"The Impact of Online Valued-Living Interventions on Depression and Well-Being: Exploring the Role of Adaptability"

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Abstract

Introduction: University students face increasing mental health challenges, and online interventions offer an accessible solution to address these needs. This study aimed to evaluate the effectiveness of an online short-term valued-living intervention in enhancing well-being and reducing depressive symptoms among university students, with the ability to adapt as a potential moderator. **Methods**: A randomized controlled trial design was designed with 45 participants in total. The participants were assigned to a control group (14 participants) and two intervention groups: Intervention (with no photo) (INWB) (16 participants) and Intervention (with photo) (IWB) (15 participants). The Intervention focused on values clarification and alignment. Pre- and post-intervention assessments included the Mental Health Continuum – Short Form (MHC-SF) for well-being, the Patient Health Questionnaire-9 (PHQ-9) for depression, and the Generic Sense of Ability to Adapt Scale (GSAAS) for ability to adapt. Data analysis employed linear mixed models and repeated-measures ANOVA to evaluate intervention effects and the moderating role of the Ability to Adapt. **Results**: The interventions did not produce significant improvements in well-being or reductions in depressive symptoms compared to the control group ($p > .05$). The Ability to Adapt also did not significantly moderate intervention effectiveness ($p > .05$). **Conclusion**: The study highlights the feasibility of short-term online values-based interventions for university students but underscores the need for longer durations to allow participants to internalize and act on their values.

Keywords: Valued living, Ability to Adapt, Short-Term Online Intervention, Well-Being, Depression, Randomized Control Trial

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Introduction

Depression and moderate to low well-being are mental health problems commonly experienced by university students (Roberts et al., 2023). 1 in 3 students experience moderate to severe depressive symptoms during their studies (Sanci et al., 2022). In the Netherlands, little above 50% of university students experience at least mild depressive symptoms during their studies (Amanvermez et al., 2023). Among the reasons for the student's affected mental health, ones that could be highlighted are work overload, uncertainty regarding their future, excess of information, the need to be perfect and comparison with others (Costa et al., 2013). Mcgorry (2011) and Acharya et al. (2018) found that people aged between 18 and 24 are more prone to mental disorders than the general population. The age range of 17 - 24 years old is the general age of students attending higher education (Lipson & Eisenberg, 2017). Age itself is not a factor; rather, excessive stressful events happen during this lifetime to most young people, especially students, resulting in mental health problems. (Mcgorry, 2011; Acharya et al., 2018). To cope with those issues, students seek mental help from various medical facilities (Osborn et al., 2022).

According to a meta-analysis by Osborn et al. (2022) in which mental health services across different universities were measured, students' use of mental health services ranges between 13.7% to 68.6%, depending on the university. Moreover, Sanci et al. (2022) analysed 14880 university students and found out that 3000 students reported needing mental or emotional care but could not access it in the past 12 months. The most common reported reasons by students for not being able to access mental health services were: cost, limited opening hours and no appointment possibilities (Osborn et al., 2022; Sanci, et al., 2022). Due to the increasing demand for student mental well-being and mental health as well as care institutions' limited capabilities, alternative well-being interventions are increasingly required

to meet the student's mental demands. One of the low-cost accessible alternative solutions are online interventions, with their virtually unlimited user capacity and supported efficiency in reducing pathological symptoms in students (Davies et al., 2014).

Online interventions

Online interventions focused on university students' mental health were mostly started to be developed only around 25 years ago, with the main focus on reducing negative symptoms like depression (Andersson et al., 2019; Harrer et al., 2018; Proudfoot et al., 2011). Davies et al. (2014), who conducted one of the meta-analyses of online interventions aiming specifically to reduce depression and improve well-being among university students, found online interventions to be generally efficient in reducing depression symptoms, but not in increasing well-being among students. 93% of the studies included in the Davies et al. (2014) meta-analysis however, were cognitive-behavioural therapy (CBT) based interventions, which by design focus only on symptom reduction, instead of increasing well-being (Hofmann et al., 2012). Therefore, due to the dominance of CBT online interventions focused on university students' mental health, depressive symptoms seem to be addressed, but not the well-being of students. (Davies et al., 2014).

The same conclusion was reached by another meta-analysis of online interventions designed to improve the mental health of university students (Harrer et al., 2018). In this meta-analysis, online interventions had much less significant impact on depression symptoms, however, this meta-analysis included 66% CBT-based online interventions and 20% skilled training online interventions focused mostly on acculturation and relationships. Despite the lower percentage of CBT online interventions in this meta-analysis, well-being seems not to be significantly improved by interventions focused on symptom reduction in general (Harrer et al., 2018). Such dominance of CBT in both Harrer et al. (2018) and Davies et al. (2014) analyses is attributed to the fact that CBT are the most prevalent online interventions for

university students. There is an increasing demand for online interventions focusing on well-being improvement, instead of diminishing negative symptoms (Davies et al., 2014; Harrer et al., 2018). The plausibility of interventions focused on well-being improvement lies in their combined efficiency with depressive symptom reduction, thus covering both sides of the mental health problem (Hendriks et al., 2019).

Valued-living

An effective way to increase overall well-being while reducing depression symptoms seems to be living according to one's values. (Donahue et al., 2017; Moyer et al., 2018). Valued living, is defined as the consistency with which individuals live according to what they identify as most important (e.g., family, friends, work, etc.) (Moyer et al., 2018, p. 271). Valued living is based on two components, first is knowing one's "values", which are defined as "freely chosen, verbally constructed consequences of ongoing, dynamic, evolving patterns of activity, which establish predominant reinforcers for that activity that are intrinsic in engagement in the valued behavioural pattern itself" (Wilson & DuFrene, 2009, p. 66). The second component is living according to those values (Hayes et al., 2012). To summarize, people strive to move in valued directions; therefore, values establish the behavioural patterns that direct us toward our goals, ideally resulting in valued living (Hayes et al., 2012). Engagement with one's values enhances a person's purpose in life, therefore increasing self-esteem and overall greater positive emotions, correspondingly diminishing the depressive symptoms and increasing well-being in the process (Kashdan & McKnight 2013). The amount of current valued living online interventions is very scarce, especially in the context of university students well-being improvement (Ferrari et al., 2022). Therefore an online intervention targeting valued living among university students seems like a promising area of research needing further investigation (Ferrari et al., 2022). However, as students tend to have

a high amount of stressful events during their university life period, flexibility seems to be a possible crucial component in effectiveness of such an intervention (Waldeck et al., 2021).

Ability to adapt

As university students encounter problems and distressful situations in life, adhering to one's values along the way requires endurance and flexibility to practice valued living (Hayes et al., 2012). Inflexible commitment to avoid painful experiences often comes at the expense of engaging in valued-living creating experiential avoidance (Kashdan & Rottenberg, 2010). This finding is supported by the fact that valued living is negatively correlated with experiential avoidance (Michelson et al., 2011; Smout et al., 2014; Wilson et al., 2010;). In order to engage in valued living "Psychological Flexibility" is needed. As defined by Hayes et al. (2013) it is an ability to be open, aware, and able to maintain or modify behaviours in the service of one's values (Hayes et al., 2013). Psychological flexibility seems to be a possible crucial component to living according to one's values, as a person has to moderate behaviour to either adapt or maintain one's behaviour to sustain valued living across different life situations (Berghoff et al., 2018; Hayes et al., 2013). Finkelstein – Fox et al. (2020) suggest psychological flexibility can be impactful due to its "buffer" role, which helps in adapting to day-to-day stressful situations. A person who has exhibited psychologically flexible behaviour for a prolonged time, should have acquired a general ability to adapt (Waldeck et al., 2021).

The ability to adapt refers to an individual's cognitive, behavioural, and emotional regulation or adjustment in situations of change, novelty, and uncertainty (Martin et al., 2012). It is a very similar concept to psychological flexibility. However, the difference is that a psychologically flexible person is open to behaviour adaptation, whereas an adaptable person should already be skilled in behaviour adaptation (Waldeck et al., 2021). Psychological flexibility has already been measured in regards to its impact on living in accordance with one's values. However, the ability to adapt as an independent construct from

psychological flexibility has not been compared with valued living (Waldeck et al., 2021). As the ability to adapt could represent a stronger variable predicting living according to one's values than psychological flexibility, research measuring its impact on valued living should be conducted (Waldeck et al., 2021). One aspect which could facilitate the ability to adapt to a valued-living online intervention is making values more tangible.

As values are abstract concepts (Hayes et al., 2013), representing them in a more concrete form could be beneficial for the effectiveness of values-based online intervention (Hayes et al., 2012). The benefits of valued-living become tangible for people who engage in valued living behaviour (Hayes et al., 2012). However, in a values-based online intervention, achieving the tangibility of those future valued-living actions could be achieved to some degree by the addition of imagery representing the values themselves. This is supported by research indicating that viewing photographs, can elicit mental imagery resulting in people imagining themselves in envisioned situations elicited by photographs (Pearson, 2019). By a visual values representation, participants of such intervention could foresee the benefits of valued-living action possibly before performing the action itself, therefore increasing the effectiveness of such an intervention (Hagger & Conroy, 2020). Support for this concept was also given by studies indicating there is a significant effect of mental imagery on positive well-being interventions regarding their quality and effectiveness (Lee et al., 2021; Peters et al., 2010). Adding imagery to a values-based online intervention could help investigate whether this aspect could facilitate the tangibility of values themselves, therefore possibly increasing the intervention's effectiveness.

As mentioned above, there is an increasing demand for well-being online interventions for university students that simultaneously reduce depressive symptoms (Harrer et al., 2018). Valued living seems to be a promising topic for such an intervention (Moyer et al., 2018). Therefore, the current study aims to implement and examine valued-living online

intervention effectiveness designed for university students to improve their well-being while simultaneously reducing depressive symptoms. Moreover, the aspect of mental imagery was added to one of the intervention groups in order to inspect its possible facilitating role in such an intervention. Therefore two intervention groups were created (Intervention (with no photo), and Intervention (with photo)), with the only difference being the implementation of photos in the same intervention in one of the groups. Additionally, the ability to adapt was examined in a role of moderator for the intervention effectiveness. The study used a 3-group pre-post intervention design (Dominguez-Rodriguez et al., 2024). The current study is part of a broader study conducted between the University of Twente and the University of Valencia, Spain. Therefore, this research paper will focus only on a specific part of this study related to evaluating the effectiveness of positive psychology's valued living online intervention. The research questions for this study are:

Research questions:

1. *To what extent does a valued-living online intervention help reduce depressive symptoms and improve well-being among students?*
2. *To what extent does the ability to adapt moderate the intervention's effectiveness regarding reducing depression symptoms and improving well-being?*

With the hypotheses:

1. *Valued living online intervention (with no photo) (IWNP) will lead to reduced depressive symptoms.*
2. *Valued living online intervention (with photo) (IWP) will lead to reduced depressive symptoms.*

3. *Valued living online intervention (with no photo) (IWP) will have a significant positive impact on well-being improvement.*
4. *Valued living online intervention (with photo) (IWP) help will have a significant positive impact on well-being improvement.*
5. *The ability to adapt will act as a significant positive moderator in the effectiveness both valued-living online intervention groups regarding well-being improvement.*
6. *The ability to adapt will act as a significant positive moderator in the effectiveness of both valued-living online intervention groups regarding depressive symptom reduction.*

Methods

Study Design

The study used a 3-group pre-post intervention design (Dominguez-Rodriguez et al., 2024). That means an Intervention was designed with a control group and two intervention groups: Intervention (with no photo) (INWP) and Intervention (with photo) (IWP). The INWP group received the same intervention as the IWP group, but with one difference regarding the inclusion of photos described in detail later in the paper. The survey was given at the beginning of the intervention. Followingly, the intervention took place, and the day after the intervention, another survey was taken. The study was approved by the Ethics Committee of the University of Twente (request nr. 240732). Data collection took place between the 21st of October 2024 and the 28th of November 2024.

Participants

Sampling method

Snowball convenience sampling was applied to reach the participants for this study. Researchers were using their own social networks to reach the participants via tools such as WhatsApp and Instagram. Additionally, researchers recruited participants personally on the campus of the University of Twente to promote this study. Moreover, participants were recruited through the University of Twente's online recruitment platform, SONA Systems. SONA allows psychology students to participate in research studies in exchange for course credits, often referred to as SONA points. Eligible students could sign up for this study on the platform, where they received 2,5 SONA points upon completion of this study.

Inclusion criteria

The study included only students enrolled in Dutch universities, currently following either a bachelor's, master's, or doctoral program. To avoid potential issues with data processing for minors, they had to be at least 18 years old. Proficiency in English was necessary, checked by their ability to understand and sign the English-language consent form for this study. Additionally, participants needed to possess sufficient smartphone skills to use the Twente Intervention and Interaction Machine (TIIM) app on their mobile devices.

Exclusion Criteria

Participants were excluded from the study if they were currently diagnosed with a severe mental disorder, specifically major depressive disorder, bipolar disorder, schizophrenia, or borderline personality disorder. Additionally, participants who reported taking psychiatric medication, experiencing suicidal thoughts or previous suicide attempts, or

currently undergoing psychological or psychiatric treatment were excluded from the study as well. These criteria were assessed through self-report questions with yes/no responses.

Materials

In order to test the hypotheses of this research, a battery of three questionnaires was utilized at the beginning and the end of the intervention. The first survey was implemented in the 'Qualtrics" programme and the last survey identical to the first survey was implemented in the Twente Intervention and Interaction (TIIM) app. Moreover, two intervention groups different only in one aspect were implemented and evaluated. The questionnaires measured the following variables: well-being (MHC-SF), depression (PHQ-9) ability to adapt (GSAAS) and sociodemographic data.

Depression (PHQ-9)

To assess the depression variable, the Patient Health Questionnaire-9 (PHQ-9; Kroenke et al., 2001) was utilized. This 9-item self-report scale prompts participants to rate their symptoms based on their frequency during the week prior to the survey. Items (e.g. "Feeling down, depressed, or hopeless.") are rated on a 4-point Likert scale from 0 (not at all) to 3 (nearly every day). Scores across all items are summed, resulting in a total score range between 0-27, with higher scores indicating more severe depression. The PHQ-9 scoring allows for classification into depression severity categories: minimal (0-4), mild (5-9), moderate (10-14), moderately severe (15-19), and severe (20-27). This scale has demonstrated strong reliability ($\alpha = 0.89$) and criterion validity (Martin et al., 2006: Titov et al., 2011).

Well-being (MHC-SF)

In order to measure the well-being variable, the Mental Health Continuum – Short Form (MHC-SF) was applied (Keyes et al., 2008). This 14 items questionnaire assesses well-being across three domains: emotional well-being (3 items, e.g., 'In the past week, how often

did you feel, that the way our society works made sense to you?'), social well-being (5 items, e.g., 'In the past week, how often did you feel people are basically good'), and psychological well-being (6 items, e.g., 'In the past week, how often did you feel that your life has a sense of direction or meaning to it?'). Each item is rated on a 6-point scale from 0 (never) to 5 (every day), with total scores ranging from 0 to 70, where higher scores indicate greater overall well-being. The MHC-SF has demonstrated strong reliability ($\alpha = 0.74 – 0.89$) and construct validity across various populations (Keyes et al., 2008; Lamers et al., 2010).

Ability to adapt (GSAAS)

The Generic Sense of Ability to Adapt Scale (GSAAS) (Franken et al., 2023) was utilized to assess participants' ability to adapt. This 10-item scale evaluates the ability to adapt after a challenging experience (e.g., 'If something unexpected happens, I can easily adapt.'). This is a 5-point Likert scale with answers ranging from 1 (not at all) to 5 (completely). To calculate the ability to adapt, scores across items are summed, yielding a total score range of 10 to 50, where higher scores represent a greater ability to adapt. The GSAAS is a relatively new questionnaire, but has demonstrated strong reliability ($\alpha = 0.89$) and construct validity (Franken et al., 2023).

Socio-Demographic data

The socio-demographic questionnaire was used to establish some baseline sample characteristics. Participants were asked about their age, gender, educational level and nationality. For the age variable, participants were asked to fill in their age with a number. For gender, five options were given to choose from: 'woman', 'man', 'non-binary' 'other' (with a request to specify if that option was chosen) and 'prefer not to specify'. For marital status, six options were given: 'Single', 'Informal relationship', 'Married or in a civil relationship', 'separated or divorced', 'widowed' and 'other' (with a request to specify). Educational level

was measured by three items to choose from: ‘Undergraduate student (Bachelor's degree)’, ‘Postgraduate student (Master's degree)’, and ‘Doctorate student (PhD or equivalent)’. The nationality was measured by giving two choices: ‘Dutch’ and ‘other’ (with a request to specify).

Qualtrics and Twente Intervention and Interaction Machine (TIIM)

The data was collected via Qualtrics (Cushman et al., 2021) and Twente Intervention and Interaction Machine (TIIM) (Van ’t Klooster et al., 2024). Qualtrics is an online survey platform that allows for the creation and distribution of customizable surveys with easy access to the collected data. TIIM is an app developed by the University of Twente for data collection among human participants. It has been designed with a focus on the Ecological Sampling Method that allows real-time, momentary data collection by applying customizable surveys throughout the day for prolonged periods of time (days, weeks, months). The complete intervention has been designed in the TIIM app for a mobile device. Each action is required by a participant during each of the two interventions and the control group is reminded to him/her by a notification coming from the TIIM app on his/her phone.

Procedure

The study, including the intervention period, lasted a total of nine days, beginning with baseline measurements on Day 0. Participants accessed the study either through a direct link or a QR code, which directed them to the Qualtrics website. After viewing the study’s welcome page, they were presented with the informed consent form (Appendix A), which required a Yes/No response to confirm agreement. Upon consenting, participants created an anonymized code based on their initials and the last three digits of their phone number for data tracking. They then provided contact information (email and phone number) to allow for

study communications from the researchers. Following these steps, all emails and phone numbers have been removed from the database to ensure confidentiality and anonymity.

Followingly, participants answered sociodemographic questions. Additionally, participants were asked about any of the exclusion criteria mentioned previously in the 'participants' section. If any of those criteria were met, participants were automatically excluded from the study and could not continue the survey. This was followed by baseline psychological assessments to measure various variables. The variables measured were consecutively: depression, well-being and ability to adapt. Other measures were also taken as this study is a part of a wider research project, however, these are not relevant for the purpose of this research. After finishing these assessments, on the last page of the Qualtrics questionnaire participants received a message outlining the next steps and instructions to install the TIIM app, where further study activities would take place. This concluded on Day 0.

On Day 1, participants were randomly assigned to one of three groups using the Study Randomizer Software (2017): a control group, "Intervention (with no photo)" (INWP) or "Intervention (with photo)" (IWP). Then participants completed either one of the interventions or solely surveys from the control group at the same times as the intervention groups, but without the intervention elements (exercises), which are described further in the section below.

Intervention Groups

This intervention consists of a range of online exercises and reminders throughout every day, during a 7-day period, with objectives to define and follow values individually established by each participant. It is the same intervention for both the INWP group as well as

IWP group, with little difference that will be explained further in the text. Figure 1 presents the layout of the intervention to illustrate its process.

Day 1

The first day of the intervention began with the "EMI_A" initial module, available only during the "Day 1" between 06:00 to 23:59 hours. This module consisted of a brief assessment and one audio exercise (Exercise 1). The brief assessment consisted of items regarding participants' current symptomatology (4 items, e.g., 'At this moment, to what extent you are not being able to stop or control worrying?') well-being (4 items) (e.g., 'At this moment, what is your level of well-being?'), and engagement with personal values (5 items) (e.g., 'In the last 24 hours, how many of your actions have been aligned with your values?'). This was followed by an audio-guided values clarification exercise (Exercise 1). This exercise required participants to reflect on the life they would be proud of while celebrating their 50th birthday. Participants then imagined three dear people approaching them and asking prompt questions regarding what enabled them to achieve their fulfilled life by this time. The imagined answers that participants provided to their most dear people during this meaningful moment clarified the five most important values in life they would like to follow. The transcript of this exercise can be found in Appendix B.

INWP and IWP difference

As the last part of Exercise 1, participants in Intervention (with no photo) (INWP) were then required to write down their five values on any device/notebook that was easily accessible to them. However, in Intervention (with photos) (IWP) participants were required to save five photos on their phone, with each photo representing one value they established for themselves. This is the only difference between INWP and IWP groups.

1st Day (continued)

After the exercise, participants were required to answer 2 questions about the exercise they just completed, which regarded the place where they completed it and their experience with it. That concluded Day 1.

2nd – 7th Day

For the following six days (days 2-7), each morning participants completed an EMI_B module, which consisted of a brief reflection exercise (Exercise 2) (Appendix C for transcript) and a brief assessment in the TIIM app. Exercise 2 purpose, was to remind participants each morning about their five previously established values either by looking at photos (IWP) or text (IWNP) corresponding to them. This was followed by short assessments of symptomatology, well-being, and valued living, the same as the ones that participants received during the EMI_A brief assessment. Additionally, participants received 3 notifications throughout each day (days 2-7) which acted as reminders of the values established during the 1st day of the intervention. Those reminders were being sent at 15:00, 18:00 and 21:00 during each day (days 2-7) and participants had exactly two hours to confirm receiving each of those reminders by answering one item ("Since the last notification, to what extent have you been consciously aware of your values?").

8th Day

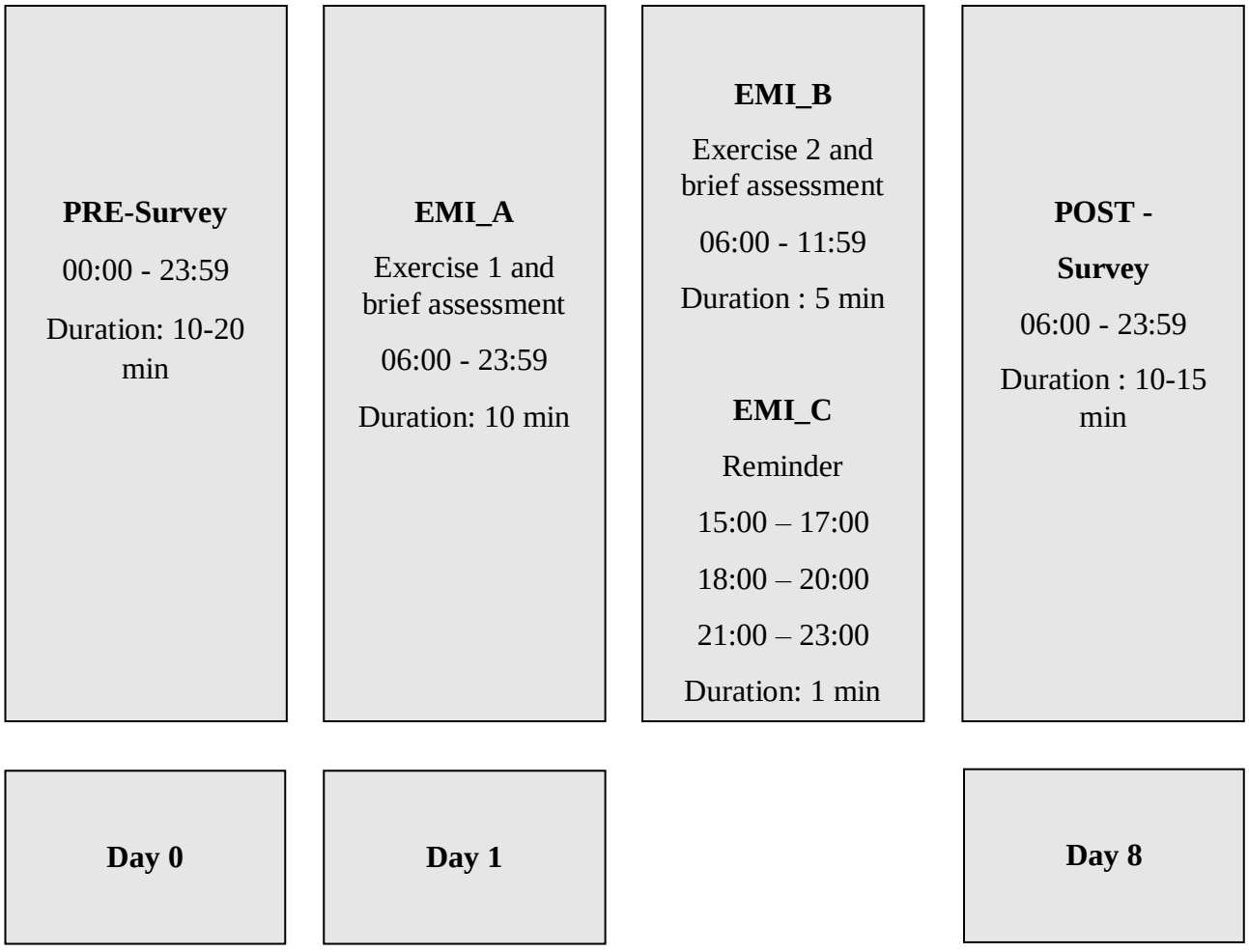
The final day of the study (Day 8) included post-intervention assessments identical to those on Day 0 excluding socio-demographic items, allowing for pre-and post-intervention comparisons.

Control group

The control group was created to compare the results with a group of participants not receiving the intervention. This group received no exercises; however, they received surveys, assessments and reminders during the same time as the intervention groups throughout the 9-day period. The only relevant surveys from the control group for the purpose of this study include pre-post assessments implemented during day 0 and day 8 of the study duration. The control group did not receive any intervention by the end of the study.

Figure 1

Figure representing schedule for each condition group (Control, INWP, IWP)



Note: EMI_A refers to exercise 1 and brief assessment presented to intervention groups during day 1. EMI_B refers to exercise 2 and brief assessment provided to the intervention groups each morning (06:00 – 11:59 hours) between days 2-7 of the study. EMI_C refers to reminders sent to intervention groups between days 2-7 of the study. Control group has completed the same modules as intervention groups, but without any exercises within them.

Data analysis

Data was downloaded from TIIM and Qualtrics app into R programme version 4.2.2. After cleaning the data, the first step was to exclude all irrelevant variables from all condition groups. 3 new datasets were created for each condition, which contained answers from Pre- and Post- assessments of Well-Being (MHC-SF), Depression (PHQ-9), and Ability to Adapt (GSAAS). Additionally, two datasets (one per intervention group) were created which gave percentage representations of intervention adherence per each component (EMI_A, EMI_B and EMI_C) of every participant. This was done to determine whether participants took the minimum amount of effort in the intervention to deem it impactful. Participants from both intervention groups were required to complete the whole initial EMI_A module, 50% of six EMI_B modules and 33% of 21 EMI_C modules in order to be included in the analysis. This minimal threshold was implemented, as all participants meeting this criterion have fulfilled at least one module per day on average, which was deemed crucial for this intervention's effectiveness. Only when the participants met those criteria their scores were further analysed.

Day 2-7

Assumptions

Before the main analyses, assumptions testing was conducted. Normality of the pre- and post-intervention residual scores for depression, well-being, and ability to adapt were assessed using the Shapiro-Wilk test to confirm the appropriateness of parametric testing. Levene's test was used to evaluate the homogeneity of variance across participants in each of the three groups, ensuring that the groups were comparable in terms of variability. The independence assumption was checked using residual scatterplot on all three groups as well.

In order to examine the intervention's effectiveness for increasing well-being and reducing depressive symptoms, Linear Mixed Models and mixed-design repeated-measures ANOVA were performed. Those measures enabled the comparison of depressive symptoms (PHQ-9) and well-being (MHC-SF) scores from pre- to post-intervention across the intervention groups and the control group. This analysis aimed to determine if the intervention had a significant impact on these scores.

In addition, a Linear Mixed Model with “Ability to Adapt” as a moderator was conducted to test the hypothesis that adaptability (measured by GSAAS) moderated the intervention’s effect. This determined whether the ability to adapt is an influential factor. Statistical significance was set at $\alpha = 0.05$ for all analyses, with p-values below this threshold considered indicative of meaningful differences.

Results

Sociodemographic characteristics

A total of 93 participants participated in the survey, of which 48 participants were excluded. Eight participants were excluded due to not finishing the pre- or post-survey from the study. 40 participants were excluded due to not adhering to the requirement of completing the EMI_A module, 50% of six EMI_B modules and 33% of 21 EMI_C modules, which resulted in insufficient involvement in the intervention to deem it impactful. Therefore, a total

of 45 participants were put under the analysis (31 participants from the intervention groups and 14 from the control group).

Most participants who took part in the study were female (n = 33; 73.33%), followed by male (n = 10; 22.22%) and non-binary (n = 2; 4.44%). The mean age was 21.98 (SD = 3.64), with the youngest participant being 18 years old and the oldest 36. 16 participants had Dutch nationality (35.56%), 16 were German (35.56%) and 13 had other nationality (28.88%). As all participants were students, educational level was measured. 35 students reported currently following their bachelor programme (77.78%), nine reported attending their master programme (20%) and one was during the doctorate (2.22%). Details regarding sociodemographic data can be found in Table 1.

Table 1

Sociodemographic information about the participants in all condition groups

Variable	N=45	%
Gender		
Female	33	73.33
Male	10	22.22
Non-binary	2	4.44
Age	45 (M = 21.98) (SD = 3.64)	100
Nationality		
Dutch	16	35.56
German	16	35.56
Other	13	28.88
Educational Level		

Bachelor	35	77.78
Master	9	20
Doctorate	1	2.22

Results overview

Well-being and depressive symptoms were not affected by the valued-living online intervention either in Intervention (with no photo) (INWP) (16 participants) or Intervention (with photo) (IWP) (15 participants) group in any significant manner according to ANOVA and Linear Mixed Model comparing the three conditions. Additionally, the ability to adapt was also not a significant moderator for the intervention in any of the condition groups according to the conducted Linear Mixed Model. The details of these findings are presented below.

Baseline assessment

In Table 2, it can be observed that at the baseline assessment, except for the depression variable, there is not any significant difference between any of the 3 condition groups in any of the dependent variables. The mean depression score in the control group (M = 4.71, SD = 2.67) is notably lower than the mean depression score of INWP (M = 7.05, SD = 4.49) and IWP (M = 6, SD = 3.76) groups.

Table 2

Differences in baseline assessments between all condition groups

Variable/Condition	Control Group	INWP	IWP
Depression – Mean (SD; range)	4.71 (2.67; 1-11)	7.05 (4.49; 2-19)	6 (3.76; 0-14)
Well-Being – Mean (SD; range)	40.43 (7; 28-53)	39.15 (9.73; 21-64)	43.53 (10.74; 23-61)

Ability to Adapt – Mean (SD; range)	33.07 (7.36; 22-45)	33.85 (6.94; 19-45)	33.89 (7.89; 22-48)

Assumptions

Before conducting a within-group analysis, assumptions for normality, homogeneity and independence were checked. Shapiro-Wilk test was conducted to check normality, with high p-values ($p > 0.05$), therefore confirming the normality assumption across all condition groups. Homogeneity was measured using Levene's test to determine if variances were equal. This assumption was also met in all 3 conditions. The independence assumption was checked using a residual scatterplot. The residuals were randomly scattered across the plot, confirming the independence assumption across all 3 conditions.

Within and between groups Analysis

Linear mixed models were conducted to compare pre and post-intervention measurements within two intervention groups and the control group. The measurements were taken during day 0 and day 8 of the study for all groups. Additionally, mixed-design repeated measures ANOVA was conducted to check the difference between interventions' influence on well-being and depression.

Hypotheses 1 and 2

A linear mixed model was conducted to examine the effects of two valued-living intervention groups INWP and IWP on depressive symptoms compared to a control group. Results showed initially a significant main effect for INWP ($p = 0.22$), such that participants in this group reported higher depressive symptoms overall compared to the control group, $\beta = 3.17$, $SE = 1.35$, $t(50) = 2.36$, $p = .022$. However, as mentioned previously in the baseline assessment section, the pre-depression scores of the control group were significantly lower

than both intervention groups. When the time of the intervention was taken as a variable in order to compare changes across all three condition groups, change in pre-post PHQ-9 (Depression) scores were not significant in comparison to changes of control group $\beta = -0.84$, $SE = 0.98$, $t(50) = -0.85$, $p = .399$. This suggests that depressive symptom reduction in the post-INWP scores of this group was not distinctly greater than that of the control group after the passage of the same time.

For IWP (Table 3), neither the main effect, ($\beta = 1.47$, $SE = 1.36$, $t(50) = 1.08$, $p = .286$) nor the change in pre-post PHQ-9 scores in comparison to changes of the control group with Time, ($\beta = -0.18$, $SE = 0.99$, $t(50) = -0.18$, $p = .857$) were significant. This indicates that IWP did not significantly impact depressive symptoms. The control group's depressive symptoms remained stable across time, ($\beta = 0.29$, $SE = 0.75$, $t(50) = 0.38$, $p = .706$) confirming that any observed reductions in depressive symptoms in the intervention groups were not due to natural changes over time.

Table 3

Linear Mixed Model Examining the Effectiveness of Valued-Living Intervention groups on Depressive Symptoms (PHQ-9) Over Time

Covariate	β (95% CI)
Intercept	4.43 (2.41, 6.45)
INWP*	3.17 (0.52, 5.82)**
IWP*	1.47 (-1.20, 4.14)
Time	0.29 (-1.18, 1.76)
INWP * x time	-0.84 (-2.76, 1.08)
IWP* x time	-0.18 (-2.12, 1.76)

* Reference group = Control group

** $p < 0.05$

Mixed-design repeated measures ANOVA for Depression (PHQ-9)

In order to measure any significant difference between conditions regarding the difference of their influence on depression (Table 4), a mixed-design repeated measures ANOVA was conducted. The main effect of the condition was not statistically significant, ($F(2, 50) = 2.45$, $p = .097$) indicating no significant differences in PHQ-9 scores between the three conditions. The main effect of time was also not significant, ($F(1, 50) = 0.02$, $p = .893$) suggesting that depression scores did not significantly change over time regardless of the condition group. Furthermore, the Condition × Time interaction was not significant, ($F(2, 50) = 0.44$, $p = .649$) indicating that the change in depression scores from pre- to post-intervention did not differ significantly between the control and intervention groups. Based on those results, the hypotheses 1 and 2 are rejected.

Table 4

Mixed Design Repeated Measures ANOVA across three groups examining the Effectiveness of Valued-Living Intervention on Depressive Symptoms Over Time

Measure	T1 Mean (SD)	T2 Mean (SD)	F-value	p-value	η^2
Control Group	4.71 (2.67)	4.43 (2.10)	0.02	.893	0.00
INWP	7.05 (4.49)	7.7 (4.67)	2.45	.97	0.09
IWP	6 (3.76)	5.89 (4.01)	0.45	.649	0.01

Hypothesis 3 and 4

A linear mixed model was conducted to examine the effects of two online valued-living interventions on well-being scores compared to a control group (Table 5). Results

showed no significant main effect for INWP, indicating that participants in this group did not report significantly different well-being scores overall (β = -2.29, SE = 3.25, t(50) = -0.71, p = .484) compared to the control group. Additionally, the comparison between INWP and the control group when the effect of time was accounted for, showed no significant influence of the intervention, (β = 1.01, SE = 2.24, t(50) = 0.45, p = .652) suggesting that well-being improvement in the post-intervention scores of this group was not distinctly greater than the control group over time.

For IWP, the main effect was also not significant, (β = 4.30, SE = 3.28, t(50) = 1.31, p = .196) indicating no overall difference in well-being scores compared to the control group. Similarly, change in pre-post MHC-SF (well-being) scores in comparison to changes of the control group with time was not significant, (β = -1.21, SE = 2.26, t(50) = -0.53, p = .596) suggesting that the intervention did not significantly improve well-being scores over time. The control group's well-being scores showed no significant change across time, (β = -2.21, SE = 1.71, t(50) = -1.29, p = .203) confirming that any changes in well-being scores in the intervention groups were not due to natural variations over time.

Table 5

Linear Mixed Model Examining the Effectiveness of Valued-Living Intervention Groups on Well-Being Over Time

Covariate	β (95% CI)
Intercept	42.64** (37.76, 47.52)
INWP*	-2.29 (-8.66, 4.08)
IWP*	4.3 (-2.13, 10.73)
Time	-2.21 (-5.56, 1.14)
INWP* x Time	1.01 (-3.38, 5.4)

IWP* x Time	-1.21 (-5.64, 3.22)

* Reference group = Control group

** $p < 0.05$

Mixed-model repeated-measures ANOVA for Well-Being

In order to measure any significant difference between conditions regarding the difference of their influence on well-being a mixed-model repeated-measures ANOVA was conducted to evaluate the effect of condition (control, INWP, IWP) and time (pre-post) on well-being scores (Table 6). Results showed a significant main effect of time, ($F(1, 50) = 6.52$, $p = .014$) indicating that well-being scores changed significantly from pre- to post-intervention across all conditions. However, the main effect of the condition was not significant, ($F(2, 50) = 1.97$, $p = .150$) suggesting no significant differences in well-being scores between the conditions overall. The interaction effect between condition and time was also not significant, ($F(2, 50) = 0.58$, $p = .561$) indicating that the change in well-being scores over time was not significantly different among the conditions. Based on those results hypotheses 3 and 4 are rejected.

Table 6

Mixed Design Repeated Measures ANOVA across three groups examining the Effectiveness of Valued-Living Intervention on Well-Being Over Time

Measure	T1 Mean (SD)	T2 Mean (SD)	F-value	p-value	η^2
Control Group	40.43 (7)	42.64 (6.34)	6.52	0.14*	0.20
INWP	39.15 (9.73)	40.35 (10.53)	1.97	1.50	0.07
IWP	43.53 (10.74)	46.95 (9.25)	0.58	.561	0.02

* $p < 0.05$

Hypothesis 5

A linear regression analysis was conducted to examine whether the ability to adapt moderated the effect of online intervention INWP and IWP on well-being improvement (Table 7). The overall model was not significant, ($F(5, 47) = 0.53$, $p = .751$) indicating that the predictor (ability to adapt) did not explain a significant amount of variance in well-being improvement ($R^2 = 0.054$, Adjusted $R^2 = -0.047$). The main effect was not significant for either INWP ($\beta = -1.35$, $SE = 11.15$, $t = -0.12$, $p = .904$) or IWP ($\beta = -1.81$, $SE = 10.71$, $t = -0.17$, $p = .867$), suggesting that neither intervention led to significantly different well-being improvements compared to the control group. The main effect of the Ability to Adapt was not significant for either ($B = -0.19$, $SE = 0.25$, $t = -0.78$, $p = .441$).

Moreover, the interaction terms for the ability to adapt with INWP ($\beta = 0.01$, $SE = 0.33$, $t = 0.04$, $p = .965$) and IWP ($\beta = 0.09$, $SE = 0.31$, $t = 0.30$, $p = .766$) were not significant. These findings indicate that the ability to adapt did not significantly moderate the relationship between the interventions and well-being improvement. Therefore hypothesis 5 has been rejected.

Table 7

Linear Mixed Model Assessing the Moderating Role of Ability to Adapt on Well-Being in Valued-Living Intervention Groups (INWP and IWP)

Predictor	Estimate (β)	SE	t	p-value
Intercept	8.53	8.31	1.03	.310

INWP	-1.35	11.15	-0.12	.904
IWP	-1.81	10.71	-0.17	.867
Ability to Adapt	-0.19	0.25	-0.78	.441
Ability to Adapt x Well- Being INWP	0.01	0.33	0.04	.965
Ability to Adapt x Well-Being IWP	0.09	0.31	0.30	.766

Hypothesis 6

Furthermore, a linear regression analysis (Table 8) was conducted to examine whether the ability to adapt moderated the effect of valued living online intervention groups (INWP and IWP) on depressive symptom reduction. The overall model was not significant, ($F(5, 47) = 0.53$, $p = .755$) indicating that the predictor (ability to adapt) did not explain a significant amount of variance in depressive symptom reduction ($R^2 = 0.053$, Adjusted $R^2 = -0.048$). The main effect of ability to adapt was also not significant (= 0.12, SE = 0.11, t = 1.15, p = .255). Additionally, the interaction terms for Ability to Adapt with INWP ($\beta = -0.15$, SE = 0.14, t = -1.08, p = .287) and IWP ($\beta = -0.07$, SE = 0.14, t = -0.54, p = .596) were not significant. These findings indicate that the ability to adapt did not significantly moderate the relationship between the interventions and depressive symptom reduction. Therefore, the hypothesis 6 is rejected.

Table 8

Linear Mixed Model Assessing the Moderating Role of Ability to Adapt on Depressive Symptoms in Valued-Living Interventions

Predictor	Estimate (β)	SE	t	p-value
Intercept	-4.39	3.64	-1.21	.234
INWP	5.95	4.89	-1.22	.229
IWP	2.57	4.69	0.55	.586
Ability to Adapt	0.12	0.11	1.15	.225
Ability to Adapt x Depression INWP	-0.15	0.14	-1.08	.287
Ability to Adapt x Depression IWP	-0.07	0.14	-0.54	.596

Discussion

The present study aimed to evaluate the effectiveness of an online valued-living intervention in reducing depressive symptoms and improving well-being among university students, with the ability to adapt as a possible moderator. Results showed no significant increase in any of the variables of interest. Neither well-being nor depression group average scores significantly improved in the intervention (with no photo) (INWB) group or intervention (with photo) (IWB) group ($p > 0.05$) when compared to the control group. Moreover, the ability to adapt did not moderate with any significant effect on either of the interventions regarding well-being or depression. All hypotheses of this research have been therefore rejected.

Well-being and depression

The lack of a significant increase in well-being and therefore lack of subsequent reduction among depressive symptoms in this study raises questions regarding the cause of this occurrence. Meanwhile, it is problematic to determine exactly which factor contributed to the lack of increased well-being for the participants and reduced depressive symptoms in both

of the intervention groups, other similar studies shed light on possible causes. In a similar study, researchers also created an online intervention focused specifically on values awareness, however not specifically aimed at the student population (Russo-Netzer and Atad., 2024). The Russo-Netzer and Atad (2024) study created two interventions: one focused solely on values awareness and one focused on values awareness along with facilitating action adherent to those values. Interestingly, the intervention aiming solely for values awareness did not produce any significant results regarding well-being or reducing depressive symptoms. Only intervention actively facilitating action adherent to the values-based behaviour showed significant results regarding well-being improvement and psychopathology reduction (Russo-Netzer and Atad., 2024). The present study intervention focused mostly on values clarification with an attempt to substitute some of the values-based behaviour benefits by adding photos enabling future values-based behaviour visualization among participants. However, taking into consideration this study's non-significant results it is indicated that this aspect could simply not be impactful to even partially obtain well-being benefits emerging from an actual valued-based behaviour.

This study is in line with the research of Kibbey et al. (2024), who also found participants undertaking actions adherent to their values exhibiting less depressive symptoms and having improved well-being. The current study, however, as one of the few studies using the valued-based approach to improve well-being and reduce depressive symptoms among students, focused primarily on values clarification. Measurement regarding undertaking action by the participants values has not been implemented in this study. The values-based behaviour variable, taking into consideration this study's findings along with previously mentioned research (Kibbey et al., 2024, Russo-Netzer and Atad., 2024) could potentially explain the lack of significant results in this study. Moreover, undertaking action adherent to values

requires time, whereas this study intervention lasted only eight days, which could be another possible cause of the lack of significant results.

Similar to this study, time has been a possible factor contributing to non-significant results in a study evaluating a valued-based online intervention designed for chronic back patients (Zerth et al., 2023). In this study, the intervention lasted a total of 10 days, with values awareness and valued-living action among participants as the desired outcome. Despite its intervention's positive qualitative feedback from the participants, it failed to produce any significant results regarding well-being or depressive symptoms (Zerth et al., 2013). Moreover, a one-session pilot study among college students investigating valued-living online intervention effectiveness also did not produce any significant effect on well-being improvement (Firestone et al., 2019). It should be underlined, however, that Firestone et al. (2019) study was a single-session intervention study, completed in one day. Based on previously mentioned studies (Firestone et al., 2019; Zerth et al., 2013) and findings of the current research, time could be an influential factor regarding valued-living online interventions.

This is supported by the meta-analysis of Hendriks et al. (2019) who measured that an average online intervention for well-being improvement lasts 8.1 weeks or 8.6 sessions. Other online interventions are not directly comparable to an online values-based intervention as this study implemented, however, it shows how shorter this intervention was in comparison to an average online intervention. It should be noted however that online interventions are only effective if participants are engaged in their completion (Groot et al., 2023). Making an online intervention longer increases the risk of attrition of participants (Groot et al., 2023). Therefore a balance should be found between possible increased duration of valued-living online intervention and attrition risk of potential participants.

Ability to adapt

Furthermore, the ability to adapt was measured as a separate concept from psychological flexibility, as mentioned in the introduction section. Whereas psychological flexibility seems to be an influential moderator regarding valued-living (Finkelstein-Fox et al., 2020), the ability to adapt variable failed to moderate the valued-living online intervention effectiveness in the current study. As a different concept, it can produce different results than those found by Finkelstein – Fox et al. (2020). However, the ability to adapt seems to be possibly an even stronger component of psychological flexibility to influence the efficiency of this sort of intervention, as the ability to adapt represents an already acquired resilience to life situations (Waldeck et al., 2021). Psychological flexibility entails only being open to adjustments, instead of active engagement in them (Hayes et al., 2013). A possible explanation is also connected to the duration of this particular intervention. As suggested by Finkelstein-Fox (2020), psychological flexibility acts as a 'buffer' role for life situations. This entails that through a prolonged period of time, this can be influential due to resilience and commitment to one's values. This is supported by the studies, suggesting resilience and adherence to one's values are more pronounced in prolonged challenges, as these traits require repeated practice and application to produce noticeable outcomes (Ceary et al., 2019; Schetter & Dolbier, 2011). In this intervention, values had to be adhered to for only a week by the participants. The absence of the ability to adapt moderation could be simply attributed to the fact, that not enough situations required resilience from participants to make it a noticeable difference during a one-week period. It is possible, however, that other unexplained factors a caused lack of ability to adapt moderation in this study, which has not yet been explained by the current research.

Limitations and Future Research Directions

This study was subject to some limitations which need to be accounted for. Most notably, this study has a relatively short duration of the intervention, which lasted only eight

days. This limited duration could have caused lack of sufficient engagement of the participants to their identified values. This in turn could have caused a possible lack of transferring those values into meaningful actions (Ameral & Reed, 2020). Research suggests that longer interventions allow for greater reflection and application, which are critical for achieving significant changes in well-being and depressive symptoms (Hendriks et al., 2019; Kazantzis et al., 2018). Additionally, the ability to adapt and adherence to values may require participants to encounter and navigate various life situations over an extended period of time. This could be hindered within the time constraints of this study. Consequently, the brevity of the intervention may have contributed to the lack of significant findings. A longer duration of valued-living online intervention in future research is advised, in order to examine the influence of time in such interventions.

Moreover, the sample size of this study equalled 45 participants across all condition groups, with 15 participants on average per group. A sample for small-sized effects is recommended to have at least 50 participants per condition (Brysbaert, 2019). The Lack of a representative sample in this study could be attributed to the fact that students can perceive the risks and costs of participating in a study as outweighing the possible benefits. This study offered possible improvement in mental well-being, reduced depressive symptoms and SONA points, however, further enticements should be implemented in future studies to make the sample size more representative.

Another limitation of this study is the absence of qualitative and follow-up data from the participants. Incorporating qualitative data, such as open-ended responses or interviews, could have provided valuable insights into participants' subjective experiences with the intervention. For example, qualitative approaches have been shown to deepen understanding of how participants apply values-based interventions (Pereira et al., 2024). Similarly, follow-up assessments could have evaluated the potential long-term impacts of the intervention on

well-being and depressive symptoms. Previous research suggests that the impact of psychological interventions often manifests over extended periods of time (Anderson & Ozakinci, 2018). Therefore, follow-up data and qualitative feedback are advised in future valued-living online intervention studies in order to deepen understanding of possible improvements of such interventions.

Strengths

This study presented several notable strengths. Firstly, its novel approach allowed for short online intervention implementation, with the incorporation of valued living as a core element of well-being improvement and depressive symptoms reduction. Unlike more traditional approaches, such as cognitive-behavioural therapy (CBT), which primarily targets reducing specific symptoms of mental health conditions, this intervention focused on a holistic approach with well-being improvement as a pathway to depressive symptoms reduction. This novel perspective provides a foundation for future research to explore the potential of values-based interventions, especially in the digital context, which remains an under-researched area (Boden et al., 2021).

Followingly, the study's RCT design represents another key strength. The study ensured comparability across conditions by randomly assigning participants to either a control group or one of the two intervention groups (Hariton & Locascio, 2018). This allowed for a more accurate assessment of the intervention’s effectiveness. RCTs are widely recognized as the gold standard in clinical and psychological research, offering evidence of causal relationships (Hariton & Locascio, 2018). Moreover, the inclusion of pre- and post-measures provided valuable data for examining changes in well-being and depressive symptoms, caused by the intervention. This design enabled the study to capture short-term outcomes effectively, even if follow-up data was not collected. This approach increases the probability that the study’s findings are the result of the intervention instead of other external factors (Hariton &

Locascio, 2018). While the results were not statistically significant, the rigour of the methodology strengthens the probability that the findings can serve as a reliable baseline for future studies.

Thirdly, the strength of the study is the use of the Twente Intervention and Interaction app for the intervention implementation. As the TIIM app can be accessed digitally through the phone, it enabled participants to engage in the intervention regardless of their location. This is especially advantageous to students who have usually busy schedules and would have difficulty following traditional intervention schema for eight days. This aligns modern trend of digital health cost-effective solutions to address mental health challenges (Andersson et al., 2019). By demonstrating the feasibility of using mobile apps for values-based interventions, this study contributes to the growing need for accessible interventions among students and mental health care. Furthermore, this approach has the potential to reach a broader audience, especially individuals who might face barriers to accessing traditional in-person therapy, because of geographic or financial constraints. Although the intervention was brief, the successful use of the TIIM app highlights the promise of digital tools in delivering accessible and impactful mental health interventions.

Conclusion

This study explored the effectiveness of an online values-based intervention in enhancing well-being and reducing depressive symptoms among university students, with the ability to adapt as a potential moderator. While the interventions did not produce significant improvements in either well-being or depressive symptoms compared to the control group, the findings offer valuable insights into the challenges of short-term online interventions. The brief 8-day intervention format likely limited participants' ability to fully internalize their values and translate them into meaningful actions. This highlights the importance of designing

interventions with sufficient duration and depth to facilitate meaningful mental health improvement.

Despite its limitations, the study contributes a novel perspective by implementing values-based interventions in a digital context. This approach aligns with broader trends in positive psychology, emphasizing personal values as key to mental health improvement. By using a randomized controlled trial design, the study provides a reliable foundation for future research to build upon. Additionally, longer intervention periods, the inclusion of qualitative feedback, and follow-up assessments are recommended to optimize such interventions. As the need for accessible mental health interventions grows, this research underscores the potential of online values-based interventions while identifying areas for improvement to enhance their effectiveness.

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Appendices

Appendix A: The Materials

Informed Consent Form

Being of legal age, I agree to the following:

1) I have been informed of the characteristics of this study titled: "Capturing What Matters: Fostering Quality of Practice in a Values-Based Positive Intervention." Click the following link to read more about the study: Informed Consent143

2) I have read and understood the study information and my questions have been satisfactorily answered.

3) I voluntarily consent to participate in this study and understand that I can refuse to answer questions or withdraw at any time without providing a reason.

Furthermore, the following points are clear to me:

- I understand that participation requires using the Qualtrics platform and TIIM app for a week, receiving notifications, and completing questionnaires.
- All collected data will be anonymous and untraceable to my identity.
- The information I provide will be used only for teaching, research, or publication.
- I acknowledge the potential risk of mental discomfort when discussing sensitive topics, such as past personal experiences.
- I agree not to share details of the study to avoid affecting its results.
- I give permission for my answers to be archived for future research and learning.
- I consent to being contacted for future studies.

By virtue of these conditions, I agree to participate in this study by clicking YES:

Appendix B

EMI_A Materials

Exercise 1

[Audio starts] *I would like you to do an exercise that could help you clarify your central values that drive your life. This is a visualization to discover what you consider important in this life. People have all sorts of different experiences with this exercise. This visualization has proven to be revealing for some people, while for others it has simply confirmed something they have always known, or it has had no effect at all. So there are no right or*

wrong experiences, nor better or worse experiences. I just ask you to observe whatever arises within you. Are you ready?

Great, let's begin by closing your eyes or, if you prefer, you can fix your gaze on a point on the floor. Take a moment to notice your breathing and how your body feels. (Pause). If you get distracted or notice your mind wandering, that's okay. Just notice and bring your attention back to this exercise. (Pause)

Let's start by visualizing your own figure in front of you, in that mental visual space (pause). When you have your figure, imagine that we are moving forward in time. Picture yourself aging and growing older as the years pass. You have reached the age of 50 and observe how your figure looks again—what do you look like? I will ask you to become, for a moment, that figure, and start to feel yourself in that body in the first person (pause). Now, imagine that you are celebrating this 50th birthday.

It has not been just any life, but a life that you would be proud to have lived. You have lived it your way, and you have decided and chosen how you wanted to live it, despite any difficulties that may have arisen. Take a moment to feel this. (pause)

The most special people to you, those you care about the most, have come to celebrate your 50th birthday with you. I invite you to imagine not who you think might be there, but who you would most like to be at your 50th birthday party. These people are here for you and because of you.

It is now time for several people to start dedicating words to you. Again, I am not asking you

to imagine what they would probably say. I invite you to imagine what you would most like them to say. Imagine who is the first person you are visualizing to start.

Visualize how this person approaches you, stands in front of you, and takes a moment to speak. Observe the face. And try to really listen to what this person is going to say to you. And remember, imagine you have been living the life you chose and wanted. Listen, (1) What does this person say about how you have lived this life? (2) What does this person say about what you have dedicated your time and energy to in recent years? (3) What does this person say about what you have found important in your life? And observe how you feel as you listen to their words.

Now imagine how a second person approaches. Who is this person? Observe the face and imagine what you would most like this person to say about the life you chose and wanted. Listen, (1) What does this person say about how you have lived this life? (2) What does this person say about what you have dedicated your time and energy to in recent years? (3) What does this person say about what you have found important in your life? And observe how you feel as you listen to their words.

Now imagine how a third person approaches. Who is this person? Observe the face and imagine what you would most like this person to say about the life you chose and wanted. Listen, (1) What does this person say about how you have lived this life? (2) What does this person say about what you have dedicated your time and energy to in recent years? (3) What does this person say about what you have found important in your life? And observe how you feel as you listen to their words.

Your values are what is important to you in life. This means that you determine what you believe is valuable and prioritized in your life, what makes everything worth it, and what motivates you. Values become more visible in our moments closest to our farewell. It is when we realize what truly deserves our time and energy. [Audio ends].

Brief Asessment:

1/13. At this moment, to what extent are you feeling nervous, anxious, or on edge?

2/13. At this moment, to what extent you are not being able to stop or control worrying?

3/13. At this moment, to what extent are you feeling little interest or pleasure in doing things?

4/13. At this moment, to what extent are your feeling down, depressed or hopeless?

5/13. At this moment, what is your level of well-being?

6/13. How happy do you feel right now?

7/13. At this moment, to what extent are you satisfied with your life?

8/13. At this moment, to what extent are you feeling that your life has a sense of direction or meaning to it?

9/13. At this moment, how easy is it for you to identify the values that drive your life?

10/13. In the last 24 hours, to what extent have you been consciously aware of your values?

11/13. In the last 24 hours, how many of your actions have been aligned with your values?

12/13. And how aware were you, while doing them, that you were acting according to your values?

13/13. To what extent do you INTEND to take actions aligned with your values in the following hours?

Post – 10' Audio Assessment

Where did you complete the practice?

1/10. At this moment, how easy is it for you to identify the values that drive your life?

2/10. To what extent do you INTEND to take actions based on your values in the following hours?

Appendix C

EMI_B Materials

Exercise 2

[Audio starts] *Take a few moments to connect with what matters to you (pause), with what is most important to you in your life (pause). Connect with each of your central values and feel the significance of each as it resonates in your heart. (30' pause)*

Now, think about why these values matter to you and how they shape your life. (30' pause)

Now, visualize moments in your day where you can do things that are aligned with these values. Picture yourself engaging in these activities. (30' pause)

Take a moment to appreciate this connection (pause) and when you're ready, gently bring your awareness back to the present, carrying this sense of alignment with you throughout your day. Thank you for taking this time to connect with your values. [Audio ends]

POST – Audio Assessment

Where did you complete the practice?

1/10. At this moment, how easy is it for you to identify the values that drive your life?

2/10. To what extent do you INTEND to take actions based on your values in the following hours?

3/10. At this moment, what is your level of well-being?

4/10. How happy do you feel right now?

5/13. At this moment, to what extent are you satisfied with your life?

6/10. At this moment, to what extent are you feeling that your life has a sense of direction or meaning to it?

7/10. At this moment, to what extent are you feeling nervous, anxious, or on edge?

8/10. At this moment, to what extent you are not being able to stop or control worrying?

9/10. At this moment, to what extent are you feeling little interest or pleasure in doing things?

10/10. At this moment, to what extent are your feeling down, depressed or hopeless?

11/14. During the practice, I had many difficulties constructing the mental scene that I was using to connect with my values.

12/14. During the practice, I had a hard time manipulating the mental scene that I was using to connect with my values.

13/14. During the practice, I managed to generate a sense of meaning and significance towards my life.

14/14. During the practice, I noticed a sense of vitality or expansion in my body.

You have completed your morning visualization. Throughout the day, we will send you 3 brief notifications with messages, do not miss them! Thank you for continuing to collaborate; your reward is getting closer. Now, click "Next".

Appendix D

R code

```
#Renaming the dataset and removing timestamps



TIIM_C1 <- TIIM_Intervention_Condition_1
```

```
columns_to_keep <- c(1:4, seq(6, ncol(TIIM_C1), by = 2))

TIIM_C1_cleaned <- TIIM_C1[, columns_to_keep]

#Create POST Depression data subset condition 1

DEPPOST1 <- TIIM_C1_cleaned[, c(1, 2, 4, 122:132)]

#Create POST Well being data subset condition 1

WBPOST1 <- TIIM_C1_cleaned[, c(1, 2, 4, 141:155)]

#Create POST Ability to Adapt data subset condition 1

ATAPOST1 <- TIIM_C1_cleaned[, c(1, 2, 4, 197:207)]

#Renaming column names in DEPPOST1 so they fit the rest of the data

colnames(DEPPOST1)[5:14] <- paste("PHQ", 1:10, "P", sep = "")
```

```
#Renaming column names in WBPOST1 so they fit the rest of the data

colnames(WBPOST1)[5:18] <- paste("MHC", 1:14, "P", sep = "")

#Renaming column names in ATAPOST1 so they fit the rest of the data

colnames(ATAPOST1)[5:14] <- paste("GSAAS", 1:10, "P", sep = "")

#Recoding answers in POST data, to be corresponding to PRE data
#DEPPOST1

unique_values <- lapply(DEPPOST1[, 5:14], unique)
unique_values
DEPPOST1[, 5:14] <- lapply(DEPPOST1[, 5:14], function(x) {
  # Convert to character for consistent matching
  x <- as.character(x)
  # Apply recoding
  recoded <- ifelse(x == "[1, 0 = Not at all]", 0,
                    ifelse(x == "[2, 1 = Several days]", 1,
```

```
                    ifelse(x == "[3, 2 = More than half the days]", 2,
                           ifelse(x == "[4, 3 = Nearly every day]", 3, NA))))
  return(as.numeric(recoded)) # Convert to numeric
})

#WBPOST1
unique_values <- lapply(WBPOST1[, 5:18], unique)
unique_values

WBPOST1[, 5:18] <- WBPOST1[, 5:18] %>%
  mutate(across(everything(), ~case_when(
    . == "[1, Never]" ~ 0,
    . == "[2, Seldom]" ~ 1,
    . == "[3, Sometimes]" ~ 2,
    . == "[4, Regularly]" ~ 3,
    . == "[5, Often]" ~ 4,
    . == "[6, (Almost) always]" ~ 5,
    TRUE ~ as.numeric(.)
  )))
```

```
#In original dataset the answers coded themselves by only numbers instead of numbers with phrase. This is manual adjustment to make them corresponding to actual score

WBPOST1[4, 9] <- 2

WBPOST1[4, 10] <- 4


#ATAPOST1


unique_values <- lapply(ATAPOST1[, 5:14], unique)

unique_values


ATAPOST1[, 5:14] <- ATAPOST1[, 5:14] %>%

  mutate(across(everything(), ~case_when(

    . == "[1, 1 = Not at all]" ~ 1,

    . == "[2, 2 = Somewhat]" ~ 2,

    . == "[3, 3 = Reasonably]" ~ 3,

    . == "[4, 4 = Mostly]" ~ 4,

    . == "[5, 5 = Totally]" ~ 5,

    TRUE ~ as.numeric(.)

  )))
```

```
#Creating Depression PRE score for Condition 1


C1Scores <- PRE_Condition1 %>%
  mutate(
    DEPPRE = rowSums(select(PRE_Condition1, 12:20), na.rm = TRUE)
  ) %>%
  select(1, DEPPRE)


#Adding Condition remark
C1Scores <- cbind(Condition = ATAPOST1[[2]], C1Scores)


#Creating Depression POST score for Condition 1


C1Scores <- C1Scores %>%
  mutate(
    DEPPOST = rowSums(select(DEPPOST1, 5:13), na.rm = TRUE)
  )


#Creating Well Being PRE score for Condition 1
```

```
C1Scores <- C1Scores %>%
  mutate(
    WBPRE = rowSums(select(PRE_Condition1, 22:35), na.rm = TRUE)
  )

#Creating Well Being POST score for Condition 1

C1Scores <- C1Scores %>%
  mutate(
    WBPOST = rowSums(select(WBPOST1, 5:18), na.rm = TRUE)
  )

#Creating PRE Ability to Adapt score for Condition 1

C1Scores <- C1Scores %>%
  mutate(
    ATAPRE = rowSums(select(PRE_Condition1, 36:45), na.rm = TRUE)
  )

#Creating POST Ability to Adapt score for Condition 1
```

```
C1Scores <- C1Scores %>%
  mutate(
    ATAPOST = rowSums(select(ATAPOST1, 5:14), na.rm = TRUE)
  )
#Removing timestamps and renaming the dataset for condition 2

TIIM_C2 <- TIIM_Intervention_Condition_2

# Identify columns to keep: 1-4 and every second column starting from 6
columns_to_keep <- c(1:4, seq(6, ncol(TIIM_C2), by = 2))

# Create the cleaned dataset
TIIM_C2_cleaned <- TIIM_C2[, columns_to_keep]

#Creating EMI_A for Condition 2

EMI_A2 <- TIIM_C2_cleaned[, c(1, 2, 4, 5, 19, 20, 21, 43, 44)]

#Creating EMI_B for condition 2
```

```
EMI_B2 <- TIIM_C2_cleaned[, c(1, 2, 4, 45, 75, 76, 77, 107, 108, 109,

                              139, 140, 141, 171, 172, 173, 203, 204, 205,

                              235, 236)]

#Creating EMI_C for Condition 2


EMI_C2 <- TIIM_C2_cleaned[, c(1, 2, 4, 237, 239, 241, 243, 245, 247,

                              249, 251, 253, 255, 257, 259, 261, 263,

                              265, 267, 269, 271)]


#Create POST Depression data subset Condition 2


DEPPOST2 <- TIIM_C2_cleaned[, c(1, 2, 4, 274, 275, 276, 277, 278, 279,

                                280, 281, 282, 283, 284)]


#Create POST Well Being data subset Condition 2


WBPOST2 <- TIIM_C2_cleaned[, c(1, 2, 4, 293:307)]


#Create POST Ability to Adapt data subset Condition 2
```

```
ATAPOST2 <- TIIM_C2_cleaned[, c(1, 2, 4, 349:359)]

#Renaming columns in EMI_A2 to facilitate analyzing

colnames(EMI_A2)[c(5, 8)] <- c("EMI_AB", "EMI_AE")

#Renaming columns in EMI_B2 to facilitate analyzing

colnames(EMI_B2)[c(4, 5, 7, 8, 10, 11, 13, 14, 16, 17, 19, 20)] <- c(
  "EMI_B1B", "EMI_B1E", "EMI_B2B", "EMI_B2E",
  "EMI_B3B", "EMI_B3E", "EMI_B4B", "EMI_B4E",
  "EMI_B5B", "EMI_B5E", "EMI_B6B", "EMI_B6E"
)

#Renaming columns in EMI_C2 to facilitate analyzing

colnames(EMI_C2)[4:21] <- paste("EMI_C", 1:18, sep = "")

#Renaming the columns in DEPPOST2 to facilitate analyzing
```

```
colnames(DEPPOST2)[5:14] <- paste("PHQ", 1:10, "P", sep = "")

#Renaming the columns in WBPPOST2 to facilitate analyzing

colnames(WBPOST2)[5:18] <- paste("MHC", 1:14, "P", sep = "")

#Renaming the columns in ATAPOST2 to facilitate analyzing

colnames(ATAPOST2)[5:14] <- paste("GSAAS", 1:10, "P", sep = "")

#Recoding answers in POST data, to be corresponding to PRE data Condition 2
#DEPPOST2

library(dplyr)

DEPPOST2[, 5:14] <- DEPPOST2[, 5:14] %>%
  mutate(across(everything(), ~case_when(
    . == "[1, 0 = Not at all]" ~ 0,
    . == "[2, 1 = Several days]" ~ 1,
    . == "[3, 2 = More than half the days]" ~ 2,
```

```
    . == "[4, 3 = Nearly every day]" ~ 3,
    TRUE ~ as.numeric(.)
  )))

#WBPOST2

WBPOST2[, 5:18] <- WBPOST2[, 5:18] %>%
  mutate(across(everything(), ~case_when(
    . == "[1, Never]" ~ 0,
    . == "[2, Seldom]" ~ 1,
    . == "[3, Sometimes]" ~ 2,
    . == "[4, Regularly]" ~ 3,
    . == "[5, Often]" ~ 4,
    . == "[6, (Almost) always]" ~ 5,
    TRUE ~ as.numeric(.)
  )))

#ATAPOST2

ATAPOST2[, 5:14] <- ATAPOST2[, 5:14] %>%
```

```
  mutate(across(everything(), ~case_when(
    . == "[1, 1 = Not at all]" ~ 1,
    . == "[2, 2 = Somewhat]" ~ 2,
    . == "[3, 3 = Reasonably]" ~ 3,
    . == "[4, 4 = Mostly]" ~ 4,
    . == "[5, 5 = Totally]" ~ 5,
    TRUE ~ as.numeric(.)
  )))


#Checking if there is any particpant who answered first question of EMI_A but did not finish whole component
rows_with_missing_end <- EMI_A2 %>%
  mutate(
    col5_numeric = as.numeric(EMI_A2[[5]]),
    col8_numeric = as.numeric(EMI_A2[[8]])
  ) %>%
  filter(between(col5_numeric, 1, 100) & !between(col8_numeric, 1, 100))


print(rows_with_missing_end)
```

```
#Checking if there is any particpant who answered first question of EMI_B during any day
but did not finish whole component


rows_with_missing_end <- EMI_B2 %>%
  mutate(
    check_B1 = between(EMI_B2[[4]], 1, 100) & is.na(EMI_B2[[5]]),
    check_B2 = between(EMI_B2[[7]], 1, 100) & is.na(EMI_B2[[8]]),
    check_B3 = between(EMI_B2[[10]], 1, 100) & is.na(EMI_B2[[11]]),
    check_B4 = between(EMI_B2[[13]], 1, 100) & is.na(EMI_B2[[14]]),
    check_B5 = between(EMI_B2[[16]], 1, 100) & is.na(EMI_B2[[17]]),
    check_B6 = between(EMI_B2[[19]], 1, 100) & is.na(EMI_B2[[20]])
  ) %>%
  filter(check_B1 | check_B2 | check_B3 | check_B4 | check_B5 | check_B6)


print(rows_with_missing_end)


#Checking adherence to the intervention in condition 2 per participant
#EMI_A2


EMI_2P <- EMI_A2 %>%
```

```
  select(1:3) %>%
  mutate(EMI_A2P = ifelse(between(EMI_A2[[8]], 1, 100), 100, 0))


# EMI_B2


# Add the EMI_B2P column to EMI_2P, while keeping original columns from EMI_A and
EMI_B2
EMI_2P <- EMI_2P %>%
  mutate(
    EMI_B2P = (rowSums(
      sapply(c(5, 8, 11, 14, 17, 20), function(col) {
        # Convert values between 1-100 to 100 and NA to 0
        ifelse(is.na(EMI_B2[[col]]), 0, ifelse(between(as.numeric(EMI_B2[[col]]), 1, 100), 100,
0))
      })
    ) / 600) * 100  # Total possible score (6 questions * 100 each)
  )


#EMI C2
```

```
EMI_2P <- EMI_2P %>%
  mutate(
    EMI_C2P = (rowSums(
      sapply(4:21, function(col) {
        # Convert values between 1-100 to 100 and NA to 0
        ifelse(is.na(EMI_C2[[col]]), 0, ifelse(between(as.numeric(EMI_C2[[col]]), 1, 100), 100,
0))
      })
    ) / (18 * 100)) * 100  # Total possible score (18 questions * 100 each)
  )

#Creating Depression PRE score for Condition 2

C2Scores <- PRE_Condition2 %>%
  select(1) %>%
  mutate(
    DEPPRE = rowSums(select(PRE_Condition2, 12:20), na.rm = TRUE)
  )

#Adding Condition Remark
```

```
C2Scores <- cbind(Condition = ATAPOST2[[2]], C2Scores)


#Creating Depression POST score for Condition 2


C2Scores <- C2Scores %>%
  mutate(
    DEPPOST = rowSums(select(DEPPOST2, 5:13), na.rm = TRUE)
  )


#Creating Well Being PRE score for Condition 2


C2Scores <- C2Scores %>%
  mutate(
    WBPRE = rowSums(select(PRE_Condition2, 22:35), na.rm = TRUE)
  )


#Creating Well Being POST score for Condition 2


C2Scores <- C2Scores %>%
```

```
  mutate(
    WBPOST = rowSums(select(WBPOST2, 5:18), na.rm = TRUE)
  )

#Creating PRE Ability to Adapt score for Condition 2

C2Scores <- C2Scores %>%
  mutate(
    ATAPRE = rowSums(select(PRE_Condition2, 36:45), na.rm = TRUE)
  )

#Creating POST Ability to Adapt score for Condition 1

C2Scores <- C2Scores %>%
  mutate(
    ATAPOST = rowSums(select(ATAPOST2, 5:14), na.rm = TRUE)
  )

#Removing 4 participants due to too low adherence to the intervention

PRE_Condition2 <- PRE_Condition2[-c(1, 2, 4, 6), ]
```

```
#Renaming the dataset and removing timestamps


TIIM_C3 <- TIIM_Intervention_Condition3

columns_to_keep <- c(1:4, seq(6, ncol(TIIM_C3), by = 2))

TIIM_C3_cleaned <- TIIM_C3[, columns_to_keep]


#Create EMI_A Subset Data Condition 3

EMI_A3 <- TIIM_C3_cleaned[, c(1, 2, 4, 5, 19, 20, 21, 43, 46)]


#Create EMI_B Subset Data Condition 3

EMI_B3 <- TIIM_C3_cleaned[, c(1, 2, 4, 47, 78, 79, 80, 111, 112, 113,

                              144, 145, 146, 177, 178, 179, 210, 211, 212,

                              243, 244)]


#Create EMI_C Subset Data Condition 3

EMI_C3 <- TIIM_C3_cleaned[, c(1, 2, 4, 245, 247, 249, 251, 253, 255,

                                  257, 259, 261, 263, 265, 267, 269, 271,

                                  273, 275, 277, 279)]

#Create POST Depression Subset Data Condition 3

DEPPOST3 <- TIIM_C3_cleaned[, c(1, 2, 4, 282, 283, 284, 285, 286, 287,
```

```
                288, 289, 290, 291, 292)]

#Create POST Well Being Subset Data Condition 3

WBPOST3 <- TIIM_C3_cleaned[, c(1, 2, 4, 301:315)]



#Create POST Ability to Adapt Subset Data Condition 3

ATAPOST3 <- TIIM_C3_cleaned[, c(1, 2, 4, 357:367)]



#Removing 10th row from EMI_A3, EMI_B3 and EMI_C3, DEPPOST, WBPOST3,

ATAPOST3 data due to no inputs

EMI_A3 <- EMI_A3[-10, ]



EMI_B3 <- EMI_B3[-10, ]



EMI_C3 <- EMI_C3[-10, ]



DEPPOST3 <- DEPPOST3[-10, ]



WBPOST3 <- WBPOST3[-10, ]



ATAPOST3 <- ATAPOST3[-10, ]
```

```
#Renaming columns in EMI_A2 to facilitate analyzing

colnames(EMI_A3)[c(4, 8)] <- c("EMI_AB", "EMI_AE")

#Renaming columns in EMI_B3 to facilitate analyzing

colnames(EMI_B3)[c(4, 5, 7, 8, 10, 11, 13, 14, 16, 17, 19, 20)] <- c(
  "EMI_B1B", "EMI_B1E", "EMI_B2B", "EMI_B2E",
  "EMI_B3B", "EMI_B3E", "EMI_B4B", "EMI_B4E",
  "EMI_B5B", "EMI_B5E", "EMI_B6B", "EMI_B6E"
)

#Renaming columns in EMI_C3 to facilitate analyzing

colnames(EMI_C3)[4:21] <- paste("EMI_C", 1:18, sep = "")

#Renaming the columns in DEPPOST3 to facilitate analyzing

colnames(DEPPOST3)[5:14] <- paste("PHQ", 1:10, "P", sep = "")
```

```
#Renaming the columns in WBPPOST3 to facilitate analyzing


colnames(WBPOST3)[5:18] <- paste("MHC", 1:14, "P", sep = "")


#Renaming the columns in ATAPOST3 to facilitate analyzing


colnames(ATAPOST3)[5:14] <- paste("GSAAS", 1:10, "P", sep = "")


#Recoding answers in POST data, to be corresponding to PRE data Condition 2

#DEPPOST2


DEPPOST3[, 5:14] <- DEPPOST3[, 5:14] %>%

  mutate(across(everything(), ~case_when(

    . == "[1, 0 = Not at all]" ~ 0,

    . == "[2, 1 = Several days]" ~ 1,

    . == "[3, 2 = More than half the days]" ~ 2,

    . == "[4, 3 = Nearly every day]" ~ 3,

    TRUE ~ as.numeric(.)

  )))
```

```
#WBPOST3


WBPOST3[, 5:18] <- WBPOST3[, 5:18] %>%
  mutate(across(everything(), ~case_when(
    . == "[1, Never]" ~ 0,
    . == "[2, Seldom]" ~ 1,
    . == "[3, Sometimes]" ~ 2,
    . == "[4, Regularly]" ~ 3,
    . == "[5, Often]" ~ 4,
    . == "[6, (Almost) always]" ~ 5,
    TRUE ~ as.numeric(.)
  )))


#ATAPOST3


ATAPOST3[, 5:14] <- ATAPOST3[, 5:14] %>%
  mutate(across(everything(), ~case_when(
    . == "[1, 1 = Not at all]" ~ 1,
    . == "[2, 2 = Somewhat]" ~ 2,
```

```
    . == "[3, 3 = Reasonably]" ~ 3,
    . == "[4, 4 = Mostly]" ~ 4,
    . == "[5, 5 = Totally]" ~ 5,
    TRUE ~ as.numeric(.)
  )))

#Checking if there is any particpant who answered first question of EMI_B during any day
but did not finish whole component

rows_with_missing_end_B3 <- EMI_B3 %>%
  mutate(
    check_B1 = between(EMI_B3[[4]], 1, 100) & is.na(EMI_B3[[5]]),
    check_B2 = between(EMI_B3[[7]], 1, 100) & is.na(EMI_B3[[8]]),
    check_B3 = between(EMI_B3[[10]], 1, 100) & is.na(EMI_B3[[11]]),
    check_B4 = between(EMI_B3[[13]], 1, 100) & is.na(EMI_B3[[14]]),
    check_B5 = between(EMI_B3[[16]], 1, 100) & is.na(EMI_B3[[17]]),
    check_B6 = between(EMI_B3[[19]], 1, 100) & is.na(EMI_B3[[20]])
  ) %>%
  filter(check_B1 | check_B2 | check_B3 | check_B4 | check_B5 | check_B6)
```

```
print(rows_with_missing_end)


#Checking adherence to the intervention in condition 2 per participant


#EMI_A3


EMI_3P <- EMI_A3 %>%
select(1, 2, 3) %>%  # Keep columns 1, 2, 3 from EMI_A3
  mutate(
    EMI_A3P = ifelse(
      between(EMI_A3[[8]], 1, 100),  # Check if column 8 has value between 1 and 100
      100,
      0
    )
  )


#EMI_B3


# Add EMI_B3P to EMI_3P without repeating the first 3 columns
EMI_3P <- EMI_3P %>%
```

```
  mutate(
    EMI_B3P = (rowSums(
      sapply(c(4, 7, 10, 13, 16, 19), function(col) {
        # Convert values between 1-100 to 100 and NA to 0
        ifelse(is.na(EMI_B3[[col]]), 0, ifelse(between(as.numeric(EMI_B3[[col]]), 1, 100), 100,
0))
      })
    ) / 600) * 100  # Total possible score (6 questions * 100 each)
  )


#EMI_C3


EMI_3P <- EMI_3P %>%
  mutate(
    EMI_C3P = (rowSums(
      sapply(4:21, function(col) {
        # Convert values between 1-100 to 100 and NA to 0
        ifelse(is.na(EMI_C3[[col]]), 0, ifelse(between(as.numeric(EMI_C3[[col]]), 1, 100), 100,
0))
      })
```

```
    ) / (18 * 100)) * 100  # Total possible score (18 questions * 100 each)
  )

#Creating Depression PRE score for Condition 3

C3Scores <- PRE_Condition3 %>%
  select(1) %>%
  mutate(
    DEPPRE = rowSums(select(PRE_Condition3, 12:20), na.rm = TRUE)
  )

#Creating Condition Remark

C3Scores <- cbind(Condition = ATAPOST3[[2]], C3Scores)

#Creating Depression POST score for condition 3

C3Scores <- C3Scores %>%
  mutate(
    DEPPOST = rowSums(select(DEPPOST3, 5:13), na.rm = TRUE)
```

```
  )


#Creating Well Being PRE score for Condition 3


C3Scores <- C3Scores %>%
  mutate(
    WBPRE = rowSums(select(PRE_Condition3, 22:35), na.rm = TRUE)
  )


#Creating Well Being POST score for Condition 3


C3Scores <- C3Scores %>%
  mutate(
    WBPOST = rowSums(select(WBPOST3, 5:18), na.rm = TRUE)
  )


#Creating PRE Ability to Adapt score for Condition 3


C3Scores <- C3Scores %>%
  mutate(
```

```
    ATAPRE = rowSums(select(PRE_Condition3, 36:45), na.rm = TRUE)
  )

#Creating POST Ability to Adapt score for Condition 3

C3Scores <- C3Scores %>%
  mutate(
    ATAPOST = rowSums(select(ATAPOST3, 5:14), na.rm = TRUE)
  )

#Removing 4 participants due to too low adherence to the intervention

PRE_Condition3 <- PRE_Condition3[-c(1, 2, 3, 15), ]
#Creating PRE Subset Data Condition 3

#Renaming the Dataset
Qualtrics_PRE <- Qualtrics_PRE_93_22_11_2024

#Creating the dataset only with Relevant Variables
Cleaned_PRE <- Qualtrics_PRE[, c(20:24, 26:31, 36:45, 53:66, 103:112)]
```

```
#Creating PRE Condition 3

rows_to_include <- c(1, 6, 8, 13, 15, 19, 20, 30, 31, 34, 38, 41, 45, 48, 58, 60, 74, 76, 81)

PRE_Condition3 <- Cleaned_PRE[rows_to_include, ]

#Creating PRE_ Condition 2

rows_to_include <- c(2, 4, 5, 9, 21, 23, 27, 33, 36, 37, 49, 51, 54, 55, 57, 61, 71, 73, 79, 82)

PRE_Condition2 <- Cleaned_PRE[rows_to_include, ]

#Creating PRE_Condition 1

rows_to_include <- c(7, 10, 12, 16, 25, 26, 29, 32, 43, 44, 50, 69, 77, 84)

PRE_Condition1 <- Cleaned_PRE[rows_to_include, ]

#Excluding Row 10 participant, due to not filling participant code
```

```
TIIM_Intervention_Condition_3 <- TIIM_Intervention_Condition3[-10, ]

#Excluding participant 15 from POST and intervention row, as he doesn't apper in TIIM Intervention condition with any data

TIIM_POST_Condition_1 <- TIIM_POST_Condition_1[-15, ]

TIIM_Intervention_Condition_1 <- TIIM_Intervention_Condition_1[-15, ]

#Excluding participant 10 from POST and intervention row, as he doesn't apper in TIIM Intervention condition with any data

TIIM_Intervention_Condition3 <- TIIM_Intervention_Condition3[-10, ]

TIIM_POST_Condition_3 <- TIIM_POST_Condition_3[-10, ]

#Rearranging rows in PRE_Condition 2 so that all participants have same row numbers across all Condition 2 datasets

PRE_Condition2 <- PRE_Condition2[c(
```

```
  1:5,     # Rows 1 to 5 remain unchanged
  7, 6,    # Switch rows 6 and 7
  10, 8, 9, # Move row 10 to 8, 8 to 9, and 9 to 10
  11:16,   # Rows 11 to 16 remain unchanged
  18, 17,  # Switch rows 17 and 18
  19:nrow(PRE_Condition2) # Remaining rows remain unchanged
), ]
PRE_Condition2 <- PRE_Condition2[c(
  1:7,     # Rows 1 to 7 remain unchanged
  10, 8, 9, # Move row 10 to 8, 8 to 9, and 9 to 10
  11:nrow(PRE_Condition2) # Remaining rows remain unchanged


  # Rearranging rows in PRE_Condition 3 so that all participants have the same row numbrs
across all Condition 3 datasets


  PRE_Condition3 <- PRE_Condition3[c(
    1,       # Row 1 remains unchanged
    3, 2,    # Swap rows 2 and 3
    4:12,    # Rows 4 to 12 remain unchanged
    16,      # Move row 16 to the 13th position
```

```
    13:15,   # Rows 13 to 15 follow
    17:nrow(PRE_Condition3) # Remaining rows remain unchanged
  ), ]
), ]

PRE_Condition3 <- PRE_Condition3[c(
  1:12,    # Rows 1 to 12 remain unchanged
  15, 16,  # Move row 15 to 13th, row 16 to 14th
  13, 14,  # Move row 13 to 15th, row 14 to 16th
  17:nrow(PRE_Condition3) # Remaining rows remain unchanged
), ]

# Rearranging rows in PRE_Condition 1 so that all participants have the same row numbrs
across all Condition 2 datasets

PRE_Condition1 <- PRE_Condition1[c(
  3, 4, 2, 5, 6, 7, 8, 1, 9, 10, 11, 12, 13, 14, 15:nrow(PRE_Condition1) # Rearranged rows
), ]
```

```
#Removing accidental 2 new rows

PRE_Condition1 <- PRE_Condition1[-c(15, 16), ]

#Combining datasets

PRE_Combined <- rbind(PRE_Condition1, PRE_Condition2, PRE_Condition3)

#Calculating Mean and SD of age

mean_col4 <- mean(as.numeric(PRE_Combined[[4]]), na.rm = TRUE)

sd_col4 <- sd(as.numeric(PRE_Combined[[4]]), na.rm = TRUE)

# Print the results

mean_col4

sd_col4

#Nationality check

library(haven)
```

```
column_10_numeric <- as.numeric(as_factor(PRE_Combined[[10]]))

count_value_1 <- sum(column_10_numeric == 1, na.rm = TRUE)

count_value_1

#Checking for educational level

column_8_values <- as.numeric(as.character(PRE_Combined[[8]]))

value_counts <- table(column_8_values)

value_counts

#Calculating mean, standard deviation and range of Condition 1

mean_col3 <- mean(C1Scores[[3]], na.rm = TRUE)

sd_col3 <- sd(C1Scores[[3]], na.rm = TRUE)

range_col3 <- range(C1Scores[[3]], na.rm = TRUE)
```

```
# Print the results

mean_col3

sd_col3

range_col3



# Calculate mean, standard deviation, and range for PRE Well_Being of Condition 1

mean_col5 <- mean(C1Scores[[5]], na.rm = TRUE)

sd_col5 <- sd(C1Scores[[5]], na.rm = TRUE)

range_col5 <- range(C1Scores[[5]], na.rm = TRUE)



# Calculate mean, standard deviation, and range for PRE Ability to Adapt of Condition 1

mean_col7 <- mean(C1Scores[[7]], na.rm = TRUE)

sd_col7 <- sd(C1Scores[[7]], na.rm = TRUE)

range_col7 <- range(C1Scores[[7]], na.rm = TRUE)



mean_col5

sd_col5

range_col5
```

```
mean_col7

sd_col7

range_col7



#Calculate mean, standard deviadion and range for Depression, Well being and Ability to Adapt for
Condition 2


#Depression

mean_col3 <- mean(C2Scores[[3]], na.rm = TRUE)

sd_col3 <- sd(C2Scores[[3]], na.rm = TRUE)

range_col3 <- range(C2Scores[[3]], na.rm = TRUE)


# Well-Being

mean_col5 <- mean(C2Scores[[5]], na.rm = TRUE)

sd_col5 <- sd(C2Scores[[5]], na.rm = TRUE)

range_col5 <- range(C2Scores[[5]], na.rm = TRUE)


# Ability to Adapt

mean_col7 <- mean(C2Scores[[7]], na.rm = TRUE)
```

```
sd_col7 <- sd(C2Scores[[7]], na.rm = TRUE)

range_col7 <- range(C2Scores[[7]], na.rm = TRUE)



cat("Column 3 - Mean:", mean_col3, "SD:", sd_col3, "Range:", range_col3, "\n")



cat("Column 5 - Mean:", mean_col5, "SD:", sd_col5, "Range:", range_col5, "\n")



cat("Column 7 - Mean:", mean_col7, "SD:", sd_col7, "Range:", range_col7, "\n")



#Calculate mean, standard deviadion and range for Depression, Well being and Ability to Adapt for
Condition 3



mean_col3 <- mean(C3Scores[[3]], na.rm = TRUE)

sd_col3 <- sd(C3Scores[[3]], na.rm = TRUE)

range_col3 <- range(C3Scores[[3]], na.rm = TRUE)



mean_col5 <- mean(C3Scores[[5]], na.rm = TRUE)

sd_col5 <- sd(C3Scores[[5]], na.rm = TRUE)

range_col5 <- range(C3Scores[[5]], na.rm = TRUE)
```

```
mean_col7 <- mean(C3Scores[[7]], na.rm = TRUE)

sd_col7 <- sd(C3Scores[[7]], na.rm = TRUE)

range_col7 <- range(C3Scores[[7]], na.rm = TRUE)



cat("Column 3 - Mean:", mean_col3, "SD:", sd_col3, "Range:", range_col3, "\n")



cat("Column 5 - Mean:", mean_col5, "SD:", sd_col5, "Range:", range_col5, "\n")



cat("Column 7 - Mean:", mean_col7, "SD:", sd_col7, "Range:", range_col7, "\n")



#Calculate mean, standard deviadion and range for Depression, Well being and Ability to Adapt for
Condition 1



mean_col4 <- mean(C1Scores[[4]], na.rm = TRUE)

sd_col4 <- sd(C1Scores[[4]], na.rm = TRUE)

range_col4 <- range(C1Scores[[4]], na.rm = TRUE)



mean_col6 <- mean(C1Scores[[6]], na.rm = TRUE)

sd_col6 <- sd(C1Scores[[6]], na.rm = TRUE)

range_col6 <- range(C1Scores[[6]], na.rm = TRUE)
```

```
mean_col8 <- mean(C1Scores[[8]], na.rm = TRUE)

sd_col8 <- sd(C1Scores[[8]], na.rm = TRUE)

range_col8 <- range(C1Scores[[8]], na.rm = TRUE)


cat("Column 4 - Mean:", mean_col4, "SD:", sd_col4, "Range:", range_col4, "\n")


cat("Column 6 - Mean:", mean_col6, "SD:", sd_col6, "Range:", range_col6, "\n")


cat("Column 8 - Mean:", mean_col8, "SD:", sd_col8, "Range:", range_col8, "\n")


#Calculate mean, standard deviadion and range for Depression, Well being and Ability to Adapt for
Condition 2


mean_col4 <- mean(C2Scores[[4]], na.rm = TRUE)

sd_col4 <- sd(C2Scores[[4]], na.rm = TRUE)

range_col4 <- range(C2Scores[[4]], na.rm = TRUE)


mean_col6 <- mean(C2Scores[[6]], na.rm = TRUE)

sd_col6 <- sd(C2Scores[[6]], na.rm = TRUE)
```

```
range_col6 <- range(C2Scores[[6]], na.rm = TRUE)


mean_col8 <- mean(C2Scores[[8]], na.rm = TRUE)

sd_col8 <- sd(C2Scores[[8]], na.rm = TRUE)

range_col8 <- range(C2Scores[[8]], na.rm = TRUE)


cat("Column 4 - Mean:", mean_col4, "SD:", sd_col4, "Range:", range_col4, "\n")


cat("Column 6 - Mean:", mean_col6, "SD:", sd_col6, "Range:", range_col6, "\n")


cat("Column 8 - Mean:", mean_col8, "SD:", sd_col8, "Range:", range_col8, "\n")


#Calculate mean, standard deviadion and range for Depression, Well being and Ability to Adapt for
Condition 3



# Calculate mean, standard deviation, and range for column 4 in C3Scores

mean_col4 <- mean(C3Scores[[4]], na.rm = TRUE)

sd_col4 <- sd(C3Scores[[4]], na.rm = TRUE)

range_col4 <- range(C3Scores[[4]], na.rm = TRUE)
```

```
# Calculate mean, standard deviation, and range for column 6 in C3Scores

mean_col6 <- mean(C3Scores[[6]], na.rm = TRUE)

sd_col6 <- sd(C3Scores[[6]], na.rm = TRUE)

range_col6 <- range(C3Scores[[6]], na.rm = TRUE)



# Calculate mean, standard deviation, and range for column 8 in C3Scores

mean_col8 <- mean(C3Scores[[8]], na.rm = TRUE)

sd_col8 <- sd(C3Scores[[8]], na.rm = TRUE)

range_col8 <- range(C3Scores[[8]], na.rm = TRUE)



# Print the results for column 4

cat("Column 4 - Mean:", mean_col4, "SD:", sd_col4, "Range:", range_col4, "\n")



# Print the results for column 6

cat("Column 6 - Mean:", mean_col6, "SD:", sd_col6, "Range:", range_col6, "\n")



# Print the results for column 8

cat("Column 8 - Mean:", mean_col8, "SD:", sd_col8, "Range:", range_col8, "\n")
```

```
#Counting ANOVA for Group 1



group_summary_1 <- C1Scores %>%

 group_by(Condition) %>%

 summarise(

   Mean_DEPPRE = mean(DEPPRE, na.rm = TRUE),

   Mean_DEPPOST = mean(DEPPOST, na.rm = TRUE),

   Mean_WBPRE = mean(WBPRE, na.rm = TRUE),

   Mean_WBPOST = mean(WBPOST, na.rm = TRUE),

   Mean_ATAPRE = mean(ATAPRE, na.rm = TRUE),

   Mean_ATAPOST = mean(ATAPOST, na.rm = TRUE)

 )



# View the summarized data

print(group_summary)



library(tidyr)



long_format_1 <- pivot_longer(group_summary_1,

                      cols = starts_with("Mean_"),
```

```
                names_to = c("Variable", "Time"),
                names_pattern = "Mean_(.*)(PRE|POST)")

head(long_format_1)

install.packages('afex')

library(afex)

combined_data <- bind_rows(
  C1Scores %>% mutate(Condition = "Control"),
  C2Scores %>% mutate(Condition = "Intervention1"),
  C3Scores %>% mutate(Condition = "Intervention2")
)

# Reshape the data into long format
long_format_data <- combined_data %>%
  pivot_longer(
    cols = c(DEPPRE, DEPPOST, WBPRE, WBPOST, ATAPRE, ATAPOST),
    names_to = "Variable_Time",
```

```
  values_to = "value"
 ) %>%
 separate(Variable_Time, into = c("Variable", "Time"), sep = 2) %>%
 mutate(
  Condition = as.factor(Condition),
  Time = as.factor(Time)
 )


str(long_format_data)
summary(long_format_data)


# ANOVA for depression scores
anova_dep <- aov_ez(
 id = "CODE",
 dv = "value",
 within = "Time",
 between = "Condition",
 data = long_format_data %>% filter(Variable == "DE")
)
```

```
summary(anova_dep)



anova_wb <- aov_ez(
  id = "CODE",
  dv = "value",
  within = "Time",
  between = "Condition",
  data = long_format_data %>% filter(Variable == "WB")
)



# Summary of the ANOVA for well-being
summary(anova_wb)



#Doing within groups comparisons
control_data <- long_format_data %>% filter(Condition == "Control")
intervention1_data <- long_format_data %>% filter(Condition == "Intervention1")
intervention2_data <- long_format_data %>% filter(Condition == "Intervention2")



# Control Group
t_test_dep_control <- t.test(
```

```
  value ~ Time,
  data = control_data %>% filter(Variable == "DE"),
  paired = TRUE
)
print(t_test_dep_control)

# Intervention 1
t_test_dep_intervention1 <- t.test(
  value ~ Time,
  data = intervention1_data %>% filter(Variable == "DE"),
  paired = TRUE
)
print(t_test_dep_intervention1)

# Intervention 2
t_test_dep_intervention2 <- t.test(
  value ~ Time,
  data = intervention2_data %>% filter(Variable == "DE"),
  paired = TRUE
)
```

```
print(t_test_dep_intervention2)



# Control Group

t_test_wb_control <- t.test(

  value ~ Time,

  data = control_data %>% filter(Variable == "WB"),

  paired = TRUE

)

print(t_test_wb_control)



# Intervention 1

t_test_wb_intervention1 <- t.test(

  value ~ Time,

  data = intervention1_data %>% filter(Variable == "WB"),

  paired = TRUE

)

print(t_test_wb_intervention1)



# Intervention 2

t_test_wb_intervention2 <- t.test(
```

```
  value ~ Time,
  data = intervention2_data %>% filter(Variable == "WB"),
  paired = TRUE
)
print(t_test_wb_intervention2)


install.packages('effsize')
library(effsize)



control_data <- control_data %>%
  mutate(
    Time = case_when(
      Time == "PPRE" ~ "PRE",
      Time == "PPOST" ~ "POST",
      TRUE ~ Time # Retain other time points as they are
    )
  )


control_diff_dep <- control_data %>%
```

```
  filter(Variable == "DE") %>%
  spread(Time, value) %>% # Create wide format
  mutate(Difference = POST - PRE) # Calculate differences


shapiro.test(control_diff_dep$Difference)


long_format_data <- long_format_data %>%
  mutate(
    Time = case_when(
      Time == "PPRE" ~ "PRE",
      Time == "PPOST" ~ "POST",
      TRUE ~ Time
    )
  )


intervention1_diff_dep <- intervention1_data %>%
  filter(Variable == "DE") %>%
  spread(Time, value) %>%
  mutate(Difference = PPOST - PPRE)
```

```
intervention2_diff_dep <- intervention2_data %>%
  filter(Variable == "DE") %>%
  spread(Time, value) %>%
  mutate(Difference = PPOST - PPRE)

#Normality Condition 2

shapiro.test(intervention1_diff_dep$Difference)

#Normality Condition 3

shapiro.test(intervention2_diff_dep$Difference)

#Homogeneity assumption check

library(car)
long_format_data <- long_format_data %>%
  mutate(
    Time = case_when(
      Time == "PPRE" ~ "PRE",
```

```
    Time == "PPOST" ~ "POST",
    TRUE ~ Time
   )
 )
long_format_data_dep <- long_format_data %>%
 filter(Variable == "DE") %>%
 spread(Time, value) %>%
 mutate(Difference = POST - PRE)

leveneTest(Difference ~ Condition, data = long_format_data_dep)

long_format_data_wb <- long_format_data %>%
 filter(Variable == "WB") %>%
 spread(Time, value) %>%
 mutate(Difference = POST - PRE)

leveneTest(Difference ~ Condition, data = long_format_data_wb)

#Checking Independence Assumption
```

```
residuals_dep <- residuals(anova_dep)


# Plot residuals to look for patterns
plot(residuals_dep, main = "Residual Plot (Depression)", ylab = "Residuals", xlab = "Fitted Values")
abline(h = 0, col = "red")


#Checking for moderation effect


combined_data <- combined_data %>%
  mutate(
    WellBeingChange = WBPOST - WBPRE,
    DepressionChange = DEPPOST - DEPPRE
  )


# Ensure Condition is a factor
combined_data$Condition <- as.factor(combined_data$Condition)


library(lmtest)


# Fit a linear model with an interaction term
```

```
moderation_model_wb <- lm(
  WellBeingChange ~ Condition * ATAPRE,
  data = combined_data
)

# Summary of the model
summary(moderation_model_wb)

# Fit a linear model with an interaction term
moderation_model_dep <- lm(
  DepressionChange ~ Condition * ATAPRE,
  data = combined_data
)

# Summary of the model
summary(moderation_model_dep)

# Fit a linear model with an interaction term
moderation_model_dep <- lm(
  DepressionChange ~ Condition * ATAPRE,
```

```
  data = combined_data

)



# Summary of the model

summary(moderation_model_dep)



#Running ANOVA



str(combined_data)



#Linear Mixed Model

install.packages("Matrix")

library(Matrix)

library(tidyverse)

library(lme4)

library(lmerTest)



# Model for Well-Being Change

wellbeing_model <- lm(

  WellBeingChange ~ Condition + ATAPRE + Condition:ATAPRE,
```

```
  data = combined_data
)
summary(wellbeing_model)

plot(wellbeing_model)

#Linear Mixed Model for Depression

library(nlme)

depression_model_alt <- lme(
  fixed = Depression ~ Condition * Time,
  random = ~ 1 | CODE,
  data = long_combined_data
)

summary(depression_model_alt)

#Linear mixed model for well-being
```

```
long_combined_data_wb <- combined_data %>%
  pivot_longer(
    cols = c(WBPRE, WBPOST),  # Specify columns for Well-Being
    names_to = "Time",        # Create a new column for Time
    values_to = "WellBeing"   # Create a column for the values
  ) %>%
  mutate(Time = ifelse(Time == "WBPRE", "PRE", "POST"))  # Rename for clarity


# Linear mixed model for well-being
wellbeing_model_nlme <- lme(
  WellBeing ~ Condition * Time,  # Fixed effects
  random = ~1 | CODE,           # Random effects for participants
  data = long_combined_data_wb   # Data
)


summary(wellbeing_model_nlme)


#Moderation model of Ability to Adapt to well-Being


moderation_wb_model <- lm(
```

```
  WellBeingChange ~ Condition * ATAPRE,
  data = combined_data
)
summary(moderation_wb_model)
```

Moderation model of Ability to Adapt to Depression

```
moderation_dep_model <- lm(
  DepressionChange ~ Condition * ATAPRE,
  data = combined_data
)
summary(moderation_dep_model)
```

#Mixed model Anova

```
long_data <- combined_data %>%
  pivot_longer(
    cols = c(DEPPRE, DEPPOST),  # Specify pre- and post-scores
    names_to = "Time",          # Create a new column for Time
```

```
  values_to = "Depression"    # Column for the outcome variable
 ) %>%
 mutate(Time = ifelse(Time == "DEPPRE", "PRE", "POST"))  # Clean up labels


install.packages("afex")
library(afex)


# Conduct the mixed-model ANOVA for Depression
anova_model <- aov_ez(
 id = "CODE",       # Participant identifier
 dv = "Depression", # Dependent variable (Outcome)
 within = "Time",   # Within-subject factor (e.g., Pre, Post)
 between = "Condition", # Between-subjects factor (e.g., Control, Interventions)
 data = long_data   # Your dataset in long format
)


# Print summary
summary(anova_model)


#Conduct mixed-model ANOVA for Well - Being
```

```
long_combined_data_wb <- combined_data %>%
  pivot_longer(
    cols = c(WBPRE, WBPOST),  # Specify columns for Well-Being
    names_to = "Time",        # Create a new column for Time
    values_to = "WellBeing"   # Create a column for the values
  ) %>%
  mutate(Time = ifelse(Time == "WBPRE", "PRE", "POST"))  # Rename for clarity


# Perform the repeated-measures ANOVA
anova_wb <- aov_ez(
  id = "CODE",              # Unique identifier for participants
  dv = "WellBeing",         # Dependent variable
  within = "Time",          # Repeated-measures factor (PRE, POST)
  between = "Condition",    # Grouping factor (Control, Intervention1, Intervention2)
  data = long_combined_data_wb
)


# View the summary of the ANOVA
summary(anova_wb)
```

```
# Save all objects in the environment

save(list = ls(), file = "all_dataframes.RData")
```