation estimated indirect effects through emotion regulation and insomnia. A  $\geq 70\%$ -adherence sample provided a per-protocol sensitivity analysis, and an exploratory cross-lagged model examined longitudinal associations.

**Results:** ETUCARE assignment was associated with improved emotion regulation ( $\beta = .166$ ,  $p < .001$ ) and reduced insomnia ( $\beta = -.142$ ,  $p < .001$ ). Both showed significant indirect effects on distress and well-being: better emotion regulation and lower insomnia were associated with lower distress and higher well-being. Combined pathways accounted for 33.6% of the total association with distress. A constrained model was compatible with similar absolute magnitudes but opposite directions across outcomes, without establishing equivalence. ITT and per-protocol estimates were closely aligned.

**Conclusions:** These findings are consistent with a process-based account of digital interventions in which emotion regulation and sleep represent candidate shared processes statistically associated with changes across multiple domains of mental health. The findings do not establish causal mechanisms or temporal precedence. Nevertheless, targeting emotion regulation and sleep may represent a promising strategy for scalable digital interventions. Future experimental research should clarify their temporal dynamics and identify the most active intervention components.

## 1. Introduction

University students represent a population at high risk for mental health difficulties. Epidemiological surveys consistently document elevated rates of clinically significant psychological distress (including anxiety, depression, and sleep disorders) in this group, with prevalence estimates ranging from 25% to 40% across European and North American samples (Auerbach et al., 2018; Bruffaerts et al., 2019; Charbonnier et al., 2021). Beyond diagnosable disorders, students also exhibit deficits

in subjective well-being, academic engagement, and meaning, which compound functional impairment and increase dropout risk (Alavi et al., 2025; Martinie et al., 2023; Martinie & Shankland, 2024; Szabó et al., 2024). Despite this burden, treatment uptake remains low: structural barriers including stigma, cost, and limited service capacity leave many students with clinically relevant needs without support (Bennett et al., 2020; Lipson et al., 2021; Pinho et al., 2025; Theurel & Witt, 2022).

Digital mental health interventions (DMHIs), delivered via smartphones or web-based platforms, have emerged as a scalable response to

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<https://doi.org/10.1016/j.brat.2026.105123>

Received 22 April 2026; Received in revised form 23 July 2026; Accepted 29 July 2026

Available online 31 July 2026

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this treatment gap, demonstrating moderate effectiveness for distress reduction across meta-analytic syntheses (Lattie et al., 2019; Lehtimäki et al., 2021; Linardon et al., 2019). However, most DMHIs evaluated to date have been designed and tested for single outcomes, typically depression or anxiety symptoms, with limited attention to the psychological mechanisms through which they produce change or to their effects on positive dimensions of mental health (Díaz-García et al., 2021; Domhardt et al., 2021; Torous et al., 2025; van Agteren et al., 2021). More critically, few studies have examined whether these mechanisms operate equivalently across both negative (distress) and positive (well-being) domains of mental health.

A central theoretical limitation of this literature is its predominant reliance on negative symptoms reduction as the primary criterion for effectiveness. The dual-factor model (DFM) of mental health proposes that psychopathology and well-being are empirically related but dimensionally distinct constructs, each with its own antecedents, trajectories, and intervention targets (Keyes, 2005, 2005, 2005; Magalhães, 2024; Suldo & Shaffer, 2008). Individuals may exhibit low symptom levels yet remain impaired in flourishing, defined as the presence of positive affect, engagement, meaning, and accomplishment. Such deficits carry independent prognostic significance for academic outcomes, interpersonal functioning, and long-term disorder risk (Burns et al., 2022; Iasiello et al., 2019; Keyes et al., 2010; Lamers et al., 2015). Effective interventions therefore need not only to reduce distress but also to actively promote well-being, and mechanistic research should determine whether identified change processes operate equivalently across both dimensions of the dual-factor model and show domain-specific effects.

Emotion regulation (ER) is widely recognised as a key transdiagnostic process involved in the development and maintenance of a broad range of mental health disorders (Aldao et al., 2010; Lincoln et al., 2022). Meta-analytic evidence consistently identifies ER skills improvement as a key mediator of symptom change across anxiety, depression, and comorbid disorders (Berkling, 2024; Cludius et al., 2020; Muñoz-Navarro et al., 2022), as well as with emotional disorders more generally, which are characterised by frequent and intense negative emotions, aversive responses to emotional experiences, and repeated efforts to avoid or downregulate these emotions (Bullis et al., 2019). In contrast, effective ER facilitates adaptation to stressful situations and is associated with better psychological and physical health outcomes (Bonanno & Burton, 2013; Hu et al., 2014). The Adaptive Coping with Emotions (ACE) model (Berkling & Whitley, 2014) provides a theoretically grounded account of this process, positing a hierarchical skill structure in which modification capacity and acceptance/tolerance function as core regulatory hubs driving downstream benefits, including reductions in negative affect and improvements in adaptive functioning. Beyond symptom reduction, this framework suggests that ER may also facilitate well-being by freeing cognitive and emotional resources for goal-directed behaviour and positive engagement. Accordingly, ER constitutes a plausible process relevant to both distress and well-being. However, whether improvements in ER show comparable associations with these two dimensions within digital interventions has not yet been formally tested.

Sleep problems and insomnia constitute a second candidate transdiagnostic mechanism with comparable theoretical and empirical support (Sesso et al., 2024). Insomnia affects approximately 25–40% of university students and is among the strongest predictors of depression onset, anxiety persistence, and impaired functioning in this population (Barret et al., 2024; Hershner & Chervin, 2014; Schlarb et al., 2017). At the mechanistic level, sleep disturbance alters emotional processing by increasing limbic reactivity, reducing prefrontal regulatory control, and biasing attention toward negative stimuli while attenuating positive affective responding (Palmer et al., 2024; Vandekerckhove & Cluydts, 2010). Experimental studies show that sleep loss both heightens negative affect and reduces positive affect, supporting the conceptualisation of insomnia as a transdiagnostic amplifier of emotional dysregulation

(Palmer & Alfano, 2017; Palmer et al., 2024). In addition, insomnia is associated with impairments in processes central to well-being, including motivation, social engagement, and meaning-making (Harvey et al., 2011; Vandekerckhove & Cluydts, 2010). Together, these findings suggest that insomnia reduction may contribute not only to distress alleviation but also to improvements in well-being, positioning sleep as a plausible candidate process within multicomponent interventions.

An additional unresolved question concerns the temporal relationship between ER and sleep within intervention contexts. These processes are bidirectionally linked: maladaptive ER strategies, such as rumination and worry, contribute to cognitive hyperarousal and sleep disturbance (Jansson-Fröjmark & Hossain, 2024; Nicholson et al., 2021), whereas insufficient sleep impairs subsequent daily moods, regulatory capacity and reduces the effectiveness of ER strategies (Lenneis et al., 2024; O'Leary et al., 2017; Sullivan et al., 2023; Tomaso et al., 2021). When both mechanisms are targeted simultaneously, it remains unclear which process temporally precedes the other, and whether one may facilitate changes in the other. This question has direct implications for intervention design and sequencing. However, most mediation studies assess mechanisms at a single time point, limiting inference about temporal precedence. A three-wave design, in which mediators are assessed during the intervention and outcomes at follow-up, combined with cross-lagged panel modelling, allows for the examination of temporal ordering, although such findings should be interpreted as suggestive rather than confirmatory of temporal precedence.

The present study addresses these theoretical and methodological gaps using data from ETUCARE, a three-arm randomized controlled trial evaluating an eight-week multicomponent digital mental health program co-designed with university students. ETUCARE is a multicomponent digital intervention grounded in cognitive-behavioural, third-wave, and lifestyle-based approaches. The intervention targets key processes underlying student mental health, through structured modules combining psychoeducation, skills training, and behavioural exercises (Theurel et al., 2022). ETUCARE integrates ER training derived from the ACE model (Berkling & Whitley, 2014) with evidence-based sleep modules informed by cognitive-behavioural therapy for insomnia, delivered either fully online or in a hybrid format combining digital content with group sessions. The parent trial compared two active delivery conditions (a fully online condition and a hybrid condition) with a waiting-list control group. Both active conditions received the same eight online modules in the same sequence; the hybrid condition additionally included eight standardized weekly 2-h group workshops. The primary RCT found intervention-related improvements in psychological distress, well-being, emotion-regulation skills, and insomnia severity. Detailed effect sizes, clinical transitions, and format-specific findings are reported in the primary trial publication (Theurel et al. under review).

Building on this framework, the present study uses a three-wave design (T1 baseline, T2 immediately post-intervention, T3 two-month follow-up) to address three questions: (1) whether changes in ER and insomnia statistically account for intervention effects on distress and well-being; (2) whether the estimated indirect-effect patterns are similar in absolute magnitude across the two outcomes; and (3) in an exploratory analysis, whether the longitudinal associations between ER and insomnia differ in direction when both processes are modeled simultaneously.

## 2. Method

### 2.1. Study design and participants

This secondary study used data from the ETUCARE trial, a three-arm randomized controlled trial evaluating an eight-week digital mental health intervention among university students in France. Participants were recruited from six French university sites (Poitiers, Lyon, Dijon, Grenoble, Nantes, and Nîmes) through university health services,

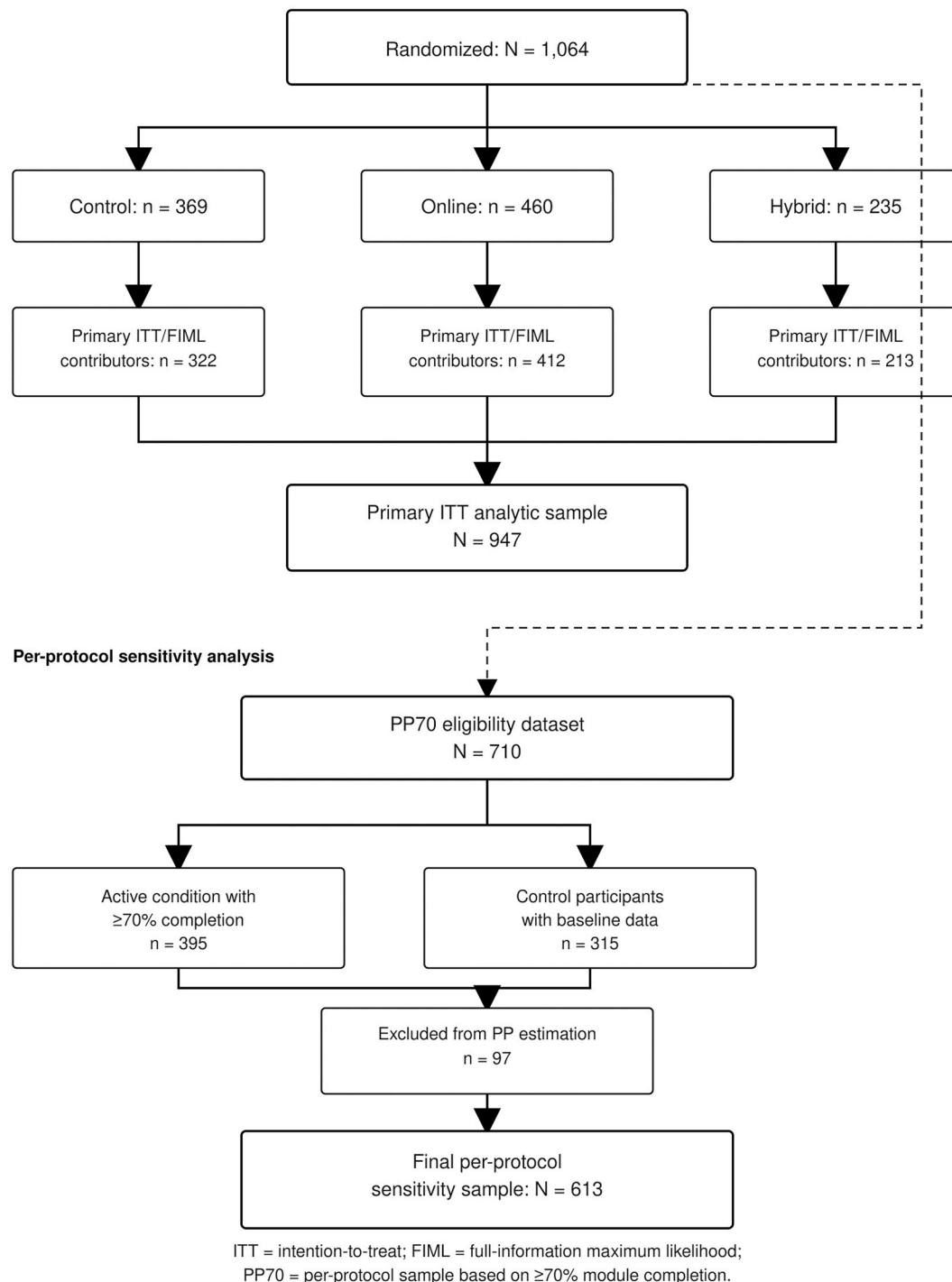
institutional mailing lists, campus posters, and in-class announcements. Eligibility criteria were being enrolled as a university student, being aged 18 years or older, and providing informed consent. No exclusion criterion based on symptom severity was applied.

The trial randomized 1064 participants to a fully online condition ( $n = 460$ ), a hybrid condition combining the same digital modules with face-to-face group workshops ( $n = 235$ ), or a waiting-list control condition ( $n = 369$ ). Baseline sociodemographic information was available for 928 randomized participants. Their mean age was 21.13 years ( $SD = 4.55$ ; median = 20; range = 18–39), and 809 (87.2%) were women. Most were French nationals (85.2%), studied psychology (66.9%), and reported uninterrupted academic progression (76.7%).

Recruitment occurred during the 2022–2023, 2023–2024, and 2024–2025 academic years. Randomization was implemented through an automated allocation system stratified by academic sector. The present study is a secondary analysis of the ETUCARE trial; the primary efficacy findings are reported elsewhere (Theurel et al. under review). The trial was not prospectively registered, and the mediation analyses were not preregistered.

## 2.2. Participant flow and analytic samples

The primary analyses followed randomized assignment irrespective of intervention adherence. The ITT dataset retained all 1064



**Fig. 1.** Participant flow from randomization to the primary intention-to-treat analysis and per-protocol sensitivity analysis.

randomized participants. Of these, 947 had at least one modeled variable at T1, T2, or T3 and therefore contributed to FIML estimation (control:  $n = 322$ ; online:  $n = 412$ ; hybrid:  $n = 213$ ). The remaining 117 participants had no observed modeled variable beyond treatment assignment and consequently provided no information to the likelihood. For the primary mediation model, the online and hybrid conditions were combined and compared with the waiting-list control.

An adherence-based analysis was retained as a per-protocol sensitivity analysis. The PP-eligible dataset initially comprised 710 participants: 395 participants assigned to an active condition who completed at least 70% of the intervention modules and 315 participants assigned to the waiting-list control who had baseline data. This PP-eligible sample had a mean age of 21.00 years ( $SD = 4.55$ ), and 622 participants (87.6%) were women. Its age and gender composition was therefore closely aligned with that of the randomized participants for whom baseline sociodemographic information was available. Mplus excluded seven participants because of missing data on exogenous baseline variables and 90 because they had no observed mediator or outcome data beyond the exogenous variables. The final per-protocol model therefore included 613 participants (control:  $n = 257$ ; online:  $n = 225$ ; hybrid:  $n = 131$ ). Because intervention adherence is a post-randomization variable, this analysis was interpreted only as a sensitivity analysis and not as the primary estimate of the intervention pathways. Fig. 1 summarizes participant flow from randomization to the primary ITT analytic sample and the per-protocol sensitivity sample.

### 2.3. Procedure and intervention

Assessments were conducted at three time points: baseline prior to randomization (T1), post-intervention (T2), and a two-month follow-up after completion of the intervention (T3). This three-wave design allowed the examination of changes in mediators during the intervention period and their prospective associations with outcomes assessed at follow-up.

The intervention consisted of the ETUCARE program, an eight-week digital intervention comprising eight sequential modules targeting key domains of student mental health (e.g., ER, sleep, stress). Modules included psychoeducational content, self-assessments, and brief exercises (5–15 min) grounded in cognitive-behavioural therapy and positive psychology. In the hybrid condition, the online program was supplemented by weekly group workshops designed to reinforce learning through experiential and collaborative activities. The digital modules addressed mental health literacy, personal resources, procrastination, stress management, emotion regulation, interpersonal relationships, sleep and insomnia, and consolidation of learning. The sleep module included sleep psychoeducation, assessment of sleep habits, sleep-hygiene strategies, stimulus control, a worry journal, and mindfulness-based sleep meditation. The emotion-regulation module included cognitive reappraisal, distress-tolerance, attentional-refocusing, gratitude, and savoring exercises. Emotion regulation also was addressed transversally across all eight modules, with each module reinforcing one or more emotion-regulation skills derived from the Adaptive Coping with Emotions (ACE) model, including emotional awareness, understanding, acceptance, tolerance, self-support, and the capacity to modify emotional responses. Both active conditions received the same eight online modules in the same sequence; the hybrid condition additionally included eight standardized weekly 2-h group workshops. The study was approved by the Ethics Committee of Nantes University (IRB No. IORG0011023, Ref. 06042023-2), and all participants provided informed consent prior to participation. Engagement and adherence are reported in detail in the parent efficacy manuscript (Theurel et al. under review). Briefly, 55% of participants assigned to the online condition and 59% of those assigned to the hybrid condition completed all eight digital modules; among participants who initiated the program, the corresponding rates were 70% and 72%. In the hybrid condition, 86% attended at least one workshop, 60% attended all eight

workshops, and 52% completed the full hybrid pathway.

### 2.4. Measures

All measures were administered online at each assessment time point.

#### 2.4.1. Psychological distress

Psychological distress was assessed using the Depression Anxiety Stress Scales – 21 items (DASS-21; Lovibond & Lovibond, 1995). The DASS-21 is a 21-item self-report measure comprising three subscales: depression, anxiety, and stress, each including seven items. Items are rated on a 4-point Likert scale ranging from 0 (“did not apply to me at all”) to 3 (“applied to me most of the time”). An example item is “I felt that I had nothing to look forward to.” The total scale showed excellent internal consistency ( $\omega = .93$ ), with good reliability for the depression ( $\omega = .90$ ), anxiety ( $\omega = .86$ ), and stress ( $\omega = .87$ ) subscales.

#### 2.4.2. Well-being

Well-being was assessed using the PERMAH Profiler (Butler et al., 2016), a 23-item self-report instrument assessing Positive Emotion, Engagement, Relationships, Meaning, Accomplishment, Negative Emotion, and Health. Each domain comprises three items rated from 0 to 10; two additional items assess loneliness and overall happiness. The PERMAH score used in the primary models was calculated as the sum of Positive Emotion, Engagement, Relationships, Meaning, Accomplishment, and Health. Negative Emotion, loneliness, and the single overall-happiness item were not included. Internal consistency for this six-domain composite was good ( $\omega = .89$ ).

#### 2.4.3. Emotion regulation

ER skills were assessed using the French version of the Emotion Regulation Skills Questionnaire (ERSQ; Nardelli et al., 2024). The ERSQ is a 27-item self-report measure based on the Adaptive Coping with Emotions (ACE) model and assesses nine domains: emotional awareness, bodily sensations, emotional clarity, understanding of emotions, modification of emotions, acceptance of emotions, tolerance of distress, emotional confrontation, and self-support. Items are rated on a 5-point Likert scale ranging from 0 (“not at all”) to 4 (“almost always”). An example item is “I was able to influence my negative emotions.” In the present sample, the ERSQ showed excellent internal consistency ( $\omega = .93$ ).

#### 2.4.4. Insomnia

Insomnia severity was assessed using the Insomnia Severity Index (ISI; Bastien et al., 2001), a 7-item self-report measure evaluating the nature, severity, and impact of sleep difficulties. Items assess sleep onset, sleep maintenance, early awakening, satisfaction with sleep, interference with daily functioning, noticeability, and distress related to sleep problems. Each item is rated on a 5-point Likert scale (0 = “no problem” to 4 = “very severe problem”), yielding a total score ranging from 0 to 28. Higher scores indicate greater insomnia severity. Internal consistency was good in the present sample ( $\omega = .88$ ).

### 2.5. Statistical analyses

Missing data were handled using full information maximum likelihood (FIML) estimation within an observed-variable path-analysis framework. Baseline covariates were explicitly brought into the model by estimating their variances and covariances, allowing participants with partially missing baseline measurements to contribute under a missing-at-random assumption. The data file retained all randomized participants, although 117 participants with no analysis data beyond treatment assignment could not contribute to the likelihood. Models were estimated in Mplus version 7.31 using maximum likelihood. Continuous analysis variables were standardized before estimation, and

indirect effects used bias-corrected and accelerated bootstrap confidence intervals based on 5000 resamples. The datasets and complete analysis syntax will be deposited in the OSF repository: [https://osf.io/6g7s5/overview?view\\_only=b8c5edf4d2004468a509c68f74d61823](https://osf.io/6g7s5/overview?view_only=b8c5edf4d2004468a509c68f74d61823). The mediation analyses were not preregistered and should be regarded as secondary analyses of the trial dataset.

Although 382 participants had complete core data across all three waves, the primary ITT models used FIML and included 947 participants with at least one analysis variable, irrespective of intervention completion. Attrition was substantial and differed by wave and study condition. Supplementary analyses did not identify consistent associations between baseline distress or insomnia and subsequent data availability, although small associations were observed for baseline well-being and emotion-regulation skills at T3. As with all observed-data analyses, selection related to unmeasured causes of missingness cannot be excluded.

For the primary confirmatory analysis (Analysis 1), the online and hybrid arms were combined to test candidate processes irrespective of delivery format. The ITT analytic sample comprised 947 participants with at least one analysis variable (control:  $n = 322$ ; online:  $n = 412$ ; hybrid:  $n = 213$ ). The  $\geq 70\%$  completion sample ( $N = 613$ ) was retained as a per-protocol sensitivity analysis. Format-specific analyses are reported in [Supplementary Material S1](#). The exploratory cross-lagged panel model (Analysis 3) was also estimated in the ITT analytic sample ( $N = 947$ ). All continuous variables were standardized before analysis. Fully standardized coefficients are reported for model paths; indirect effects and derived parameters are reported on the standardized continuous-outcome scale with bias-corrected and accelerated bootstrap confidence intervals based on 5000 resamples.

### 3. Results

#### 3.1. Descriptive statistics

Correlations revealed a coherent and theoretically consistent pattern of associations across variables and time points ([Table 1](#)). At each measurement occasion, higher ER skills were significantly associated with lower psychological distress (e.g., ERSQ T2 with DASS T3:  $r = -.39, p < .001$ ) and higher well-being (ERSQ T2 with PERMA T3:  $r = .49, p < .001$ ). Conversely, higher insomnia severity was associated with higher distress (ISI T2 with DASS T3:  $r = .36, p < .001$ ) and lower well-being (ISI T2 with PERMA T3:  $r = -.36, p < .001$ ).

The correlations showed broadly similar absolute associations of ERSQ and ISI with distress and well-being, with the expected opposite signs. This descriptive pattern motivated the subsequent signed-constraint comparison but does not itself demonstrate cross-outcome equivalence.

Longitudinally, all constructs demonstrated moderate to strong stability over time (e.g., DASS T1–T2:  $r = .62$ ; ISI T1–T2:  $r = .63$ ; PERMA

T2–T3:  $r = .85$ ), indicating substantial temporal consistency while preserving sufficient variability to examine change processes. Cross-lagged associations between mediators and outcomes were also consistent with the hypothesised directional pathways, with earlier ER and sleep variables showing significant associations with later distress and well-being.

These descriptive associations provided a basis for the adjusted mediation models. They should not be interpreted as evidence of causal processes or formal equivalence between distress and well-being pathways.

#### 3.2. Analysis 1: parallel mediation and signed-symmetry test (confirmatory)

The primary ITT parallel mediation model tested whether emotion regulation (ERSQ T2) and insomnia (ISI T2) statistically accounted for intervention associations with distress (DASS T3) and well-being (PERMA T3), controlling for the corresponding baseline levels. Model fit was acceptable (RMSEA = .047, CFI = .974, SRMR = .040). Fit indices for the free model, signed-constraint model, and exploratory CLPM are presented in [Table 2](#).

In the ITT model, intervention assignment significantly predicted improvement in both candidate mediators (ERSQ:  $\beta = .166, p < .001$ ; ISI:  $\beta = -.142, p < .001$ ). All four mediator–outcome paths were significant: higher ERSQ T2 was associated with lower DASS T3 and higher PERMA T3, whereas higher ISI T2 was associated with higher DASS T3 and lower PERMA T3 (all  $ps \leq .001$ ). As reported in the primary RCT publication, changes in the candidate mediators and mental-health outcomes were already observed over the same baseline-to-post-intervention interval. Their concurrent assessment at T2 therefore prevents establishing that changes in ERSQ or ISI preceded initial changes in DASS-T21 or well-being. [Fig. 2](#) provides a visual summary of the standardized paths in the primary ITT mediation model; complete unstandardized and standardized estimates are reported in [Table 3](#).

##### 3.2.1. Signed-constraint comparison across dual-factor mental-health outcomes

Signed constraints were imposed to examine whether model fit deteriorated when each mediator–outcome association was constrained to have the same absolute magnitude but the opposite sign across distress and well-being. The constrained ITT model did not fit significantly worse than the free model,  $\Delta\chi^2(2) = 2.12, p = .347$ . Its AIC and BIC were lower ( $\Delta AIC = -1.88$ ;  $\Delta BIC = -11.59$ ). The individual signed sums were also non-significant (ERSQ:  $b = -.024, p = .566$ ; ISI:  $b = .049, p = .235$ ).

These non-significant comparisons indicate that the data were compatible with a similar-absolute-magnitude pattern. They do not establish statistical equivalence: failure to reject a difference is not evidence that the effects are equivalent, and no formal equivalence test with prespecified bounds was conducted.

**Table 1**  
Descriptive statistics and zero-order correlations among study variables.

| Variable     | M (SD)       | 1       | 2       | 3       | 4       | 5       | 6       | 7       | 8       | 9       | 10      | 11     |
|--------------|--------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|--------|
| 1. DASS T1   | 23.2 (11.3)  | —       |         |         |         |         |         |         |         |         |         |        |
| 2. ISI T1    | 11.6 (5.76)  | .45***  | —       |         |         |         |         |         |         |         |         |        |
| 3. PERMA T1  | 106.8 (28.0) | -.58*** | -.36*** | —       |         |         |         |         |         |         |         |        |
| 4. ERSQ T1   | 60.7 (16.4)  | -.42*** | -.26*** | .58***  | —       |         |         |         |         |         |         |        |
| 5. DASS T2   | 19.1 (11.1)  | .62***  | .37***  | -.46*** | -.28*** | —       |         |         |         |         |         |        |
| 6. ISI T2    | 10.1 (5.69)  | .33***  | .63***  | -.31*** | -.22*** | .48***  | —       |         |         |         |         |        |
| 7. PERMA T2  | 112.5 (28.3) | -.44*** | -.28*** | .76***  | .40***  | -.63*** | -.38*** | —       |         |         |         |        |
| 8. ERSQ T2   | 67.2 (16.4)  | -.27*** | -.22*** | .43***  | .58***  | -.45*** | -.28*** | .56***  | —       |         |         |        |
| 9. DASS T3   | 17.7 (11.3)  | .52***  | .33***  | -.44*** | -.29*** | .67***  | .37***  | -.56*** | -.39*** | —       |         |        |
| 10. ISI T3   | 9.25 (5.90)  | .33***  | .56***  | -.33*** | -.23*** | .44***  | .65***  | -.39*** | -.29*** | .54***  | —       |        |
| 11. PERMA T3 | 116.9 (28.4) | -.39*** | -.29*** | .70***  | .37***  | -.53*** | -.36*** | .84***  | .49***  | -.62*** | -.44*** | —      |
| 12. ERSQ T3  | 69.9 (16.9)  | -.19*** | -.17*** | .38***  | .56***  | -.35*** | -.25*** | .48***  | .71***  | -.47*** | -.34*** | .56*** |

Note. Descriptive statistics use all available ITT observations for each variable; correlations are pairwise and sample sizes therefore vary by pair. ERSQ = Emotion Regulation Skills Questionnaire; ISI = Insomnia Severity Index; DASS = Depression Anxiety Stress Scales; PERMA = well-being. \* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ .

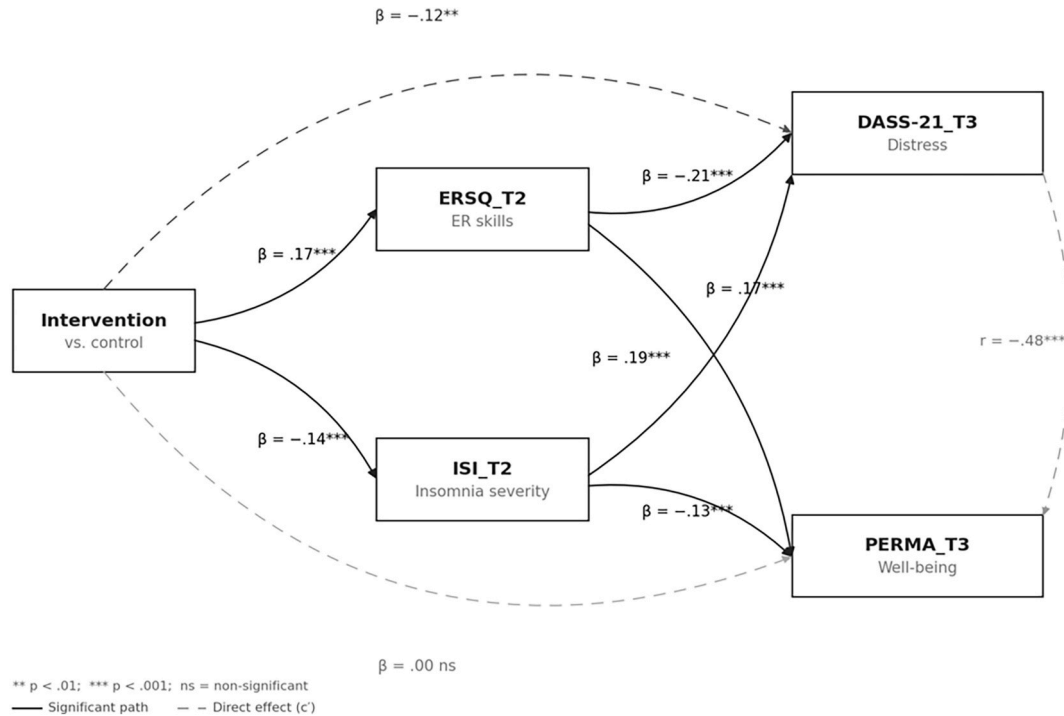
**Table 2**

Model fit for Analysis 1 (free and signed-constraint models) and Analysis 3 (cross-lagged panel model).

| Model                               | $\chi^2$  | df | AIC      | BIC      | RMSEA [90% CI]    | CFI  | SRMR |
|-------------------------------------|-----------|----|----------|----------|-------------------|------|------|
| Analysis 1 — ITT parallel mediation |           |    |          |          |                   |      |      |
| Free model                          | 49.64***  | 16 | 14338.78 | 14513.50 | .047 [.033, .062] | .974 | .040 |
| Signed-constraint model             | 51.76***  | 18 | 14336.89 | 14501.91 | .045 [.031, .059] | .974 | .040 |
| $\Delta$ (constrained – free)       | 2.12      | 2  | –1.88    | –11.59   | –.002             | .000 | .000 |
| Difference-test p-value             | p = .347  |    |          |          |                   |      |      |
| Analysis 3 — Exploratory ITT CLPM   |           |    |          |          |                   |      |      |
| Bidirectional CLPM                  | 122.20*** | 26 | 16192.09 | 16429.90 | .063 [.052, .074] | .953 | .043 |

Note. Analysis 1: The signed-constraint model imposes  $b1 = -b3$  and  $b2 = -b4$ . Negative  $\Delta AIC$  and  $\Delta BIC$  values favor the more parsimonious constrained model. Analysis 3 is an exploratory observed-variable CLPM estimated in the ITT analytic sample.

\*\*\*p < .001 (see Fig. 2).



**Fig. 2.** Parallel mediation model of intervention effects on distress and well-being via emotion regulation and insomnia in the ITT sample.

### 3.2.2. Indirect effects and mediation type

Table 3 presents the complete path coefficients, direct effects, specific and total indirect effects, total effects, proportion mediated, and signed-constraint diagnostics. All ITT bootstrapped indirect effects were statistically significant. For distress, the ERSQ-specific indirect effect was  $-.072$  and the ISI-specific indirect effect was  $-.052$ , yielding a total indirect effect of  $-.124$ , 95% bootstrap CI  $[-.177, -.080]$ ,  $p < .001$ . For well-being, the corresponding effects were  $.064$  and  $.037$ , yielding a total indirect effect of  $.101$ , 95% bootstrap CI  $[.062, .152]$ ,  $p < .001$ . The combined pathways accounted for an estimated 33.6% of the total intervention association with distress, 95% bootstrap CI  $[.201, .602]$ . The well-being indirect-to-total ratio was not interpreted because the total effect was small and non-significant and the ratio confidence interval was extremely unstable.

The direct ITT association with distress remained significant ( $b = -.246$ ,  $\beta = -.117$ ,  $p = .002$ ), indicating that the measured pathways did not statistically account for the entire intervention association with distress. The direct association with well-being was near zero ( $b = .009$ ,  $\beta = .004$ ,  $p = .891$ ), but this should not be described as full mediation, particularly because the total well-being effect was not significant ( $b = .110$ ,  $p = .100$ ).

### 3.3. Sensitivity analyses

A  $\geq 70\%$  adherence analysis was considered as a per-protocol sensitivity analysis. Its estimates closely reproduced the primary ITT results: total indirect effects were  $-.123$  versus  $-.124$  for distress and  $.107$  versus  $.101$  for well-being in the per-protocol and ITT models, respectively (Table 5). Specific indirect and direct estimates were likewise closely aligned, indicating that the substantive mediation conclusions were not dependent on adherence-based selection. Table 5 provides a direct comparison of the primary ITT and per-protocol estimates. Format-specific analyses remain exploratory and are reported in Supplementary Material S1; estimates were generally in the expected direction but were less precise in the smaller hybrid subgroup.

### 3.4. Exploratory cross-lagged panel model

An exploratory observed-variable CLPM was estimated in the ITT analytic sample ( $N = 947$ ) to examine longitudinal associations between emotion regulation and insomnia across T1–T3. Overall fit was acceptable, although not uniformly strong,  $\chi^2(26) = 122.20$ , RMSEA = .063, 90% CI  $[.052, .074]$ , CFI = .953, TLI = .919, and SRMR = .043 (Table 2). Complete autoregressive, cross-lagged, comparison, and contemporaneous outcome estimates are presented in Table 4.

**Table 3**

Primary ITT parallel mediation model: path coefficients, indirect effects, total effects, proportion mediated, and signed-symmetry diagnostics (Analysis 1).

| Path/Effect                                       | Outcome | b     | SE   | $\beta$<br>(StdYX) | 95% CI<br>for b | p      |
|---------------------------------------------------|---------|-------|------|--------------------|-----------------|--------|
| <b>a paths (Intervention → mediators)</b>         |         |       |      |                    |                 |        |
| Intervention → ERSQ_T2                            | —       | .353  | .064 | .166               | [.228, .477]    | < .001 |
| Intervention → ISI_T2                             | —       | -.299 | .061 | -.142              | [-.422, -.184]  | < .001 |
| <b>b paths (Mediator → outcomes)</b>              |         |       |      |                    |                 |        |
| ERSQ_T2 → DASS_T3                                 | DASS    | -.205 | .042 | -.206              | [-.288, -.122]  | < .001 |
| ISI_T2 → DASS_T3                                  | DASS    | .173  | .042 | .173               | [.091, .256]    | < .001 |
| ERSQ_T2 → PERMA_T3                                | PERMA   | .181  | .042 | .185               | [.096, .264]    | < .001 |
| ISI_T2 → PERMA_T3                                 | PERMA   | -.124 | .036 | -.126              | [-.197, -.055]  | .001   |
| <b>Direct effects (c' paths)</b>                  |         |       |      |                    |                 |        |
| Intervention → DASS_T3                            | DASS    | -.246 | .078 | -.117              | [-.401, -.093]  | .002   |
| Intervention → PERMA_T3                           | PERMA   | .009  | .066 | .004               | [-.125, .134]   | .891   |
| <b>Indirect effects (BCa bootstrap)</b>           |         |       |      |                    |                 |        |
| ERSQ pathway                                      | DASS    | -.072 | .021 | —                  | [-.117, -.038]  | < .001 |
| ISI pathway                                       | DASS    | -.052 | .017 | —                  | [-.094, -.025]  | .002   |
| Total indirect                                    | DASS    | -.124 | .025 | —                  | [-.177, -.080]  | < .001 |
| ERSQ pathway                                      | PERMA   | .064  | .020 | —                  | [.031, .110]    | .001   |
| ISI pathway                                       | PERMA   | .037  | .014 | —                  | [.015, .072]    | .008   |
| Total indirect                                    | PERMA   | .101  | .023 | —                  | [.062, .152]    | < .001 |
| <b>Total effects</b>                              |         |       |      |                    |                 |        |
| Total intervention effect                         | DASS    | -.370 | .079 | —                  | [-.530, -.221]  | < .001 |
| Total intervention effect                         | PERMA   | .110  | .067 | —                  | [-.027, .236]   | .100   |
| Proportion mediated (total indirect/total effect) | DASS    | .336  | .105 | —                  | [.201, .602]    | .001   |
| <b>Signed-symmetry diagnostics</b>                |         |       |      |                    |                 |        |
| ERSQ ( $b_1 + b_3$ )                              | —       | -.024 | .042 | —                  | [-.106, .059]   | .566   |
| ISI ( $b_2 + b_4$ )                               | —       | .049  | .041 | —                  | [-.030, .133]   | .235   |

Note. b = coefficient on the standardized continuous-variable scale;  $\beta$  = fully standardized coefficient (StdYX). ERSQ = Emotion Regulation Skills Questionnaire; ISI = Insomnia Severity Index; DASS = Depression Anxiety Stress Scales; PERMA = well-being. Indirect and total effects use bias-corrected and accelerated bootstrap confidence intervals based on 5000 resamples. The signed sums are compatibility diagnostics and do not constitute formal equivalence tests. Models were estimated by maximum likelihood with FIML for partially missing modeled variables. For the proportion-mediated row, the b column reports the derived total-indirect/total-effect ratio.

Both variables showed strong autoregressive stability from T2 to T3 (Table 4; ERSQ:  $\beta$  = .693; ISI:  $\beta$  = .624,  $p$ s < .001).

Higher post-intervention emotion-regulation skills predicted lower insomnia severity at follow-up ( $b$  = -.113,  $\beta$  = -.116,  $p$  = .002, 95% bootstrap CI [-.188, -.043]), whereas post-intervention insomnia did not significantly predict subsequent emotion-regulation skills ( $b$  = -.050,  $\beta$  = -.051,  $p$  = .260, 95% bootstrap CI [-.143, .031]).

However, the formal comparison between the two T2→T3 cross-lagged paths was not significant (Table 4;  $\Delta b$  = .063, 95% bootstrap

**Table 4**

Exploratory ITT cross-lagged panel model: autoregressive, cross-lagged, and contemporaneous outcome associations (Analysis 3).

| Path/Effect                                   | Outcome  | b     | SE   | $\beta$<br>(StdYX) | 95% CI<br>for b | p      |
|-----------------------------------------------|----------|-------|------|--------------------|-----------------|--------|
| <b>Autoregressive paths (T2→T3)</b>           |          |       |      |                    |                 |        |
| ERSQ_T2 → ERSQ_T3                             | ERSQ_T3  | .683  | .053 | .693               | [.569, .775]    | < .001 |
| ISI_T2 → ISI_T3                               | ISI_T3   | .611  | .042 | .624               | [.525, .691]    | < .001 |
| <b>Prospective cross-lagged paths (T2→T3)</b> |          |       |      |                    |                 |        |
| ISI_T2 → ERSQ_T3                              | ERSQ_T3  | -.050 | .045 | -.051              | [-.143, .031]   | .260   |
| ERSQ_T2 → ISI_T3                              | ISI_T3   | -.113 | .037 | -.116              | [-.188, -.043]  | .002   |
| <b>Cross-lag comparison</b>                   |          |       |      |                    |                 |        |
| ISI→ERSQ minus ERSQ→ISI                       | —        | .063  | .061 | —                  | [-.065, .180]   | .302   |
| <b>Contemporaneous associations at T3</b>     |          |       |      |                    |                 |        |
| ERSQ_T3 → DASS_T3                             | DASS_T3  | -.277 | .039 | -.277              | [-.352, -.198]  | < .001 |
| ISI_T3 → DASS_T3                              | DASS_T3  | .324  | .040 | .322               | [.246, .406]    | < .001 |
| ERSQ_T3 → PERMA_T3                            | PERMA_T3 | .299  | .033 | .305               | [.236, .365]    | < .001 |
| ISI_T3 → PERMA_T3                             | PERMA_T3 | -.173 | .035 | -.175              | [-.244, -.107]  | < .001 |

Note. b = coefficient on the standardized continuous-variable scale;  $\beta$  = fully standardized coefficient (StdYX). Confidence intervals are BCa bootstrap estimates based on 5000 resamples. ERSQ\_T3/ISI\_T3 associations with DASS\_T3 and PERMA\_T3 are contemporaneous and do not establish temporal precedence. Overall model fit was acceptable but not uniformly strong (TLI = .919).

**Table 5**

Primary ITT and per-protocol ( $\geq 70\%$  adherence) sensitivity estimates.

| Estimate               | ITT (N = 947) | PP70 (N = 613) |
|------------------------|---------------|----------------|
| ERSQ indirect → DASS   | -.072         | -.073          |
| ISI indirect → DASS    | -.052         | -.050          |
| Total indirect → DASS  | -.124         | -.123          |
| Direct effect → DASS   | -.246         | -.266          |
| Total effect → DASS    | -.370         | -.388          |
| ERSQ indirect → PERMA  | .064          | .065           |
| ISI indirect → PERMA   | .037          | .042           |
| Total indirect → PERMA | .101          | .107           |
| Direct effect → PERMA  | .009          | .015           |
| Total effect → PERMA   | .110          | .122           |

Note. Values are coefficients on the standardized continuous-outcome scale. PP70 results are retained as sensitivity analyses only.

CI [-.065, .180],  $p$  = .302). Thus, the observed pattern was compatible with a prospective association from emotion regulation to subsequent insomnia but did not establish that this pathway was stronger than the reverse pathway.

The significant ERSQ\_T2 → ISI\_T3 coefficient should not be interpreted as evidence that change in emotion regulation preceded change in insomnia. The T1→T2 cross-lagged paths were weak (ISI\_T1→ERSQ\_T2:  $p$  = .066; ERSQ\_T1→ISI\_T2:  $p$  = .050), the formal T2→T3 directional comparison was non-significant, and the three-wave schedule did not capture within-intervention ordering.

At T3, higher emotion-regulation skills and lower insomnia severity were associated with lower distress and higher well-being (all  $p$ s < .001). Because ERSQ, ISI, DASS-21, and PERMAH were assessed at the same T3 occasion, these paths were contemporaneous and cannot establish temporal precedence over distress or well-being.

#### 4. Discussion

The present study examined whether emotion regulation and

insomnia statistically accounted for subsequent differences in distress and well-being following participation in the ETUCARE program. Three main findings emerged. First, both candidate processes showed significant indirect effects across negative and positive mental-health outcomes. Second, their combined pathways accounted for approximately one third of the estimated total intervention association with distress, and the ITT findings were closely reproduced in the per-protocol sensitivity analysis. Third, the exploratory longitudinal analysis identified a prospective association from post-intervention emotion-regulation skills to subsequent insomnia severity, although the formal comparison between the two cross-lagged paths did not establish directional dominance.

#### 4.1. Emotion regulation and insomnia across distress and well-being

Better post-intervention emotion-regulation skills and lower insomnia severity were associated with both lower distress and higher well-being at follow-up. The directions of these associations were theoretically coherent, and their absolute magnitudes were broadly similar across the two outcomes. Moreover, imposing signed constraints did not significantly worsen model fit. Although this comparison does not constitute a formal equivalence test, it indicates that the observed data were compatible with a cross-outcome pattern in which emotion regulation and insomnia relate comparably, but in opposite directions, to distress and well-being. This finding contributes to the dual-factor perspective on mental health by showing that the same modifiable processes may be relevant not only to symptom reduction but also to positive functioning. Distress and well-being are related but non-redundant dimensions, and intervention research has often examined them separately. Their inclusion within the same model therefore provides a more integrated account of the processes associated with change following a digital mental-health intervention.

The results are consistent with theoretical and empirical work positioning emotion regulation as a broadly relevant process in psychological adaptation. Within cognitive-behavioural frameworks, cognitive reappraisal, behavioural activation, and exposure can modify maladaptive emotional responses (Gross & Jazaieri, 2014; Hofmann et al., 2012; Lincoln et al., 2022). Third-wave approaches additionally target experiential avoidance and promote acceptance and psychological flexibility (Berkling, 2024; Hayes et al., 2006; Levin et al., 2020). In ETUCARE, emotion regulation was embedded throughout the intervention rather than confined to a single module. Across the eight modules, participants were encouraged to develop and apply skills derived from the Adaptive Coping with Emotions model, including emotional awareness, understanding, acceptance, tolerance, self-support, and emotion modification.

Sleep represents a complementary behavioural process with relevance to both dimensions of mental health. Insomnia is highly comorbid with emotional disorders and prospectively predicts their onset (Baglioni et al., 2016). Cognitive-behavioural models highlight the cognitions and behaviours that maintain sleep difficulties (Harvey, 2002; Ong et al., 2012), while CBT-I can improve both sleep and broader mental-health outcomes (Espie et al., 2019). The present findings extend this literature by showing that lower insomnia severity was associated not only with lower distress but also with higher well-being.

Taken together, these findings identify emotion regulation and insomnia as plausible, modifiable candidate processes associated with intervention-related differences across both negative and positive mental-health outcomes.

#### 4.2. Magnitude and robustness of the indirect pathways

The emotion-regulation and insomnia pathways jointly accounted for an estimated 33.6% of the total intervention association with distress. This represents a meaningful proportion while also indicating that substantial variance remained attributable to other processes. The

direct association between intervention assignment and distress remained significant after inclusion of ERSQ and ISI, which is consistent with the multicomponent nature of ETUCARE and the likelihood that additional processes contributed to symptom change. For well-being, both specific indirect effects and their combined indirect effect were significant. The total intervention association with well-being was comparatively small and non-significant, however, making the indirect-to-total ratio unstable and unsuitable for interpretation. The near-zero direct association after inclusion of ERSQ and ISI is therefore best understood as statistical accounting within the specified model rather than evidence of complete mediation.

Importantly, the primary ITT estimates were closely aligned with those from the original  $\geq 70\%$ -adherence sample. Total indirect effects were  $-.124$  and  $-.123$  for distress and  $.101$  and  $.107$  for well-being in the ITT and per-protocol models, respectively. This convergence increases confidence that the principal pattern was not dependent on restricting the analysis to participants with higher intervention completion.

#### 4.3. Longitudinal relationship between emotion regulation and insomnia

The exploratory cross-lagged analysis provided additional insight into the relationship between the two candidate processes. Higher emotion-regulation skills immediately after the intervention predicted lower insomnia severity at follow-up, whereas post-intervention insomnia did not significantly predict subsequent emotion-regulation skills. This pattern is consistent with models in which difficulties such as rumination, worry, emotional avoidance, and limited tolerance of negative affect contribute to cognitive and physiological arousal that interferes with sleep (Harvey, 2002; Jansson-Fröjmark & Hossain, 2024; Nicholson et al., 2021).

However, the formal difference between the two cross-lagged paths was not significant. The findings therefore provide preliminary evidence of a prospective ER-sleep association but do not demonstrate that emotion-regulation change has directional priority over sleep change. More frequent assessments during intervention delivery will be required to determine how these processes influence each other over shorter timescales.

#### 4.4. Strengths and limitations

The study has several strengths. It examined distress and well-being simultaneously within a dual-factor framework, used a relatively large randomized-trial dataset, included three assessment waves, and focused on two clinically relevant and modifiable candidate processes. The primary analyses followed randomized assignment, used FIML to incorporate all available observations, and were supported by closely aligned per-protocol estimates. The study also combined an accessible parallel-mediation model with an exploratory longitudinal analysis, providing complementary information about statistical indirect effects and prospective associations.

Several limitations should nevertheless be considered. The mediators were not randomized or experimentally manipulated, so mediator-outcome confounding cannot be excluded. All constructs were assessed by self-report, creating possible common-method variance and conceptual overlap. Because initial changes in ERSQ, ISI, DASS-21, and PERMAH were assessed over the same baseline-to-post-intervention interval, the mediation model cannot establish the temporal sequence of those initial changes. Attrition was substantial and differed across conditions; although FIML used all available data and observed predictors of missingness were examined, bias related to unmeasured causes of attrition remains possible. The primary PERMAH composite included perceived Health, although Negative Emotion was excluded, and therefore was not a strictly positive-only well-being measure. Generalizability is also limited by the predominantly female French university sample and the absence of diagnostic characterization.

Finally, the waiting-list design did not control for expectancy or nonspecific engagement, and the multicomponent nature of ETUCARE prevents attribution of the observed pathways to individual intervention components.

#### 4.5. Implications and future research

The findings support further investigation of emotion regulation and sleep as complementary targets in scalable university mental-health interventions. Their associations with both distress and well-being suggest that strengthening these processes may offer benefits across multiple dimensions of mental health rather than for a single symptom domain.

These hypotheses remain to be tested using more rigorous designs. Dismantling randomized controlled trials (Levin et al., 2020) systematically varying the order of intervention components would provide a direct test of sequencing effects. In addition, ecological momentary assessment (EMA) designs tracking daily fluctuations in ER and sleep (e. g., Lenneis et al., 2024) across the course of the intervention could offer more fine-grained insights into their temporal interplay. Future research should also examine whether specific components of ER differentially contribute to sleep improvement. In particular, skills related to emotional modification and acceptance identified as central within the Adaptive Coping with Emotions framework (Berking & Whitley, 2014) may represent especially potent targets (Berking et al., 2012). Investigating whether these subcomponents show stronger temporal associations with sleep outcomes could help refine intervention content and identify the most efficient mechanisms for improving both sleep and broader mental health outcomes. Finally, investigating moderators such as engagement, motivation, and individual differences may help refine the targeting of interventions and improve their effectiveness (e.g., Choi et al., 2023).

This study showed that emotion regulation and insomnia statistically accounted for intervention-related differences in both distress and well-being following ETUCARE. The convergence of the ITT and per-protocol findings, the meaningful proportion of the distress association accounted for by the combined pathways, and the prospective association between emotion regulation and later insomnia support the relevance of these two modifiable processes. Further experimental and intensive longitudinal research is now needed to clarify their causal and temporal roles and to determine how they can be targeted most efficiently within digital mental-health interventions.

#### CRediT authorship contribution statement

**A. Theurel:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing. **M.A. Martinié:** Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing. **A. Fournier:** Data curation, Formal analysis, Methodology, Resources, Software, Supervision, Validation, Writing – original draft. **A. Witt:** Methodology, Project administration, Resources, Supervision. **I. Millot:** Funding acquisition, Resources, Supervision. **R. Shankland:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing.

#### Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place. This study was conducted in accordance with Helsinki. This study was

approved by the Ethics Committee of Nantes University. (Approval No. IRB No. IORG0011023, Ref. 06042023-2)

#### Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Rebecca Shankland reports financial support was provided by French Institute for Public Health Research. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Acknowledgements

This research was supported by the French Institute for Public Health Research (IReSP, France). The design and initial development of the ETUCARE program were funded by the Regional Health Agency of Bourgogne-Franche-Comté (ARS, France).

#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.brat.2026.105123>.

#### Data availability

Data are shared the link to my data.

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