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Impact of the global pandemic upon young people's use of technology for emotion regulation

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ABSTRACT

Technology plays an increasingly prominent role in emotional lives. Researchers have begun to study how people use devices to cope with and shape emotions: a phenomenon that has been called *Digital Emotion Regulation*. We report a study of the impact of the COVID-19 pandemic upon young people's digital habits and emotion regulation behaviors. We conducted a two-wave longitudinal survey, collecting data from 154 university students both before and during the COVID-19 pandemic. During the pandemic, participants were subject to increased emotional distress as well as restrictions on movement and social interaction. We present evidence that participants' emotion regulation strategies changed and became more homogeneous during the pandemic, with participants resorting to digital tools when offline strategies were less available, while also becoming more emotionally dependent upon their devices. This study underscores the growing significance of the digital for contemporary emotional experience, and contributes to understanding the potential role for technology in supporting well-being during high-impact events.

1. Introduction

Emotions appear as subjective, physiological, and behavioral responses to opportunities and challenges in everyday life. In many cases, emotions occur unexpectedly due to events outside of our control. Often, these are everyday events, such as an email that brings good news, or a stressful period at work. People sometimes respond to emotions by attempting to change them - in other words, engaging in emotion regulation (ER) - for example by suppressing their feelings, venting about the stress to a co-worker or friend, or calming their nerves with a drink or sugary treat. People use a range of ER strategies that help them to influence the emotions they experience, the time at which they experience them, and how they experience them (Gross, 1998b). Our motivations to regulate emotions further depend on the context, e.g., we may want to regulate emotions when they are interfering with a goal (Gross, 2015), or in order to fulfill specific instrumental or social needs (Tamir, 2016), as well as when emotions are inadequate in a particular situation (Gross, 2002). The benefits of successful ER can range from lowering stress in the short term (Collins & Cox, 2014) to reducing long term risks of heart diseases (Suls & Bunde, 2005).

The sudden emergence of the COVID-19 pandemic profoundly changed the lives of people the world over. Restrictions imposed to curb the spread of the virus have included limitations in movement, mandatory remote work for large parts of the population, and limited

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access to friends and family. Several studies have investigated the far-reaching impact of the pandemic and these restrictions on people's physical and mental states, e.g., by looking at correlations between trust in authorities and personality traits and perceived stress (Yamada et al., 2021), the importance of mental health support systems (Clomén et al., 2020; Russo, Hanel, Altnickel, & van Berkel, 2021), and the importance of digital support for emotional well-being (Colasante, Lin, DeFrance, & Hollenstein, 2020). In particular, the disruption of mental health services has further aggravated the problem (World Health Organization, 2020). However, a limitation of many of these impact studies is that they were initiated after the pandemic had already started.

In this paper, we present the analysis and findings of a survey consisting of 17 questionnaires investigating different aspects of people's emotional lives and behaviors. We collected data from an undergraduate sample in two waves: Wave 1 (W1) from October 2019 through March 2020 (N = 154), and Wave 2 (W2) from May to June 2020 amidst the COVID-19 pandemic (N = 82). Out of the 17 questionnaires, we selected instruments that are directly concerned with ER and the use and impact of digital devices. We classify participants by their preferred ER strategies, and look at their Digital Emotion Regulation (DER) behavior, the importance of the mobile phone in their emotional lives, participants' awareness of their emotions, their belief in the malleability of emotions, and the changes in these measures across both waves. A Latent Profile Analysis (LPA) yields two distinctive classes of ER behavior in W1, and one class in W2. Our analysis shows that participants displayed significant changes in their use of digital devices to regulate emotions after the pandemic and lockdowns began, while their belief in emotion malleability and their awareness of emotions were consistently high across both waves. We unpack these results and discuss their implications in a broader technology context, stressing our role as researchers in human-centered computing to develop and design tools that can support emotional well-being while being highly adaptable in the face of unprecedented events.

The recent ubiquity of personal digital devices that enable us to connect to wide-reaching social networks, audiovisual content and information has placed a new powerful tool for ER into people's hands that serves a multitude of innate needs. Our work contributes to the study of DER (Wadley, Smith, Koval, & Gross, 2020) by contributing empirical data on the role of digital devices in users' management of emotional well-being. The contributions of our work are threefold: 1) we present a comprehensive analysis of a longitudinal study consisting of five surveys mapping digital habits and the impact of pandemic conditions on ER behaviors in an undergraduate sample; 2) our survey was designed before the start of the COVID-19 pandemic, and thus organically captures the pandemic's impact on behavior; and 3) we provide empirical evidence for the occurrence of (Digital) ER in-the-wild.

2. Background

Gross (1998b) argued that emotional response tendencies are often modulated, and introduced the "process model" of emotion regulation which has become widely used in emotion research. ER refers to the strategies individuals use to influence emotions they are experiencing or to change the way they experience and express these emotions (Gross, 1998b). ER can involve attempts to change emotion parameters such as latency, rise time, magnitude, duration, and offset of responses in behavioural, experiential, and psychological domains (Gross, 1998b).

2.1. Emotion regulation strategies

Gross (1998b)'s process model describes families of ER strategies categorized according to the stages of emotion generation in which they are deployed (Gross, 2013). Here we briefly introduce the six strategies that are measured by our survey tool, and on which our profile analysis is based. These strategies are: "Distraction", "Rumination", "Reappraisal", "Suppression", "Engagement", and "Arousal Control". De France and Hollenstein (2017) state that Distraction, Rumination, and Reappraisal directly impact the cognitive component of emotions, while Suppression and Engagement directly influence the behavioral component, and Arousal Control influences the physiological/arousal component.

Distraction is defined by the divergence of ones' attention away from the event that initiated the emotional response (Thiruchselvam, Blechert, Sheppes, Rydstrom, & Gross, 2011). It does not require cognitive engagement with the stimulus or the emotion it produces. Distraction results in reduced response to the emotional stimulus (Strauss, Ossenfort, & Whearty, 2016).

Rumination, contrary to distraction, describes an ER strategy that implies the redirection of attention towards the experienced feeling and the reaction resulting from it (Gross, 1998b). Rumination can occur repeatedly, with the goal to understand a negative feeling and its consequences, and be able to deal with it better (Broderick, 2005). However, the repeated engagement with negative feelings can lead to the development of associations with negative feelings, rendering repeated rumination a strong link to depressive disorders (Spasojević & Alloy, 2001).

Reappraisal describes an ER strategy that aims at reevaluating the event that triggered an emotion, thus revising its meaning (Webb, Miles, & Sheeran, 2012). It involves different cognitive processes, attention regulation, working memory, perspective-taking, and linguistic processing, thus requiring significant cognitive resources (Goldin, Moodie, & Gross, 2019; Gross, 2013). Studies have shown that successful reappraisal has a positive impact on long-term mental well-being (Garnefski & Kraaij, 2006).

Suppression is defined as an ER strategy influencing the behavioral component of the emotional experience that aims at decreasing the expression of emotional behavior (Gross, 2002). Suppression strategies often lead to effects opposite to the actual goal, by increasing physiological arousal (Campbell-Sills, Barlow, Brown, & Hofmann, 2006) and emphasising the undesired emotional experience (Gross, 1998a).

Engagement refers to an active ER strategy that aims to modify an emotional experience through intensifying the expression of the emotional experience (Kennedy-Moore & Watson, 2001). Controlling the expression of emotions has been shown to be a coping mechanism in stressful situations (Kennedy-Moore & Watson, 2001).

Arousal Control aims to control the physiological component (arousal) of emotional experiences. Studies have proven the effectiveness of this strategy, e.g., through the use of relaxation techniques (Hazaleus & Deffenbacher, 1986) such as special breathing behavior (Ley, 1999), which enable the experiencing person to directly influence the physiological component of the emotional experience.

2.2. Supporting emotion regulation through technology

Researchers, e.g., in Human-Computer Interaction (HCI), have explored how digital technology can support people in the regulation of their emotions. A review by Sadka and Antle (2020) highlights the opportunities and challenges of using digital devices for ER training. Digital devices allow for situated interventions given their ubiquitous nature, can support (long-term) engagement by embedding motivational elements, offer emotional representation, and can embed social features that allow for emotional sharing and support.

ER intervention work often builds on the goal of supporting end-users in achieving their (ER) goals. Harris and Nass (2011) describe how reappraisal, one of the aforementioned ER strategies, can be used to regulate emotions in driving contexts. Through a user study in a driving simulator, the authors show that a reappraisal strategy designed to dampen negative emotions following a frustrating driving event resulted in improved driving behaviour and fewer negative emotions as compared to the baseline condition (no ER) and a condition in which reappraisal actively focused on the negative actions of other road users. Miri et al. (2020) present a system that uses actuators attached to a person's abdomen to provide paced vibrations to which the user can synchronise their breathing. In addition to reducing anxiety when presented with a cognitive stressor, the results from Miri et al. (2020, pp. 1–12) highlight that individual differences, such as personality traits, can affect the efficacy of the assessed ER strategy.

ER intervention research can extend beyond a focus on individual users. For example, Kiskola et al. (2021) present a research-through-design study within the context of online news comments. The authors suggest that user interfaces can adapt according to the content of a comment as it is being written, inviting the user to reflect on their emotional state or the effect their comment may have on others. Such design interventions may help to reduce the number of uncivil messages posted in the comment sections of online news outlets. Benke, Knierim, and Maedche (2020) present a chatbot designed to provide emotion management in the context of remote teamwork. While they highlight several challenges in designing chatbots, their results provide initial evidence that chatbots could support ER at a team level. Taking a more reflective approach, Kou and Gui (2020) analysed forum posts of a popular competitive online game and mapped player utterances to ER strategies. Their results indicate that it is not just the gameplay that affects players' emotions but, in particular, their cooperation with teammates.

The potential of digital technologies to support emotion regulation is not limited to interventions and tools deliberately designed for ER. Recent research has observed emotion regulation involving a broad range of digital technologies (Wadley et al., 2020). For example, Eschler, Burgess, Reddy, and Mohr (2020) studied the use of smartphones and social media for emotion by people with depression, while Kelly, Cheng, McKay, Wadley, and Buchanan (2021) observed university students' use of technologies to alleviate feelings of homesickness. Games have also been a focus of recent ER research, with Sarsenbayeva, Tag, Yan, Kostakos, and Goncalves (2020) showing that people use video games to regulate emotions and use smartphones for this when other gaming devices are not available. These observations indicate that with the current prevalence of smartphones, a variety of DER strategies are widely accessible to people in daily life, highlighting the role that technology plays in people's emotional lives. In this paper, we set out to assess the role of digital technology in young people's emotion regulation and the changes to this role during a disrupting global event, COVID-19.

2.3. Placement of the study in the global pandemic

The global emergence of COVID-19 has drawn researchers to study the effects of the pandemic on numerous topics such as emotions and stress (Yamada et al., 2021), teleworking (Galanti, Guidetti, Mazzei, Zappalà, & Toscano, 2021; Russo et al., 2021), and learning (Almaiah, Al-Khasawneh, & Althunibat, 2020). In many cases, when the focus of the study of emotion is to track qualitative behavior through surveys or interviews (Tag, Goncalves, Webber, Koval, & Kostakos, 2021), the studies are initiated after the start of the pandemic and are intentionally created to effects of the pandemic, e.g., Lieberoth et al. (2021). While these studies are important, there are obviously some limitations to the scope and knowledge they can produce. First, specifically recruiting a cohort to explore a global event such as the pandemic and its effect has the potential to prime the subjects, making it difficult to build a comparison baseline. Another limitation is the timing and initiation of the research. As research projects were launched in response to the pandemic, many studies may have essentially missed their window to capture the initial responses and perceptions, and their changes in response to the pandemic.

3. Methodology

This paper presents research comprising a survey which was conducted across two waves, one prior to and one during the Covid-19 pandemic. While our sample of an undergraduate student cohort changed in size, all participants of the second survey were also participants in the first survey. Consequently, the first survey (Wave 1) provides an accurate baseline for investigating the sample's digital habits and ER behavior prior to the pandemic.

This study took place within the context of a Canadian university in Ontario.

Due to the COVID-19 pandemic, the university underwent restrictions and lock-downs in the spring of 2020. The university had suspended all in-person classes as of March 16th, 2020,[2] which continued beyond the end of Wave 2 of our study. While the students were studying on-campus for Wave 1 (W1), their locations were unknown for Wave 2 (W2). Out of the 154 students, 140 students (>90%) had responded to the survey by March 13th, 2020, i.e., three days before the university closure, and 15 days before the restrictions on social gatherings were introduced. For the remaining 14 students a time-code of submission was not recorded. A detailed timeline of the main events can be found in Fig. 1, containing information obtained from official sources.[3]

3.1. Procedure

This study sampled the experiences of a group of undergraduate students via a set of questionnaires, aimed at understanding how digital experiences and habits influence ER and well-being. Data for Wave 1 (W1) was collected from October 2019 through March 2020 ($N = 154$, $female = 130$, $male = 24$, $mean\ age = 19.2$yrs, $SD = 1.4$), while data for W2 was collected from May to June 2020 amidst the COVID-19 pandemic ($N = 82$, $female = 73$, $male = 9$, $mean\ age = 19.4$yrs, $SD = 1.7$) (see Fig. 1. All participants were recruited from a cohort of undergraduate Psychology students, who received partial course credit for their participation.

Our survey consisted of 17 separate questionnaires, of which 5 were not part of W1 but were added to W2 to measure the impact of the pandemic on participants' mental health. In this paper, we present the analysis of a subset of the surveys that examine ER profiles, digital behavior, and emotional experiences across W1 and W2, namely the *Regulation of Emotion Systems Survey (RESS)*, the *Digital Emotion Regulation Scale (DER)*, the *I Miss My Mobile Phone survey (IMMP)*, the *Awareness Subscale of the Difficulties in Emotion Regulation Scale (DERS)*, and the *Implicit Theories of Emotion Scale (ITES)*.

3.2. Measures

3.2.1. Regulation of Emotion Systems Survey - RESS

The Regulation of Emotion Systems Survey (RESS) by De France and Hollenstein (2017) is a reliable measure of six common ER strategies, containing 38 items that assess the propensity for using Distraction, Rumination, Reappraisal, Suppression, Engagement and Arousal Control to regulate emotions. As different ER strategies can have an influence on psychopathology, it is important not to look at individual strategies in isolation. The RESS aims at identifying a participant's particular ER strategy repertoire (a combination of the six strategies addressed by the items). To achieve comparable results, the RESS assesses all strategies on identical scales. Participants rate each item on a 5-point Likert scale, from 1 ("*never*") to 5 ("*always*"). The different strategies are presented in the survey in a fixed but non-sequential order; i.e., question 1 does not necessarily belong to concept 1. The full set of items can be found in Appendix A.1.

[2] https://www.queensu.ca/gazette/stories/principal-s-statement-suspension-undergraduate-classes, last accessed March 23, 2022.

[3] https://covid-19.ontario.ca/, https://www.kflaph.ca/Modules/News/search.aspx, https://www.cityofkingston.ca/resident/covid-19, https://www.queensu.ca/safereturn/, all last accessed March 23, 2022.

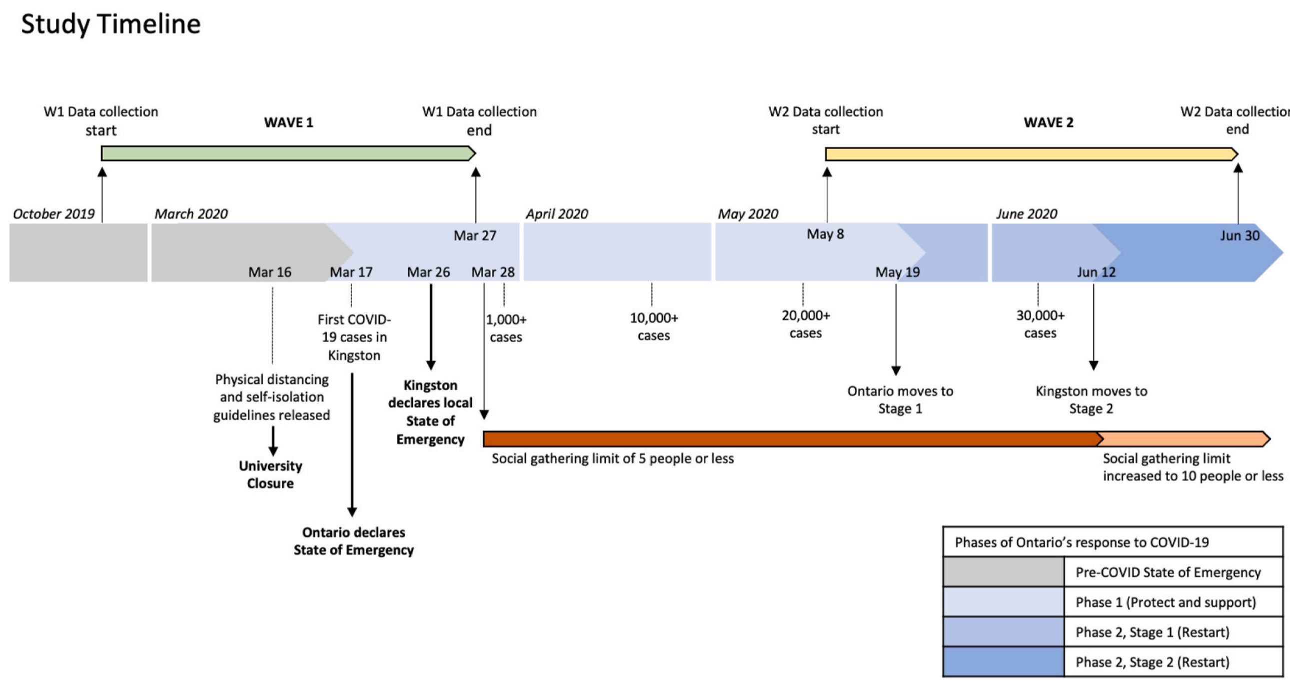

Fig. 1. Detailed study timeline, displaying the timing of the study waves W1 (green) and W2 (yellow), the development of the COVID-19 pandemic, and the responses and measures introduced by the government of Ontario and the university. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Latent Profile Analysis. To detect ER repertoires, we follow LPA best practices (Spurk, Hirschi, Wang, Valero, & Kauffeld, 2020), as well as De France and Hollenstein (2017)'s approach using LPA on the RESS scores. Compared to other clustering methods, LPA uses a set of variables to detect latent sub-profiles within a population. This means that sub-samples can be affiliated with different sub-profiles that are defined by different combinations of profile attributes. LPA has gained popularity in social and psychological sciences (e.g., Grommisch et al. (2020), but is not yet well-known in computing domains such as Human-Computer Interaction. For our example, this means that LPA will enable us to identify cohorts that are defined by a specific combination of propensities to using ER strategies, i.e., ER repertoires.

3.2.2. *Digital Emotion Regulation Scale - DER*

The Digital Emotion Regulation Scale (DER) was developed and validated for capturing a range of digitally-mediated ER strategies for which no one specific measure existed. The DER consists of nine items of the stem "*When I am upset or distressed, I use my digital devices (*e.g., *phone, tablet/iPad, computer, etc.) to* …". Participants indicate on a 5-point Likert scale from 1 (*not ever*) to 5 (*almost every time*) how frequently they used electronic devices in certain ways to help cope with strong emotions, e.g, to "*hide my feelings*" or "*look online to solve the problem*". Participants also have the choice to select "*no answer*". The full set of items can be found in Appendix A.2.

3.2.3. *I Miss My Mobile Phone - IMMP*

Mobile phones are affectively important to many people, especially young adults (Politou, Alepis, & Patsakis, 2017). The I Miss My Mobile Phone (IMMP) survey was developed to assess attachment to mobile phones, and emotional aspects of mobile phones and their role in our social and emotional life. Participants are asked to imagine that their mobile phones were unavailable for three days, and that they could not use any other digital device to substitute for the missing phone (Hoffner, Lee, & Park, 2016). The survey consists of two subscales (social and emotional), and a separate free response question. The social subscale assesses, on a 5-point Likert scale ranging from 1 (*not at all*) to 5 (*a great deal*), how much participants would miss being able to, e.g., "*communicate with family or friends*" or "*listen to music*" if they had no access to their phones for three days. Section 2 (Question 15) asks participants to fill in a free text form, answering "*What would you do more if you did not have access to your phone?*". The emotional subscale consists of fourteen items (emotions) that have to be assessed in response to the stem "*How would you feel during those 3 days without a cell phone?*". Participants answer on a 5-point Likert scale from 1 ("*not at all*") to 5 ("*very much*"), and have the option to select "*no answer*". Items are part of either of two emotion subscales, measuring negative or positive emotions. The full set of items can be found in Appendix A.3.

3.2.4. *Awareness Subscale of the Difficulties in Emotion Regulation Scale - DERS*

We used the Awareness subscale of the Difficulties in Emotion Regulation Scale (DERS), as developed and validated by (Gratz & Roemer, 2004). DERS is a multidimensional scale that aims at eliciting difficulties in ER by assessing dysregulation of emotions in a comprehensive manner. The full DERS covers four dimensions of emotions, "(a) awareness and understanding of emotions; (b) acceptance of emotions; (c) the ability to engage in goal-directed behavior, and refrain from impulsive behavior, when experiencing negative emotions; and (d) access to ER strategies perceived as effective" (Gratz & Roemer, 2004).

The Awareness subscale assesses lack of emotional awareness through six items that focus on the inclination to acknowledge and recognize emotions, i.e., "considering feelings as unimportant" (Kökönyei, Urbán, Reinhardt, Józan, & Demetrovics, 2014). Participants respond to each item by marking how often the phenomenon happens to them. The scoring happens on a 5-point Likert scale, with items indicating 1 "*almost never*" (0–10%), 2 "*sometimes*" (11–35%), 3 "*about half the time*" (36–65%), 4 "*most of the time*" (66–90%), to 5 "*almost always*" (91–100%). All items are reverse scored so that higher scores indicate a greater lack in emotional awareness (i.e., greater emotion dysregulation). The full set of items can be found in Appendix A.4.

3.2.5. *Implicit Theory of Emotions Scale - ITES*

The Implicit Theory of Emotion Scale was developed by (Tamir, John, Srivastava, & Gross, 2007). Based on the Implicit Theory of

Intelligence Scale by Dweck (1999), the ITES was created to discover whether people believe that emotions are fixed ("entity theorists") or malleable ("incremental theorists") (Tamir et al., 2007). According to Kappes and Schikowski (2013), different beliefs about emotions prompt different responses to emotions that lead to different outcomes, with generally more negative emotions and lower well-being for entity theorists. More importantly for our research, the ITES also allows for inferring why some people attempt to try and alter their emotions, and some do not.

Our participants were asked to rate the degree to which they agreed with each of the four ITES statements (two incremental items and two entity items) on a 5-point Likert scale from 1 ("*strongly disagree*") to 5 ("*strongly agree*"). To achieve a comparable score across these opposing items, we reverse score the two entity items in accordance with Tamir et al. (2007). Consequently, a high score indicates that the participant believes in the malleability of emotions, while lower scores point at entity theory beliefs. The full set of items can be found in Appendix A.5.

4. Results

4.1. Regulation of Emotion Systems Survey - RESS

We conducted a series of LPAs to identify ER strategy profiles in our sample in W1 and W2, following the best-practices described by (Spurk et al., 2020). To classify participants by their individual ER strategy repertoire, we used the R package *tidyLPA* (Rosenberg, Beymer, Anderson, van Lissa, & Schmidt, 2018). We input the raw data collected for each of the six ER strategies (Distraction, Rumination, Reappraisal, Suppression, Engagement, and Arousal Control), and ran combinations of models for goodness of fit. We used the MplusAutomation package[4] to interface to the MPlus statistical software,[5] which allowed us to extend the tested models to six.

For this analysis we only considered full datasets, i.e., we omitted all participants who either did not fully answer the RESS survey, or did not participate in W2 at all, leaving us with a total of $N = 80$ participants. We ran combinations of 10 classes and the 6 different models for goodness of fit, and based our classification on a hierarchical analysis that determined each model fit by comparing Akaike's Information Criterion (AIC), Approximate Weight of Evidence (AWE), Bayesian Information Criterion (BIC), Classification Likelihood Criterion (CLC), and Kullback Information Criterion (KIC) (Akogul & Erisoglu, 2017) statistics.

Cronbach's alpha showed consistently high values (>0.78) for all subscales, indicating high reliability. We further used Shapiro-Wilk tests to check for normality of response distributions. Half of the test showed non-parametric distributions. We inspected the skew and kurtosis of each distribution, together with the histograms. As all subscales have a $skew < 3$ and $kurtosis < 10$, and a visual inspection of the histograms did not show any problematic patterns, we used the Maximum Likelihood with robust standard errors (MLR) estimator (Spurk et al., 2020).

4.1.1. Wave 1

A summary of the descriptive statistics of the W1 sample can be found in Table 1. The LPA identified Model 1 with 2 classes as the best fit for our W1 sample. The results of the two-class model are presented in Figs. 2 and 3. Fig. 2 shows the mean values, SDs and confidence intervals (95%) of each class' ER strategy repertoire. While both classes present with a high propensity for Rumination, i.e., redirection of attention to negative emotions, Class 1 (N = 48) is characterized by 1) Arousal Control, Distraction, Rumination, and Suppression scores below the sample mean, 2) while Engagement and Reappraisal strategies were more prevalent than in Class 2. Class 2 on the other hand shows a very high propensity for using Suppression strategies, while Engagement and Reappraisal strategies are less prominent. In terms of the theoretical analysis of these strategies presented in Section 2.1, Class 2 shows tendencies to prefer less beneficial ER strategies over beneficial ones.

4.1.2. Wave 2

A summary of the descriptive statistics of the W2 sample can be found in Table 2. The LPA identified Model 3 with 1 class as the best fit for our W2 sample. The results of the one-class model are presented in Figs. 4 and 5. Fig. 4 shows the mean values, SDs and confidence intervals (95%) of the class' ER strategy repertoire. The LPA only identified one clear class in the sample of W2 (same participants as in W1). The class in W2 is defined by a relatively high propensity to Distraction and Rumination strategies, while propensity to Suppression and Engagement moved to the lower end of the spectrum. The main difference to W1 is that, except for Suppression, the other measures moved towards the average of the two classes in W1, i.e., in W2 distinct classes have disappeared.

4.1.3. Differences across waves

We have identified a two-class model for W1 and a one-class model for W2 for the sub-sample (no NA values) with identical participants across Waves. While our analysis elicits clear differences between the classes in W1, the ER strategy repertoires during W2 seems to be more homogeneous. A Wilcoxon signed rank test only identifies a statistically significant difference between the means of Rumination scores ($V = 1688.5$, $p < 0.01$), with Rumination scores being lower during W2. While other scores do not present with significant differences, we see minimal increases in mean Distraction and Arousal Control scores from W1 to W2. While it may be that the sample in W2 is too small for clearly establishing detectable distinctive classes, it is visible that people's repertoires of ER behaviors have not only changed but become less distinctive.

4.2. Digital Emotion Regulation Scale - DER

In this subsection we present the results of the Digital Emotion Regulation Scale (DER). All analyses were conducted in R. We conducted a tripartite analysis of the data collected in both W1 and W2, considering all DER items together (Table 3), the *personal subscale* (DER_1, DER_2, DER_3, DER_6, DER_8, DER_9), and the *social subscale* (DER_4, DER_5, DER_7). We calculated Cronbach's alpha for all three scales in both waves.

4.2.1. Wave 1

The mean score across all nine items of W1 was 3.12($SD = 0.56$), with a minimum score of 1.56 and a maximum score of 4.67. The items showed reliability with one another ($\alpha = 0.66$). A Shapiro-Wilk test indicated normal distribution. The mean score for the *personal subscale* was 3.31($SD = 0.64$), with a minimum score of 1.67 and a maximum of 4.83. Inter-item reliability was not given ($\alpha = 0.63$). We removed DER_09 from the scale, which presented with consistently low r ($r < 0.3$), which increased α to 0.66, changed the mean (3.40, $SD = 0.70$), and the minimum (1.40) and maximum (4.80) accordingly. DER_01, DER_02, DER_03, DER_06, DER_08 remained. A Shapiro-Wilk test indicated non-normal distribution. The mean score across the three *social subscale* items was 2.75($SD = 0.86$). The scores were distributed between the minimum score of 1.00 and the maximum of 5.00. The items of the social scale did not show inter-item reliability ($\alpha = 0.63$). We removed DER_05 from the scale, as it presented with consistently low r values ($r < 0.3$), leaving DER_04 and DER_07. This results in a corrected $\alpha = 0.78$, which indicates reliability, and a corrected mean (3.31, $SD = 1.10$), minimum (1.00), and maximum (5.00). A Shapiro-Wilk test indicated non-normal distribution.

[4] https://www.rdocumentation.org/packages/MplusAutomation/versions/1.0.0, last accessed March 23, 2022.
[5] https://www.statmodel.com/, last accessed March 23, 2022.

Table 1
Descriptive statistics for the whole sample, and the 6 subscales of the RESS survey of W1 (N = 80).

Wave 1 (overall)	Distraction	Rumination	Reappraisal	Suppression	Engagement	Arousal
Min.: 2.21	Min.: 1.25	Min.: 2.00	Min.: 1.13	Min.: 1.00	Min.: 1.00	Min.: 1.00
1st Qu.: 2.92	1st Qu.: 2.50	1st Qu.: 3.67	1st Qu.: 2.34	1st Qu.: 2.13	1st Qu.: 2.00	1st Qu.: 2.00
Median: 3.13	Median: 3.50	Median: 4.08	Median: 3.31	Median: 3.00	Median: 2.50	Median: 2.75
Mean: 3.15	Mean: 3.33	Mean: 4.03	Mean: 3.16	Mean: 3.06	Mean: 2.67	Mean: 2.72
SD: 0.40	SD: 0.97	SD: 0.84	SD: 0.92	SD: 1.00	SD: 0.93	SD: 0.94
3rd Qu.: 3.35	3rd Qu.: 4.00	3rd Qu.: 4.83	3rd Qu.: 3.88	3rd Qu.: 3.91	3rd Qu.: 3.38	3rd Qu.: 3.31
Max.: 4.26	Max.: 5.00	Max.: 5.00	Max.: 5.00	Max.: 5.00	Max.: 4.88	Max.: 5.00
α: 0.82	α: 0.90	α: 0.92	α: 0.96	α: 0.95	α: 0.94	α: 0.90

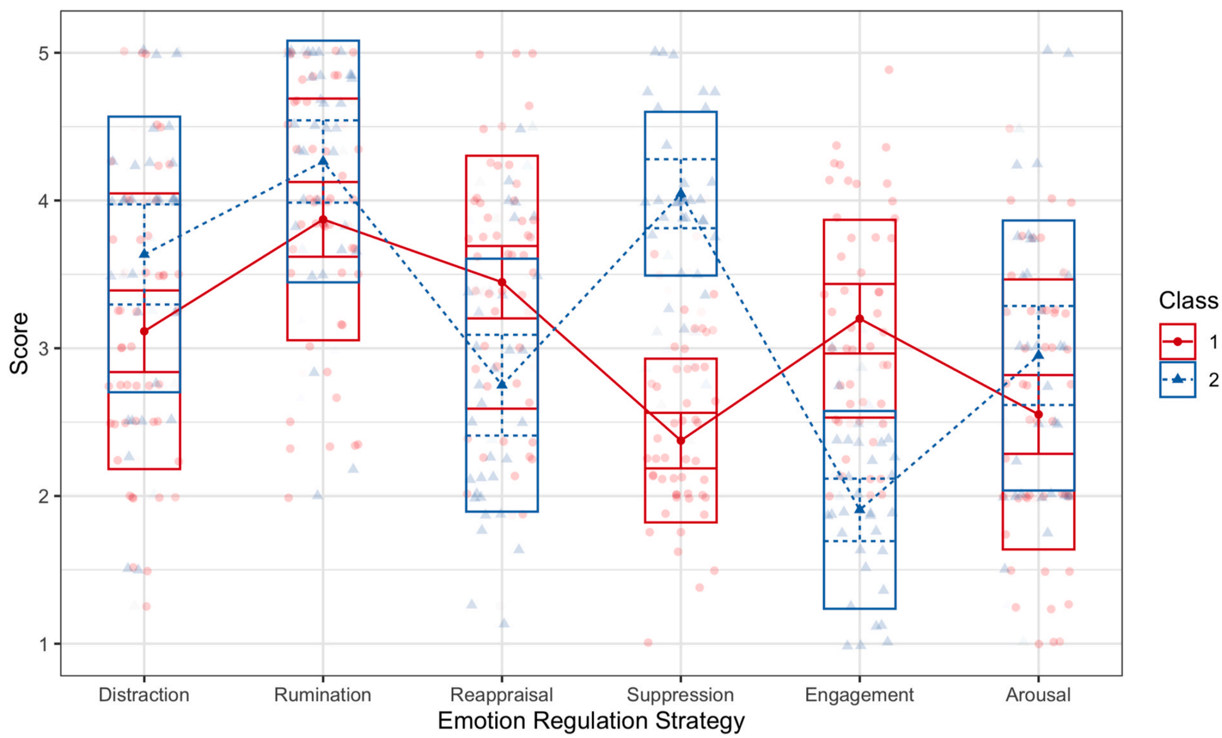

Fig. 2. Two-class Model of RESS ER strategies in W1. The graph presents mean, SD, confidence interval at 95%. The line in the color of each class connects the class centroids belonging to the same latent class. The red circles (Class 1, N = 48) and the blue triangles (Class 2, N = 32) in the background show the average ER strategy score (y-axis) for each participant. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

4.2.2. *Wave 2*

The mean score across all nine items of W2 was 3.09(SD = 0.78), with a minimum score of 1.13 and a maximum score of 5.00. The items showed reliability with one another (α = 0.82). A Shapiro-Wilk test indicated normal distribution. The mean score for the *personal subscale* was 3.49(SD = 0.90), with a minimum score of 1.67 and a maximum of 4.83. Inter-item reliability was high (α = 0.84). A Shapiro-Wilk test indicated normal distribution. The mean score across the *social subscale* items was 2.58(SD = 0.97). The scores were distributed between the minimum score of 1.00 and the maximum of 5.00. The items of the social scale were reliable (α = 0.67). A Shapiro-Wilk test indicated non-normal distribution.

4.2.3. *Differences across waves*

To detect significant changes from W1 to W2 in DER behavior, we conducted Wilcoxon signed-rank tests on each survey item across waves. There were significant mean differences for DER_02, "*using devices to hide feelings*" ($V = 351, p < 0.001$), DER_05, "*posting something about how the participant feels*" ($V = 91, p < 0.05$), and DER_07, "*seeking someone out for help*" ($V = 1032.5, p < 0.05$). These results are summarized in Fig. 6. The mean differences for using devices to "*help not to think about the situation*" (DER_10); "*help relax*" (DER_03); "*share feeling with someone directly*" (DER_04); "*help the participant to think about the situation more positively*" (DER_06); "*get away from the distressing situation*" (DER_08); or "*look online to solve the problem*" (DER_09), did not change significantly across waves.

4.2.4. *Summary*

Our analysis detected significant changes in the DER behavior of our sample from W1 to W2. The use of digital devices for hiding feelings (DER_02) and for posting about how the participant feels (DER_05) increased significantly during the pandemic. Interestingly, our data shows that participants were seeking others out for help less frequently during W2. Furthermore, while we see an overall decrease in the global mean scores between W1 and W2, we also detected a widening gap between the average minimum and maximum scores from W1 to W2.

4.3. *IMMP*

In this section, we analyze the "I Miss My Mobile Phone" survey. All analyses were conducted in R. The IMMP contains 29 questions, which were identical across W1 and W2, only differing in the period during which they were administered. Part 1 consists of 14 items asking for ("*How much would you miss each of the following?*"), part 2 requires a free

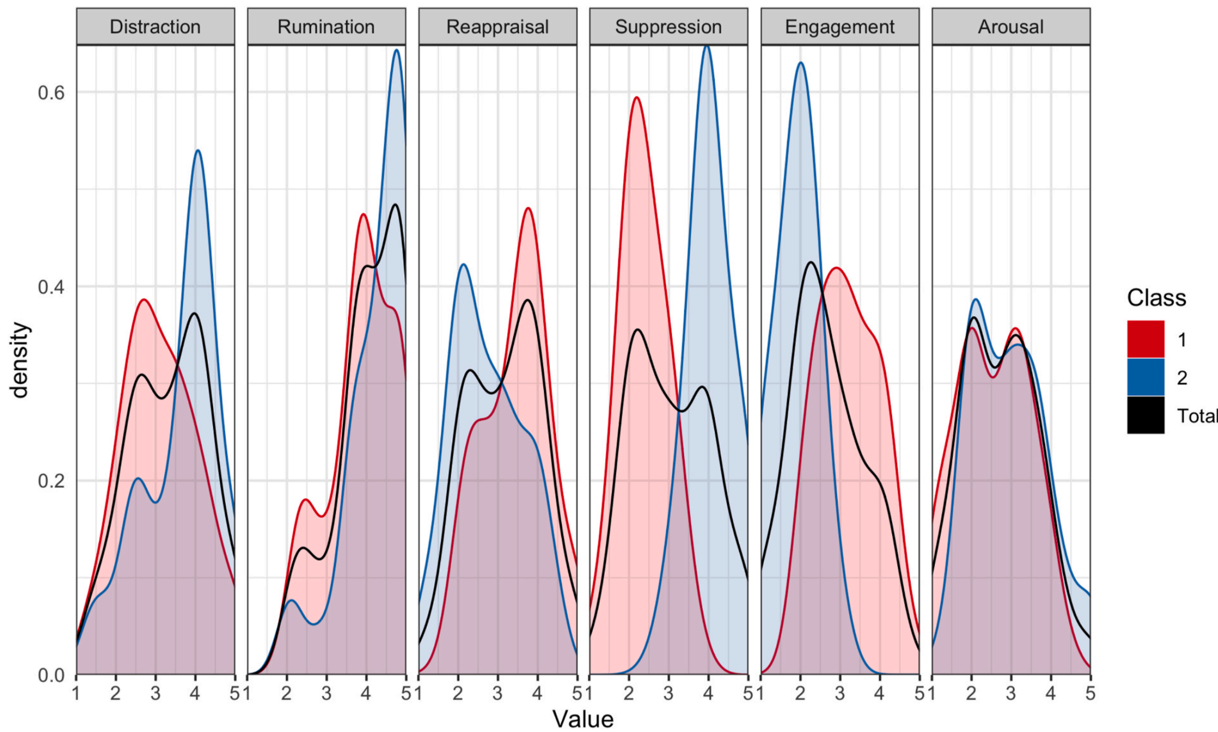

Fig. 3. Density plots showing the distribution of scores for each RESS ER strategy in our sample during W1. X-axis presents the likert scale scores.

Table 2
Descriptive statistics for the whole sample, and the 6 subscales of the RESS survey of W2 (N = 80).

Wave 2 (overall)	Distraction	Rumination	Reappraisal	Suppression	Engagement	Arousal
Min.: 2.00	Min.: 1.75	Min.: 2.00	Min.: 1.00	Min.: 1.13	Min.: 1.13	Min.: 1.00
1st Qu.: 2.69	1st Qu.: 2.94	1st Qu.: 3.17	1st Qu.: 2.25	1st Qu.: 2.00	1st Qu.: 2.22	1st Qu.: 2.00
Median: 3.01	Median: 3.50	Median: 3.83	Median: 3.00	Median: 2.75	Median: 2.63	Median: 2.75
Mean: 3.04	Mean: 3.42	Mean: 3.79	Mean: 3.09	Mean: 2.90	Mean: 2.64	Mean: 2.66
SD: 0.48	SD: 0.84	SD: 0.87	SD: 0.98	SD: 0.99	SD: 0.77	SD: 0.82
3rd Qu.: 3.34	3rd Qu.: 4.00	3rd Qu.: 4.50	3rd Qu.: 3.88	3rd Qu.: 3.66	3rd Qu.: 3.13	3rd Qu.: 3.25
Max.: 4.32	Max.: 5.00	Max.: 5.00	Max.: 5.00	Max.: 5.00	Max.: 4.38	Max.: 4.25
α: 0.89	α: 0.88	α: 0.91	α: 0.95	α: 0.95	α: 0.90	α: 0.78

text response to the question "*What would you do MORE of if you did not have access to your phone?*", and part 3 collects information on changes in 14 different emotions through the question stem ("*How would you feel during those 3 days without a cell phone?*". We do not consider part 2 of the IMMP (IMMP_15), because only 2.5% of all responses are referring to other digital technology use. The emotion subscale (Part 3) consists of a negative subscale (IMMP_17 through IMMP_24, IMMP_27, IMMP_28, and IMMP_29), and a positive subscale (IMMP_16, IMMP_25, and IMMP_26). We conducted a bipartite analysis on all items of part 1 and 2 across W1 and W2. A summary of the descriptive statistics for the overall sample can be found in Table 3.

4.3.1. *Wave 1*

The mean score across the 14 items of part 1 for W1 was 3.15(SD = 0.55), with a minimum score of 1.71 and a maximum score of 4.50. The items showed reliability with one another ($\alpha = 0.78$). A Shapiro-Wilk test indicated normal distribution. The mean score for the *negative emotion subscale* (11 items of part 3) was 2.83(SD = 0.84), with a minimum score of 1.09 and a maximum of 4.91. All items were reliable with one another ($\alpha = 0.91$). A Shapiro-Wilk test indicated normal distribution. The mean score for the *positive emotion subscale* (3 items of part 3) was 3.06(SD = 0.91), with a minimum score of 1.00 and a maximum of 5.00. All items were reliable with one another ($\alpha = 0.68$). A Shapiro-Wilk test indicated non-normal distribution.

4.3.2. *Wave 2*

The mean score across the 14 items of part 1 for W2 was 3.29(SD = 0.75), with a minimum score of 1.43 and a maximum score of 5.00. The items showed reliability with one another ($\alpha = 0.86$). A Shapiro-Wilk test indicated normal distribution. The mean score for the *negative emotion subscale* (11 items of part 3) was 3.06(SD = 0.98), with a minimum score of 1.09 and a maximum of 5.00. All items were reliable with one another ($\alpha = 0.93$). A Shapiro-Wilk test indicated normal distribution. The mean score for the *positive emotion subscale* (3 items of part 3) was 2.70(SD = 0.98), with a minimum score of 1.00 and a maximum of 5.67. All items were reliable with one another ($\alpha = 0.78$). A Shapiro-Wilk test indicated non-normal distribution.

4.3.3. *Differences across waves*

To identify significant changes in how much participants would miss certain activities over a 3-day period without having access to their mobile phones, we conducted Wilcoxon-signed rank tests on each survey item of part 1 across waves. The tests detected significant mean differences for IMMP_02, "*miss playing games*" ($V = 87$, $p < 0.001$), IMMP_03, "*miss receiving* support *from others*" ($V = 655$, $p < 0.05$), IMMP_04, "*miss getting other people's perspectives*" ($V = 399.5$, $p < 0.05$), IMMP_05, "*miss sharing when bad things happen*" ($V = 199.5$, $p < 0.001$), IMMP_06, "*miss providing* support *to others*" ($V = 360$, $p < 0.001$), IMMP_07, "*miss sharing when good things happen*" ($V = 466.5$, $p < 0.01$), and IMMP_12, "*miss*

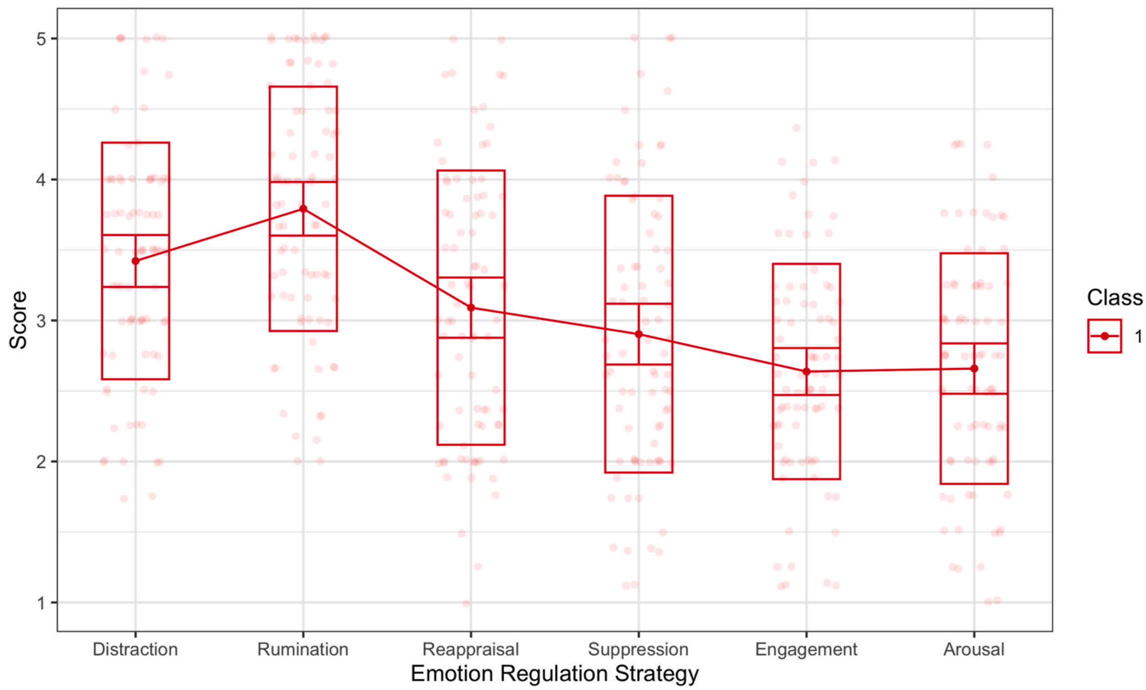

Fig. 4. One-Class Model of RESS ER strategies in W2. The graph presents mean, SD, confidence interval at 95%. The red line connects the class centroids. The red circles in the background show the average ER strategy score (y-axis) for each participant. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

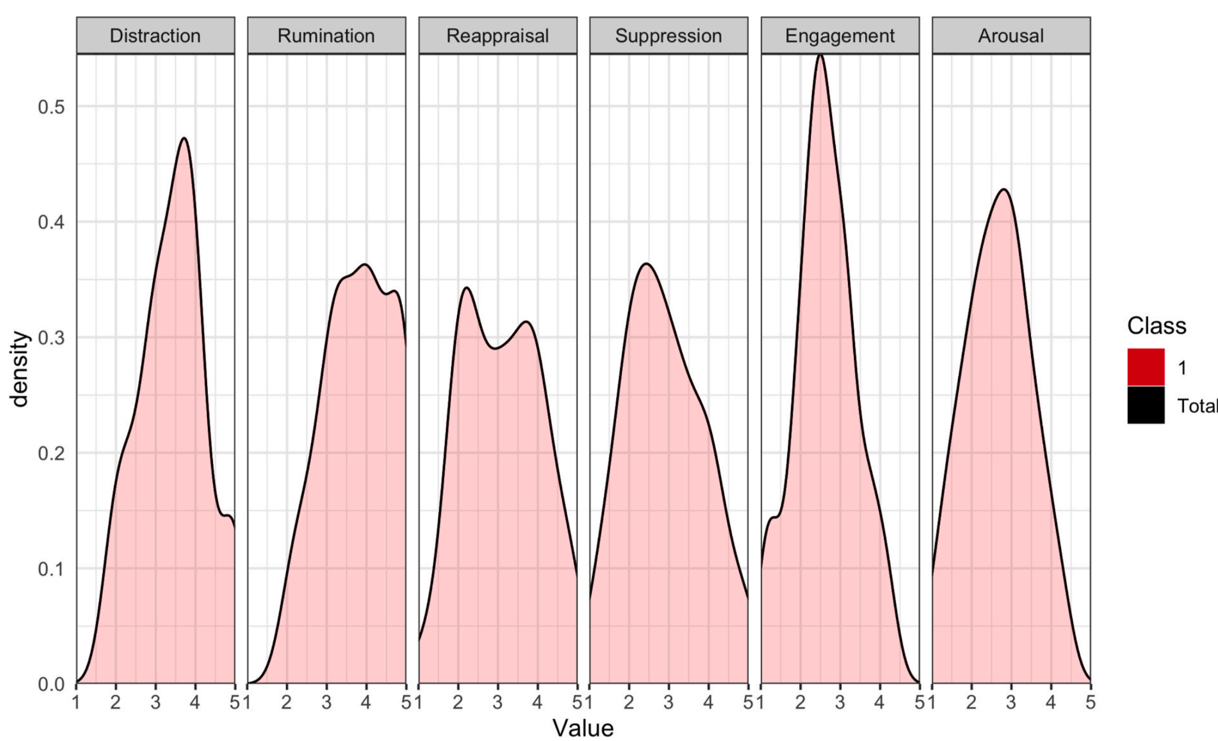

Fig. 5. Changes in Questions 2, 5, and 6 across waves.

listening to music" ($V = 591$, $p < 0.05$). These results are summarized in Fig. 7. The means for "*missing connecting with friends and family*" (IMMP_01), "*learning about breaking news*" (IMMP_08), "*keeping informed about current events*" (IMMP_09), "*watching videos or TV shows*" (IMMP_10), "*communicating with family or friends*" (IMMP_11), "*giving likes*" (IMMP_13), and "*receiving likes*" (IMMP_14) did not show any statistical differences.

Additionally, we looked at how people's emotions would change during those three days without their mobile phones. We conducted Wilcoxon-signed rank tests on the changes in means for each of the emotional scale survey items across waves. IMMP_16, "*happy*" ($V = 2803.5$, $p < 0.05$), IMMP_17, "*isolated*" ($V = 681$, $p < 0.05$), IMMP_23, "*sad*" ($V = 341$, $p < 0.01$), IMMP_24, "*depressed*" ($V = 246$, $p < 0.001$), and IMMP_28, "*lonely*" ($V = 603$, $p < 0.05$) showed statistically

Table 3
Summary of the descriptive statistics for the DER, IMMP, DERS, ITES surveys.

DER		IMMP		DERS		ITES	
Wave 1	**Wave 2**	**Wave 1**	**Wave 2**	**Wave 1**	**Wave 2**	**Wave 1**	**Wave 2**
N: 154	N: 82	N: 154	N: 82	N: 154	N: 82	N: 154	N: 82
NA's: 1	NA's: 1	NA's: 0	NA's: 1	NA's: 0	NA's: 0	NA's: 0	NA's: 1
Min.: 1.56	Min.: 1.13	Min.: 1.71	Min.: 1.43	Min.: 1.00	Min.: 1.00	Min.: 1.15	Min.: 1.50
1st Qu.: 2.78	1st Qu.: 2.63	1st Qu.: 2.79	1st Qu.: 2.75	1st Qu.: 1.67	1st Qu.: 1.67	1st Qu.: 3.00	1st Qu.: 3.25
Median: 3.11	Median: 3.13	Median: 3.21	Median: 3.29	Median: 2.00	Median: 2.17	Median: 3.75	Median: 3.75
Mean: 3.12	Mean: 3.09	Mean: 3.15	Mean: 3.29	Mean: 2.19	Mean: 2.31	Mean: 3.65	Mean: 3.65
SD: 0.56	SD: 0.78	SD: 0.55	SD: 0.75	SD: 0.84	SD: 0.93	SD: 0.78	SD: 0.76
3rd Qu.: 3.44	3rd Qu.: 3.50	3rd Qu.: 3.50	3rd Qu.: 3.86	3rd Qu.: 2.67	3rd Qu.: 3.00	3rd Qu.: 4.00	3rd Qu.: 4.00
Max.: 4.67	Max.: 5.00	Max.: 4.50	Max.: 5.00	Max.: 5.00	Max.: 5.00	Max.: 5.00	Max.: 5.00
α: 0.66	α: 0.82	α: 0.78	α: 0.86	α: 0.90	α: 0.92	α: 0.75	α: 0.75

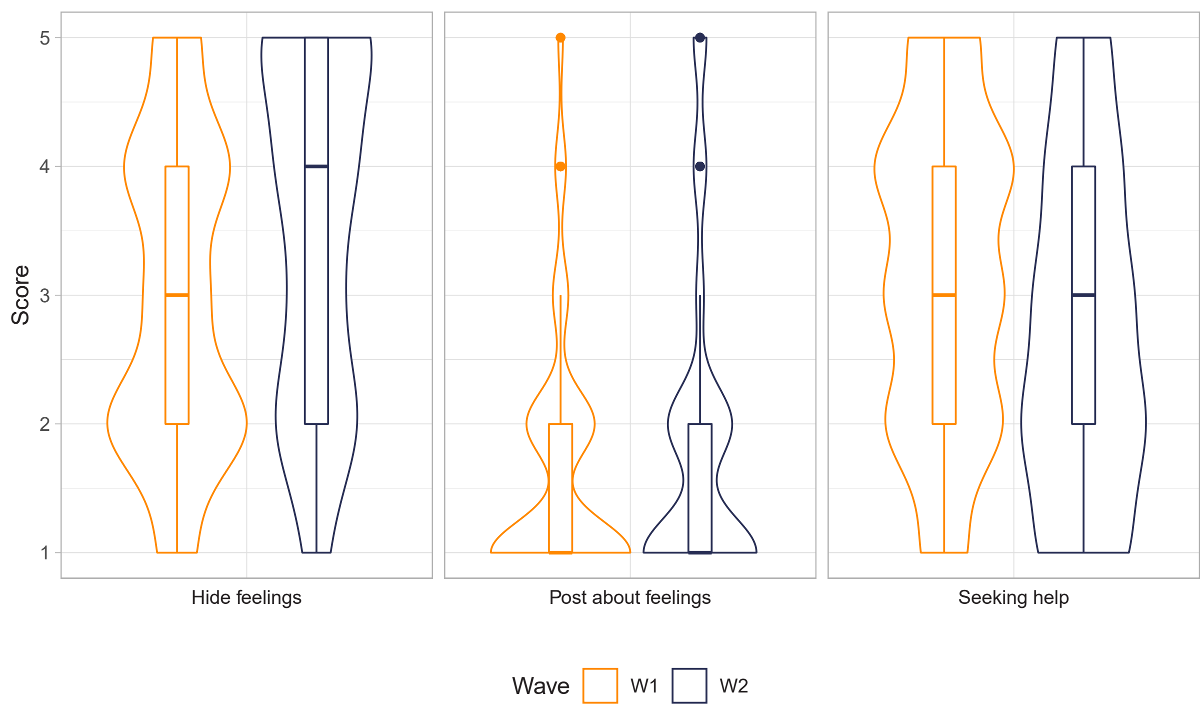

Fig. 6. Changes in Questions 2, 5, and 6 across waves.

significant changes in means. These findings are summarized in Fig. 8. The mean differences for "*anxious*" (IMMP_18), "*scared*" (IMMP_19), "*worried*" (IMMP_20), "*vulnerable*" (IMMP_21), "*insecure*" (IMMP_22), "*relieved*" (IMMP_25), "*proud*" (IMMP_26), "*bored*" (IMMP_27), and "*frustrated*" (IMMP_29) did not present with any statistically significant differences in means.

4.3.4. *Summary*

We found significant changes across W1 and W2 in responses to the IMMP. The overall mean between waves increased from W1 3.15($SD =$ 0.55) to W2 3.29($SD = 0.75$), indicating an increase in missing activities that participants use their phones for, were their phones not available. As shown in Fig. 7, during the pandemic (W2, dark blue), participants indicated that they would be increasingly missing activities such as playing games and listening to music. Furthermore, items addressing social interactions with others, e.g., receiving and providing support, also show significantly higher values, i.e., would be missed more. While the activities in the 14 items are equal in numbers between individual and social activities, our results show a clear emphasis of participants missing social activities comparably more than individual activities, if they had no access to their mobile phones.

Participants' scores also indicate significant changes in positive and negative emotions in response to a hypothetical unavailability of their mobile phones. Fig. 8 displays how happiness significantly decreases in W2, while feeling sad and depressed would occur more frequently. The other two significant changes in means, feeling isolated and feeling lonely, corroborate the findings of the missed opportunities to use the mobile phone for social interactions, e.g., sharing good and bad news. Overall, we see an increase in the occurrence of negative feelings from W1 2.83($SD = 0.84$) to W2 3.06($SD = 0.98$) and a decrease in overall positive emotions from 3.06($SD = 0.91$) in W1 to 2.70($SD = 0.98$) in W2.

4.4. *DERS*

In this section we analyze the Awareness subscale of the Difficulties in Emotion Regulation Scale (DERS) survey. All items are reverse scored, so that higher scores mean `lower` awareness and understanding of emotional signals. All analyses were conducted in R. All questions were the same and in the same order across waves. We calculated Cronbach's alpha in both waves. A summary of the descriptive statistics for the sample can be found in Table 3. Shapiro-Wilk tests indicate non-normality for scores in both waves.

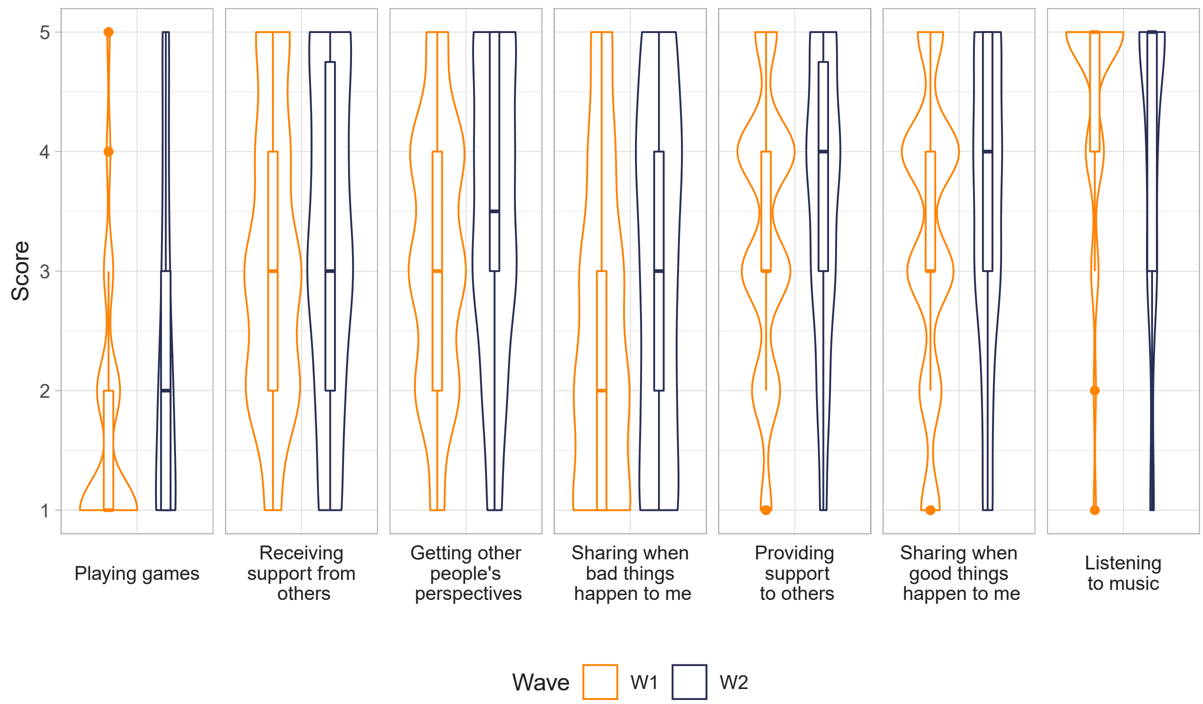

Fig. 7. Changes in how much participants miss specific activities, when not having access to their mobile phones for three days.

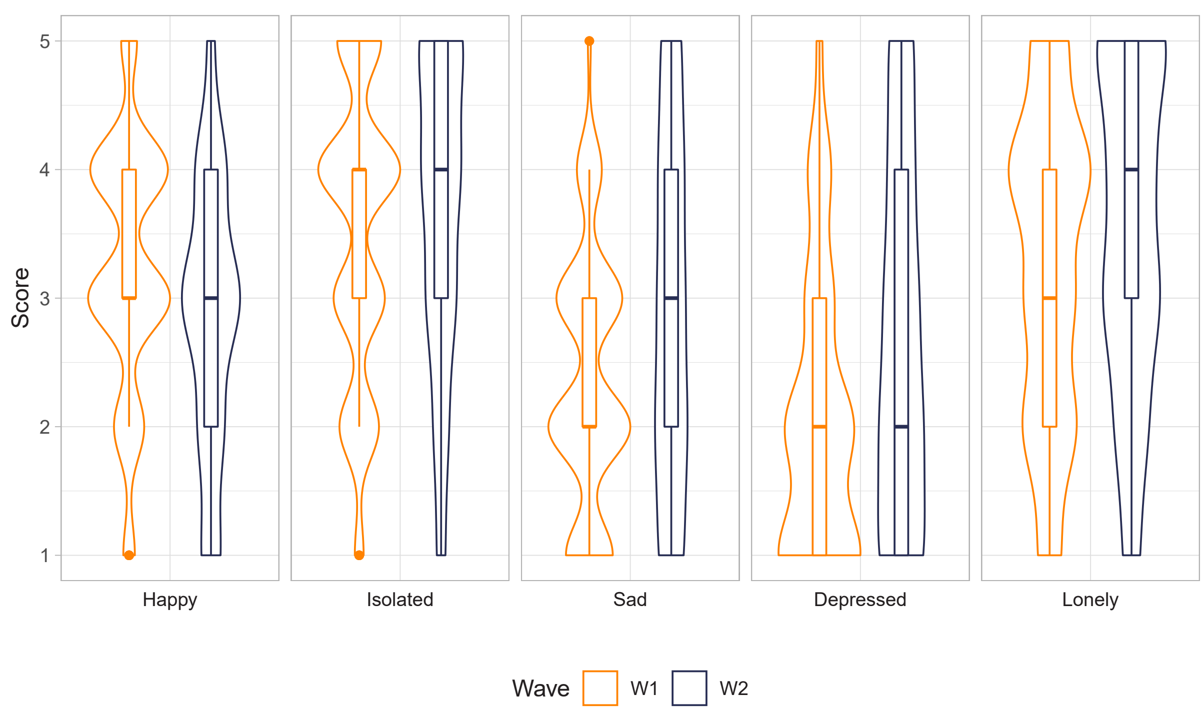

Fig. 8. Changes in emotions during the three days without access to personal mobile phones.

4.4.1. *Differences across waves*

To detect potentially significant differences in means in the lack of awareness of emotional responses, we conducted Wilcoxon-signed rank tests on each survey item across waves. The tests detected no significant mean differences for any of the six survey items across waves (Fig. 9).

4.4.2. *Summary*

We found no significant changes across W1 and W2 in the responses to the DERS Awareness subscale. The overall mean between waves increased slightly from W1 2.19($SD = 0.84$) to W2 2.31($SD = 0.93$). Overall awareness of emotional responses is high in our sample, as indicated by the low scores across the board (leaning towards 2: “most of the time”, 66–90% of the time). This means that the participants did not

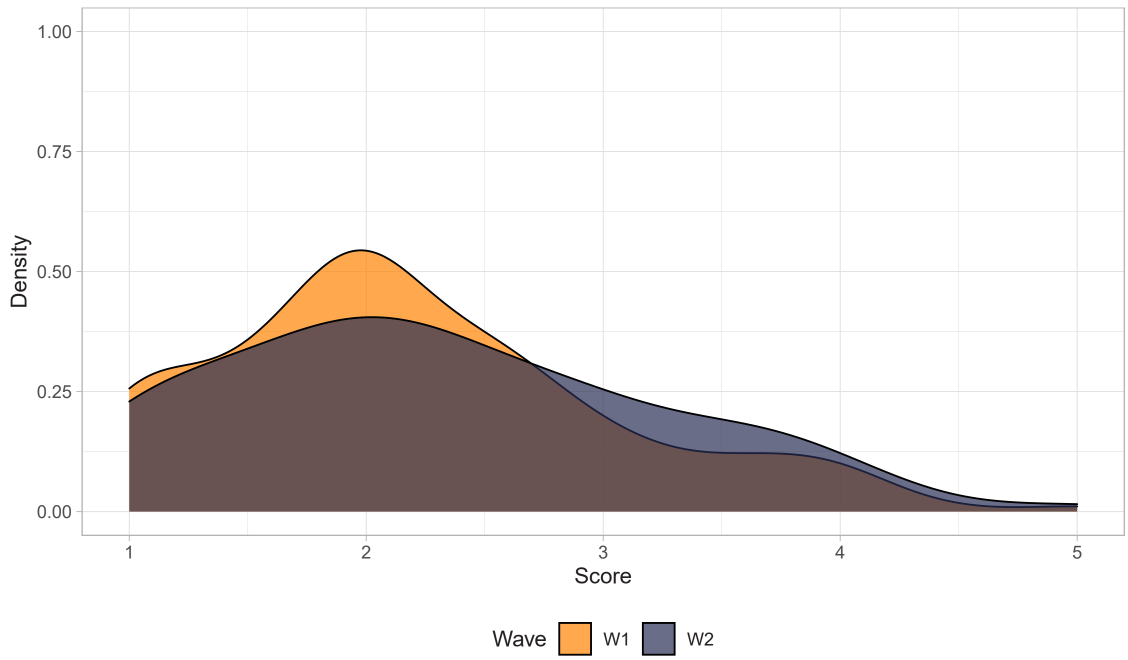

Fig. 9. Distribution of DERS scores across waves.

have frequent difficulties in noticing their emotions and feelings, both before the pandemic and during its first months.

4.5. ITES

In this section we analyze the results of the Implicit Theories of Emotion Scale (ITES) survey. Two of the four items are reverse scored, so that scores are comparable, with higher scores indicating incremental belief, i.e., seeing emotions as controllable and malleable. All analyses were conducted in R, and all questions were the same across waves. We calculated Cronbach's alpha for the scale in both waves. A summary of the descriptive statistics for our sample can be found in Table 3. Shapiro-Wilk tests indicated non-normality for scores in both waves.

4.5.1. Differences across waves

To detect changes in average belief in the malleability of emotions, we conducted Wilcoxon-signed rank tests on each survey item across both waves. The tests detected no significant mean differences for any of the four survey items (Fig. 10).

4.5.2. Summary

The overall ITES scores are high across both waves, indicating

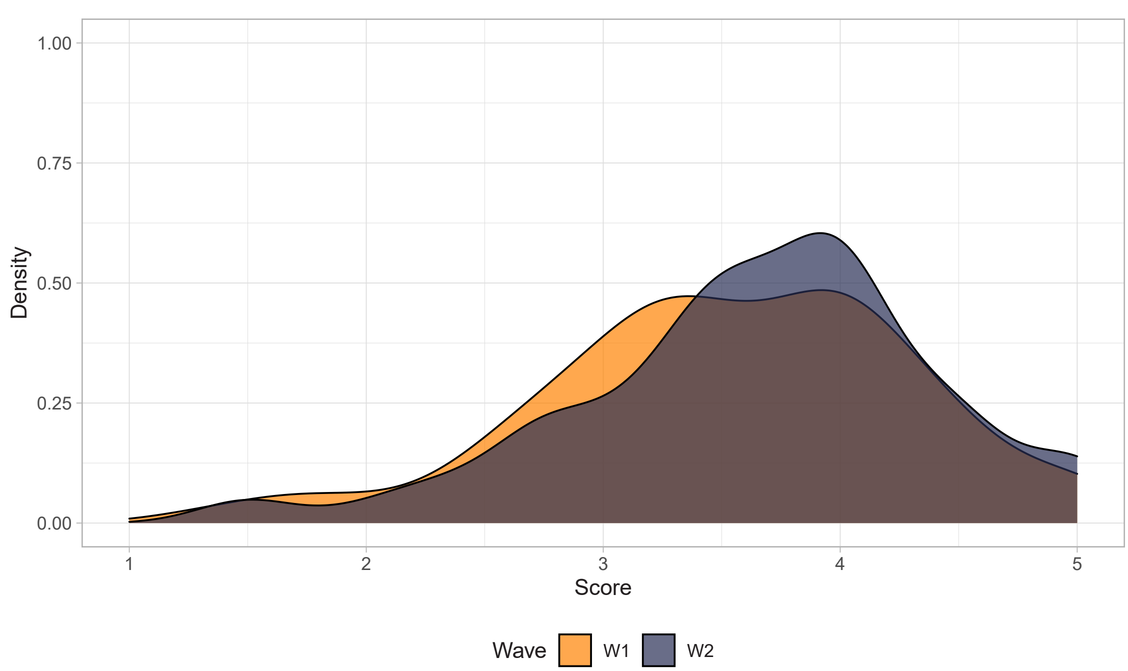

Fig. 10. Distribution of ITES scores across waves.

participants' belief in the malleability of emotions (Tamir et al., 2007). The means are identical in both waves (W1: 3.65, *SD* = 0.78; W2: 3.65 *SD* = 0.76). These that our participants lean towards strong agreement that emotions can be controlled and changed through personal effort, and that this belief was not affected by the onset of the pandemic.

4.6. Prediction of latent profile affiliation

In the last part of our analysis, we used a Logistic Regression model with a Probit Link Function to explore the relationship between the survey questions and the class of the participants as identified by the LPA.

We prepared a Logistic Regression Model in order to explore the most influential survey questions on class membership. The regression was built inductively based on visualizations, and additions were stopped when AIC started to increase. The inductive method was chosen due to the sample size and the power required for logistic regression. There was no multicollinearity in the predictor values. McFadden's Pseudo R-squared value was 0.31. As summarized in Table 4, our model identified IMMP_24 ("*sad*"), DER_08 ("*get away from the distressing situation*"), and DERS_04 ("*When I am upset, I acknowledge my emotions*") as predictors for affiliation with Class 2. IMMP_13 ("*giving likes*") and DER_06 ("*help the participant to think about the situation more positively*") on the other hand, are strong indicators for Class 1 membership.

5. Discussion

5.1. Emotion regulation repertoires

We applied LPA to our W1 and W2 cohorts to identify ER strategy repertoires among the study participants. LPA classified our W1 sample into two classes with distinct ER profiles (Fig. 2), showing preferences for more and less beneficial strategies respectively. Interestingly, in W2 this distinction between classes disappears, as the LPA places all participants in one class (Fig. 4). It is possible that this is due to the impact of the COVID pandemic, as restrictions in movement also limited the options for ER via social engagement and engagement in offline activities and have increased the necessity of digital devices to serve these and other needs.

To better highlight the differences between the two classes, we label them according to patterns in class differences, similar to (De France & Hollenstein, 2017). We compare the subscale means with the sample mean of W1 (3.15, *SD* = 0.40), and classify propensities as *low* (scores >0.5*SD* below the sample mean), *average* (all scores within 1*SD* of the sample mean), and *high* (>1*SD* above the sample mean). Class 1 is characterized by a high Rumination propensity, and low Suppression and Arousal Control propensities, while Class 2 shows a profile with high Distraction, Rumination, and Suppression propensities, while Engagement and Arousal control are low. Propensity to Arousal Control is low in both of our classes, whereas Engagement is at an average level in Class 1, but low in Class 2. Reappraisal strategies are at an average propensity in both classes.

It becomes clear that Rumination is the dominant ER strategy in our sample. Gross (1998b) describes Rumination as the redirection of attention towards experienced emotions and the reaction that results from them. As we highlighted in Section 2.1, repeatedly focusing on negative emotions in order to understand them can be detrimental to long-term mental health and contribute to the development of depressive disorders (Spasojević & Alloy, 2001). While this does not have to be the case in our sample, the high propensity of Rumination strategies across Waves (Table 2, Figs. 4 and 5) indicates long-term use of Rumination.

Table 4
Results of our Logistic Regression Model identifying predictors for affiliation to Class 1 or Class 2, as detected by the LPA for W1. Positive estimates indicate predictors for affiliation to Class 2, negative estimates to Class 1.

Question	Estimate	Std. Error	p-value
IMMP_13	−0.4193	0.2141	0.050
IMMP_24	0.4263	0.1800	0.018*
DER_06	−0.4867	0.2037	0.017*
DER_08	0.5989	0.2170	0.006**
DERS_04	0.6382	0.1910	0.001***

A major difference between the two W1 classes is the propensity for Suppression strategies. Suppression aims at decreasing the expression of emotional behavior; however, it tends to enhance undesired emotional experiences (Campbell-Sills et al., 2006; Gross, 1998a). While we see a major split in W1, with Class 1 showing a lower and Class 2 a higher propensity for Suppression strategies, interestingly, in W2 the Suppression mean lowers across the sample (Tables 1 and 2). This indicates that participants who tended to use Suppression strategies moved towards other ER strategies. Prior work has highlighted the effect that social context can have on an individual's ER strategy, with, e.g., English, Lee, John, and Gross (2017) showing that Suppression is more often used when other people are present, especially those to whom we are not closely connected, (e.g., unacquainted members of the same study group). It appears that lockdown conditions, instituted as part of national and global COVID countermeasures, reduced the diversity of ER strategies used by our sample. We hypothesize that this was due to a narrowing of the diversity of social and physical contexts experienced by participants in lockdown.

Last but not least, we see a dichotomy in the use of Engagement strategies between Class 1 and Class 2, which unifies in W2. As introduced in Section 2.1, Engagement is a coping strategy that aims at modifying emotional experiences, by expressing them, e.g., through vocalization (Kennedy-Moore & Watson, 2001). While none of our classes show a high propensity for Engagement, members of Class 2 show significantly lower Engagement scores than members of Class 1. While the sample mean does not significantly change from W1 to W2, Figs. 2 and 4, clearly show how our sample's engagement behavior unified.

5.2. Digital technology for emotion regulation

According to psychologists, e.g., Tamir et al. (2007); Kappes and Schikowski (2013), there exist two implicit theories of emotion: people believe that emotions are either fixed (entity theory) or malleable (incremental theory). This has profound implications for ER, because according to Gross (2015)' process model, the intention to control and change one's emotion is a premise of ER. We used Tamir et al. (2007)'s ITES to map our sample's implicit theories. Our analysis shows that our sample presents with high ITES scores across the board, indicating belief in the changeability of emotions.

We furthermore tested our participants' ability to recognize their emotions, another requirement for ER. Our analysis of the responses to the Awareness subscale of the DERS (low scores in W1 and W2) clearly illustrates that our participants do not show signs of dysfunctional awareness of their emotions, i.e., they do not ignore their emotions but recognize them.

To get a concrete understanding of how technology use influences our sample's emotional lives and ER, we employed the Digital Emotion Regulation Scale (DER) and the I Miss My Mobile Phone (IMMP) questionnaire. Our analysis discovered significant changes in behavior across waves, and showed how the hypothetical absence of mobile phones influenced participants' emotional states. Sarsenbayeva, Marini, et al. (2020) have shown that smartphone use directly correlates with experienced emotions. Furthermore, these authors show a bidirectional causal relationship between emotions and smartphone use, i.e., not only does smartphone use result in emotional responses, but users also use smartphones to respond to emotional experiences.

The responses to the DER demonstrate the importance of digital devices for personal and social use. The only significant change on the personal subscale was an increase in using digital devices for "*hiding how one feels*". This is a potentially troubling finding because suppression of negative emotions does not seem to alleviate negative feelings (Gross & Levenson, 1997). In fact, in already depressed people, negative information may be less likely to be inhibited (Joormann & Gotlib, 2010). However, on the social subscale, we detect stronger use of digital devices to "*post about feelings*" and "*seeking someone out for help*". Especially the latter two corroborate the findings of the IMMP, which yielded the importance of mobile phones for emotion-relevant social interactions. During W2, indications that participants would miss the ability to "*share information about emotional events*", e.g., bad or good events, with others if they had no access to their phones, were significantly higher than in W1. We found similar developments for not being able to "*receive and providing emotional* support" (interpersonal ER (Zaki & Craig Williams, 2013)), as well as "*getting other people's perspectives*". On a more individual level, participants' scores indicate that the absence of their phones would make them miss the opportunity to "*play games*" and "*listen to music*" significantly more. As prior research has shown, video games (Sarsenbayeva, Tag, et al., 2020) and music (Randall, Rickard, & Vella-Brodrick, 2014) are popular and effective ER tools.

Clearly, the breaking off of social interactions, for example, by denying access to digital devices, or caused by restrictions imposed on our everyday life, causes people distress (Yamada et al., 2021). Our analysis of the IMMP, which also scrutinizes the impact of a missing phone on participants' emotional state, yielded significant changes across both survey waves. As Fig. 8 summarizes, participants' responses to the IMMP express significant differences in the hypothetical impact of a missing mobile phone on five emotions. The findings clearly show an overall worsening of the emotional state of our sample. Feeling '*isolated*', '*sad*', '*depressed*', and '*lonely*' were significantly stronger in W2, while scores for feeling '*happy*' were significantly reduced. This clearly demonstrates the importance of digital devices, especially mobile phones, in times of profound change, restrictions to movement and social contact, and uncertainty.

5.3. Implications

International organizations such as the United Nations and the International Red Cross and Red Crescent Movement warn that events of global impact, e.g., climate-related disasters (on Climate Change, 2021), as well as the risk for coronavirus mutations and similar infectious disease outbreaks, will increase in the future (Li et al., 2020). Furthermore, disasters are increasingly intersecting with one another (Walton & van Aalst, 2020). These developments will result in increased emotional strain on all people, not only on those who fall victim to these disasters. Our work shows that high-impact global events influence our behaviour and emotions, and illustrates the importance of digital devices for managing emotions. Restricted movement, limited access to social circles, or interruption to online interaction, however, can also be consequences of accidents, physical and mental health issues, or problems of technology access. Our results highlight that digital devices play a major role in supporting ER during hardships. Consequently, researchers and developers have an opportunity and obligation to design and study technology to support people during these tremendously challenging times (Tag, Webber, et al., 2021).

Our work highlights the need for context-dependent best practices. Technologies have to be sufficiently flexible and 'smart' to adapt to unprecedented changes in individuals' everyday lives (Sarsenbayeva et al., 2019). This is also a warning regarding the use of snapshots of individuals to predict how they will behave under stressful situations. We found that the range of emotion regulation strategies deployed by our participants became narrower after the pandemic started. This indicates the need for malleable and responsive technologies. One consequence could be that we have to reconsider the increasing reliance on machine learning algorithms trained on data collected in 'regular' times. These algorithms will not be able to immediately adjust to profound changes in their user's context. Furthermore, we have seen that people would have been emotionally worse off during the pandemic had they lost access to their phones and the services they provide. As a community, we have to ensure that this technology is accessible to all people, and that we consider and develop services while bearing potential extreme scenarios in mind.

5.4. Limitations

We recognize several limitations in our work. First, our sample is heavily biased towards females and consists exclusively of students. These aspects can influence the use of ER strategies. A striking feature of our sample are the average Reappraisal and low Arousal Control propensities in both classes and across both waves. The use of these strategies, sometimes called 'adaptive ER', tends to increase from late adolescence (18 years of age and above) (Zimmermann & Iwanski, 2014). Our sample has a narrow age-range (*mean age* = 19.2yrs, *SD* = 1.4) covering exactly that late adolescent period. It may thus be that our participants have not yet fully included these strategies in their ER repertoire.

Second, our sample is not fully balanced, with close to half of the participants dropping out during the study. In response to this, we limited our analysis of ER strategies (Section 4.1) to those who participated in both waves. While the challenging circumstances can explain the dropout of participants during the COVID-19 lockdown, the characteristics of those who continued their participation versus those who dropped out may differ.

In Section 4.6, we prepared a Logistic Regression model to identify potential predictors for class affiliation in W1. The sample size and power were too low to capture all meaningful survey questions that could explain class separation. While the current logistic regression indicates that there is a meaningful relationship between some of the survey questions and class membership, the results are not fully prescriptive.

The findings of the LPA, primarily the single class result for W2, could be subject to our sample size. While the same sample resulted in a two-class model during W1, detecting distinct latent behavior profiles during times of profound change (W2), may require a larger sample. W1 overlapped with a period in which COVID-19 became more prevalent from early January to March 2020, indicating that our findings might be even starker had their been greater separation between the two waves.

Lastly, we were unable to account for any potential confounds that were introduced between W1 and W2. Most relevant being the seasonal change between the two waves, a phenomenon that is known to affect emotion and contributing to recurrent depressive disorders (Partonen & Lönnqvist, 1998). However, given our participants' location (Northern hemisphere), the seasonal change shifted from Autumn to Spring, which is generally associated with a lift in mood.

6. Conclusion

We presented a comprehensive analysis of a longitudinal study consisting of five questionnaires measuring digital habits and their influence on the emotion regulation behaviors of a late adolescent undergraduate sample. Our survey organically encapsulates the impact of the start of the COVID-19 pandemic on the sample's behavior. Our analysis provides empirical evidence for (digital) ER in-the-wild and illustrates how one high-impact event influenced individual behavior. Our findings show clear evidence for the importance of digital devices in people's emotional lives. In times of social isolation and restricted movements, digital devices become increasingly vital to serving people's emotional needs, such as through receiving support from others. Our sample shows high awareness of their own emotions and a strong belief in the malleability of emotions. Our work provides a one-of-a-kind insight into the impact of the onset of the global pandemic on individual DER behavior, highlighting the growing importance of digital technologies in supporting mental well-being on a worldwide scale.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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A. Overview of measurement instruments

A.1. Regulation of Emotion Systems Survey - RESS

- Thinking again and again
- Expressing feelings
- Hiding feelings
- Showing I was upset
- Showing what I was feeling
- Slow heart rate and breathing
- Showing feelings
- Focusing on heart rate and breathing
- Keep busy
- Thinking about event again and again
- Vocalizing feelings
- Hide what I was feeling
- Doing something else
- Looking at different angles
- Concealing feeling
- Letting emotions show
- Going over event again and again
- Identifying different angles
- Telling others how I felt
- Looking from different perspective
- Thinking of other ways to interpret
- Working on something
- Using facial expressions
- Thinking of alternate ways to see situation
- Pretend I wasn't upset
- Effort to hide my feelings
- Deep breaths
- Continually thinking about event
- Engage in activity
- Decreasing tension
- Pretending not upset
- Making sure no one could tell
- Trying to decide what went wrong
- Thinking about what was bothering me
- Acting like not upset
- Trying to see different perspective
- Trying to think of more positive light
- Trying to see more positive light

A.2. Digital Emotion Regulation Scale - DER

Question stem "*When I am upset or distressed, I use my digital devices (*e.g., *phone, tablet/iPad, computer, etc.) to …*"

- Help me not to think about it
- Hide my feelings
- Help me relax
- Share my feelings with someone directly
- Post something about how I feel
- Help me think about the situation more positively
- Seek out someone to help me
- Get away from the distressing situation
- Look online to solve the problem

A.3. I Miss My Mobile Phone - IMMP

Section 1: Social Subscale:
Question stem: "*How much would you miss each of the following*".

- Connecting with friends or family
- Playing games
- Receiving support from others
- Getting other people's perspectives
- Sharing when bad things happen to me
- Providing support to others
- Sharing when good things happen to me
- Learning about breaking news
- Keeping informed about current events
- Watching videos or TV shows
- Communicating with family or friends
- Listening to music
- Giving likes
- Receiving likes

Section 2: Free Text Response.
Section 3: Emotion Subscale:
Question Stem: "*How would you feel during those 3 days without a cell phone?*"

- Happy
- Isolated
- Anxious
- Scared
- Worried
- Vulnerable
- Insecure
- Sad
- Depressed
- Relieved
- Proud
- Bored
- Lonely
- Frustrated

A.4. Awareness Subscale of the Difficulties in Emotion Regulation Scale - DERS

- I pay attention to how I feel.
- I am attentive to my feelings.
- I care about what I am feeling.
- When I'm upset, I acknowledge my emotions.
- When I'm upset, I believe that my feelings are valid and important.
- When I'm upset, I take time to figure out what I'm really feeling.

A.5. Implicit Theories of Emotions Scale

We made minor adjustments to the original ITES questionnaire (Tamir et al., 2007) to obtain a more personal form. For completeness we include the original formulation here in brackets.

Two items referring to the malleable nature of emotions (incremental theory):

- I (everyone) can learn to control my (their) emotions.
- If I (they) want to, I (people) can change the emotions that I (they) have.

Two items referring to the fixed nature of emotions (entity theory):

- No matter how hard I (they) try, I (people) can't really change the emotions that I (they) have
- The truth is, I (people) have very little control over my (their) emotions

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