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Emotion trajectories in smartphone use: Towards recognizing emotion regulation in-the-wild

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ABSTRACT

Emotion has long been acknowledged as an important part of technology user experience. More recently, research has begun to catalogue ways in which people use technology to manage and shape emotion. These have been characterised as emerging digital forms of a category of behaviour known to psychologists as emotion regulation. Since ædigital emotion regulationg may impact wellbeing, it is important to explore ways of studying it; however most studies to date have used self-report data and it remains unknown whether this behaviour can be studied objectively. To address this gap, we present findings from a field study that measured how joy unfolds during everyday smartphone use. We built a custom Android application that uses the front-facing camera to register emotions from facial features of 20 individuals, collected over 14 days. Our analysis of 266,002 observations yielded striking non-random patterns, which we analyse as potential indicators of digital emotion regulation. This study is an important first step towards assessing how digital emotion regulation unfolds in naturalistic settings. Our findings have implications for the design of technology and in particular, interventions for psychological wellbeing.

1. Introduction

Emotions are an integral part of human life, and occur as a set of subjective, behavioural, and physiological responses to challenges and opportunities experienced (Gross, 2002). They often appear unforeseen, as a consequence of events that originate outside of our control. In a new emerging research field at the intersection of Psychology and Human-Computer Interaction (HCI), *Digital Emotion Regulation* has indicated potential benefits of the availability and flexibility of smartphones in this regard. Wadley et al. (2020) postulate that technology today offers a plethora of ways to respond to and alter affective states such as emotions.

Broadly speaking, emotion generation is the affective response that occurs when we evaluate external events, while Emotion Regulation is a second-order response that occurs when the experiencing person evaluates and tries to change an emotion because it interferes with current goals (Gross, 2015). People have different innate motivations to regulate their emotions, such as hedonic, instrumental, or social needs (Tamir, 2016), as well as when emotions seem to be ill-matched to a given situation (Gross, 2002). If an emotion is understood to be jeopardizing a goal, different strategies can be used to regulate the emotion according to the situation, and observe its success (Gross, 2015).

Previous work has already shown that smartphones are used to fulfill other innate needs. For instance, in a 2015 analysis, Jones et al. (2015) showed that the patterns of smartphone use bear strong resemblance to desktop website browsing in the pre-smartphone era. This indicates that humans seek information with whichever technology is available to them. Smartphones' "anytime, anyplace" access to information has made them constant companions to humans (Dey et al., 2011). Consequently, it would be surprising if they were not used to also proactively modify our emotions. In previous work, Sarsenbayeva et al. (2020a) show that smartphone use and emotional states correlate and that the causality of this effect is bidirectional. While this study yields that smartphone use leads to emotional outcomes, the authors also demonstrate that emotions drive smartphone and app use. In other words, smartphones are instruments that are used to generate and shape our

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emotions. The study provides evidence for the existence and direction of this effect but does not provide details of exactly how this behaviour unfolds, and what kind of patterns and strategies users adopt.

Prior research has provided evidence for the use of smartphones for Emotion Regulation, but this has usually relied on self-reports, *e.g.*, Hoffner and Lee (2015). There are no guidelines on how to automatically and objectively identify and quantify instances and patterns of Digital Emotion Regulation on smartphones. Based on this and the recent call to action in psychology (Colombo et al., 2019, 2020) to start using available technology to study user behavior such as Emotion Regulation, we present an exploratory study which analyses changes in users' levels of expressions of joy during smartphone usage. We analyse data collected over two weeks in-the-wild from 20 participants. We developed an Android smartphone application that uses the front-facing camera to estimate values of joy from the users' facial expressions at 30Hz while the phone is unlocked. In our analysis, we identify how individual expressions of joy fluctuate during smartphone use, and how these patterns vary across participants and over time. Our work proposes a novel methodology to detect patterns of emotional change within phone sessions in a longitudinal in-the-wild study, contributes to understanding how smartphones are potentially used to address our innate need for Emotion Regulation, and shows that consumer technology is able to detect non-random emotion patterns in naturalistic settings.

Beyond the short term effects, such as stress release (Collins and Cox, 2014), proactively changing ones emotion, e.g., increasing positive emotion and down-regulating negative emotions, has been shown to have positive long-term effects as well, *e.g.*, by lowering the risk of heart diseases (Suls and Bunde, 2005). Given these important implications of emotions and their regulation for mental and physical health, our work offers a tantalising new avenue toward quantifying and classifying the impact of distinct patterns of smartphone usage upon their users' emotional trajectories, thus suggesting another step towards unobtrusive and continuous support of mental and physical health.

2. Related works

2.1. Sensing emotions

Traditionally, self-reports are used to assess emotions, commonly by asking an individual to evaluate their feelings according to valence-arousal dimensions (Picard, 2009). Several techniques have employed valence-arousal dimensions to assess emotional states including the circumplex model of affect (Russell, 1980), the photographic affect meter (Pollak et al., 2011), the positive and negative affect schedule (Watson et al., 1988), and the self-assessment manikin (Lang et al., 1993); however, researchers are still in search of an automatic, trustworthy, and robust emotion detection technology (Colombo et al., 2019, 2020).

Emotion sensing has recently attracted significant attention from HCI research and scholars suggesting that everyday ubiquitous technology can be successfully used for emotion detection (Mehrotra et al., 2017; Tag et al., 2021; Yang et al., 2020; Zhang et al., 2018). For example, in a study by Bailenson et al. (2007), the researchers examined how participants communicated different emotions using a force-feedback joystick. They quantified the communication of different participants using the following measures: x- and y-coordinates of the joystick (position at every 5ms), movement direction, speed, distance, acceleration, and jerkiness. Their results show that distance, speed, and acceleration were significantly greater for joy and anger than for sadness.

Nowadays smartphones are equipped with a wide variety of sensors (*e.g.,* accelerometer, gyroscope, proximity sensor, microphone, battery) that can be successfully utilised to detect users' external (Aram et al., 2012; Overeem et al., 2013) and internal contexts including emotions (Burns et al., 2011). This was demonstrated in a study by Lee et al. (2012) where the authors used smartphone sensor data (GPS, keyboard, accelerometer) to unobtrusively sense user emotional states. Although the data collection in this study was limited to only one participant, the authors reported a 67.52% emotion detection rate (Lee et al., 2012). Ruensuk et al. (2020) have used motion sensors, eye-tracking (specific to certain Android phones), and touch interaction to infer emotions of smartphone users. While their machine learning models achieved high accuracies of up to 94.16% for self-reported valence and arousal values, the high computational demand drained the device battery significantly. The authors reproduced their findings in an extension of the first study by asking participants to use Facebook for 25 min in the lab to simulate naturalistic behavior. However, the authors admit that this design may have resulted in atypical behaviors. A study by Zhang et al. (2018) focuses on the multi-level classification problem of compound emotions, *i.e.*, multiple basic emotions. In their work, the researchers correlated self-reported emotional states with smartphone sensor data (*e.g.*, microphone, light sensors, GPS, WiFi, accelerometer, etc.) and usage patterns (*e.g.*, app usage logs, calls, SMS). A major limitation of this approach is that the initial data collection and training periods necessary take a long time, preventing a wide adoption.

Another approach was proposed by Bardram et al. (2012) and Frost et al. (2011), who developed MONARCA, a system designed for people with bipolar disorder to track whether any of their daily activities trigger particular emotional states (*e.g.,* whether sleep deprivation leads to negative emotions). However, the system did not achieve any significant improvements for the patients. A study by Springer et al. (2018), presented a system called EmotiCal, using a similar approach to MONARCA. The system used the Daily Reconstruction Method (DRM) to collect data on activities and mood. The researchers were successful in predicting user moods depending on the user activities and were able to develop individual models of activities influencing mood (Springer et al., 2018). In a study by Stone et al. (2006) DRM was used to detect diurnal cycles of positive and negative emotions among 909 women over a working day. While positive emotions peaked at noon and in the evenings, negative emotions showed mid-morning and mid-afternoon peaks. The authors could replicate different diurnal patterns from prior studies. Hasler et al. (2008) used a portable audio recorder (EAR) that periodically recorded environmental sound samples in a longitudinal field study. The authors used the audio samples to detect different behaviors of the participants wearing the EAR devices. Through their work, Hasler et al. (2008) validated previous findings of diurnal patterns of positive affect in naturalistic settings. A more recent longitudinal study used facial expressions in work environments, obtained through stationary cameras in an office, to infer changes in negative affect in an everyday setting. The authors, McDuff et al. (2019), relate their findings to two specific Emotion Regulation strategies, namely cognitive reappraisal and suppression. While narrowing their argument to these two strategies, the authors show that facial expressions describe a valid approach to observe emotional changes in-the-wild.

Given the trade-offs of different approaches, we chose to use the Affectiva API[1] using the front-facing camera of smartphones. This software is able to capture seven basic emotions using solely image recognition: anger, contempt, disgust, fear, joy, sadness, and surprise. While this does not make extensive use of all available smartphone sensors, it is a technology that is readily available to study participants and does not require any proactive input by the user or periodical interaction (as *e.g.*, Experience Sampling Method (ESM) studies), or additional hardware (*e.g.*, a joystick), thus, lowering the overall burden on the user. The Affectiva API has been benchmarked and validated (Stöckli et al., 2018), and more recently two separate studies have shown that its accuracy can vary considerably across emotions (Sarsenbayeva et al., 2020a; Yang et al., 2020). According to Sarsenbayeva et al. (2020a), surprise was detected with 97.46% accuracy and joy with 94.17% accuracy, while worst performing were anger (50.82%) and fear (7.5%). In their paper, Sarsenbayeva et al. (2020a) also provided additional validation for the

[1] https://www.affectiva.com/

robustness of the Affectiva outputs, by looking at weekly fluctuations.

2.2. Changes in emotion

Gross (2015) summarizes in his work that every emotion is defined by three major features; (1) they have beneficial (positive) or adverse (negative) effects, (2) they happen over time, and (3) they are associated with changes in behavior, experience, and physiology. Emotions usually represent valid evaluations but can misfire, such that people often wish to override them in certain contexts. People may wish to downregulate positive affect (joy),*e.g.*, at a funeral, and negative affect (anger) in work settings, while wishing to upregulate joy in a social setting and anger in a competitive setting, such as sports contests (Gross, 1998). Another reason to regulate emotions is that emotions can impact mental and physical health. The benefits of positive emotions include increased creativity and thinking (Larson, 1990), positive modulation of attention (Tyng et al., 2017), and fostering physical health (Kok et al., 2013). Accordingly, the experience of negative emotions can result in cardiovascular diseases (Suls and Bunde, 2005), and impair learning and memory (Tyng et al., 2017). Emotions are, however, not immutable. We have strategies available that enable us to modulate our emotional experiences. Gross (1998) defines these *"Emotion Regulation"* strategies as: *"all of the conscious and non-conscious strategies we use to increase, maintain, or decrease one or more components of an emotional response."*

Prior research has shown that an inability to engage in Emotion Regulation can lead to different mental health-related problems including mood (Gruber et al., 2012) and anxiety (Campbell-Sills and Barlow, 2007) disorders and decreased social functioning (Eisenberg et al., 2007). Other studies have investigated the benefits of short-term Emotion Regulation, for example how playing video games supports recovery from work-related stress (Collins and Cox, 2014). Long-term effects have also been investigated, and it was found that down-regulating negative emotions reduces the risk of heart attacks and coronary heart disease (Kubzansky et al., 2011). Moreover, interventions that help people learn better how to regulate their emotions have also been shown to effectively treat borderline personality disorders (Lynch et al., 2007), substance abuse, eating disorders, and depression (Lynch et al., 2003). Nevertheless, research has also identified potential detrimental effects of Emotion Regulation, such as a direct correlation between emotional suppression and problematic smartphone usage (Rozgonjuk and Elhai, 2019). Consequently, it is important to understand how and when people change their emotions to foster the positive effects and avoid the potential negative repercussions (Gross, 2013).

2.3. Physiological characteristics of emotion regulation

Troy et al. (2018) investigated the effects of Emotion Regulation strategies on participants' negative and positive emotions triggered by watching a sad film, using skin conductance levels (SCL) and self-reports. The authors found that different strategies had different effects on the down-regulation of negative emotions as well as the up-regulation of positive emotions (Troy et al., 2018).

Similarly, Goldin et al. (2019) studied the effects of two specific Emotion Regulation strategies (cognitive reappraisal and acceptance) on negative emotions triggered by participants' negative self-beliefs using functional magnetic resonance imaging (fMRI), skin conductance, heart rate, respiration rate, and negative emotion ratings. The results of this study show that both strategies effectively down-regulate negative emotions; however, cognitive reappraisal has a significantly greater effect on the reduction of negative emotions, autonomic activation, and mental engagement (Goldin et al., 2019).

According to Gross (1998)'s process model, strategies differ in their temporal onset after an emotional stimulus. Thiruchselvam et al. (2011) compared the temporal dynamics of Emotion Regulation strategies using electroencephalography (EEG), while participants looked at either neutral or emotional images.

Strauss et al. (2016) investigated different visual attention patterns as well as cognitive demand of Emotion Regulation. They used a set of photographs to trigger emotional responses, and while participants performed Emotion Regulation, recorded eye movement, and pupil dilation using eye trackers together with self-reports on negative emotions. The eye movements showed strategy-dependent, characteristic features such as initially stopping before looking away from the stimulating image, or an overall shorter focus on the arousing image parts (Strauss et al., 2016).

These studies indicate that, while different strategies differ in their effectiveness and temporal dimension, successful proactive attempts to change ones emotion are expressed in changes of physiological signals.

2.4. Digital emotion regulation

Parkinson and Totterdell (1999) presented an inventory of 83 cognitive and 79 behavioural Emotion Regulation strategies, which they collected via questionnaires, interviews, and group discussions. Around a quarter of the behavioural strategies involved the use of artifacts, which included alcohol, relaxation tapes, television sets, and musical instruments. Other researchers have studied particular categories of artifacts used in Emotion Regulation, including musical equipment (DeNora, 2000) and television (Finn and Gorr, 1988). More recently, researchers have begun to examine the use of digital technologies as tools for Emotion Regulation, including online video (Myrick, 2015), digital music (Randall and Rickard, 2017), videogames (Sarsenbayeva et al., 2020b; Villani et al., 2018), social networking platforms (Blumberg et al., 2016), and smartphones (Rozgonjuk and Elhai, 2019). It is suspected that smartphones, because they combine a range of digital resources in a convenient platform that individuals can use at virtually any time and place, may be a particularly widely-used tool for Emotion Regulation (Wadley et al., 2020).

However, studying Digital Emotion Regulation presents methodological challenges. As aforementioned, Emotion Regulation involves a person, their context, a situation that causes an emotion to be generated, and the person's efforts to regulate that emotion. Measuring these variables is difficult in a lab, and very challenging in-the-wild, and thus far has not been attempted using sensors but only via self-report and experience sampling (*e.g.,* Brans et al., 2013). There are calls to use smartphone-based sensing to conduct psychology research in naturalistic settings (Colombo et al., 2020; Harari et al., 2016), including the study of Digital Emotion Regulation (Wadley et al., 2020); this study is the first we are aware of to do so that offers a novel approach towards quantifying changes in emotional trajectories. Since analysing the effects of negative and positive emotions goes beyond the scope of our work, we are focusing our analysis on two of the three features Gross (2015) postulates to be defining every emotion: they happen over time, and they are associated with changes in physiology.

3. Methodology

In this study we seek to provide initial empirical data and shed light on what emotion trajectories during smartphone use may look like, how they can be detected, classified, and potentially lead to a better understanding of how people use digital technology to fulfil their innate needs.

We hypothesize that if the use of smartphones to moderate and regulate one's own emotional state is purposeful and intentional, then the emotional state of users while using their phone would not appear to be "random" but would be intentionally "shaped". Hence, in this study, we focus on identifying temporal patterns in how levels of the emotion **joy** unfold during smartphone use. In the context of this study, "joy" is based on Paul Ekman's "enjoyment" (Ekman, 2004), which he uses as an umbrella term for positive emotions such as relief, contentment, pleasure, thrill, or satisfaction (Ekman et al., 1983).

3.1. Data collection

For data collection purposes we developed a standalone Android application that employs the Affectiva Android API (McDuff et al., 2016) and the AWARE framework to collect phone use data (Ferreira et al., 2015). Our software deduces emotions from facial expressions continuously during phone use and logs emotion confidence values at Affectiva's default rate of 30Hz. When participants do not look at the screen, Affectiva does not detect emotions and no confidence values are recorded. We used the off-the-shelf Affectiva SDK [2] integrated with our custom software that ran as a background service to collect the data. We did not modify the SDK to avoid introducing external noise. The application uses the device's front-facing camera together with smartphone usage data. The app starts recording upon each unlock event and stops when the screen is locked, which we call *session*. The software records confidence values ($0 - 100$) for seven basic emotions (anger, contempt, disgust, fear, joy, sadness, and surprise) with a corresponding timestamp. For the here presented study, we only consider expressions of joy, which Affectiva can reliably detect with an accuracy of 94.17% (Sarsenbayeva et al., 2020a). For privacy purposes, the software stored all data locally on the phone. The application runs as an Android background service listening for unlock events and has a one-button interface to start the service upon deployment.

3.2. Recruitment and procedure

We recruited 30 participants aged between 20 and 45 (M = 29, SD = 6.07) via our university mailing list and snowball recruitment. All participants were owners and users of Android-based smartphones and had different educational backgrounds (*e.g.,* Accounting, Biomedicine, Computer Science, Linguistics). Each participant attended an individual intake session. During the intake session, we briefed our participants about the purpose of the study and asked for their written consent. Next, we installed the application on their personal smartphones and explained its functions. No explicit action was required of the participants during the study, as data was collected passively in the background. The data collection lasted for two weeks, and we instructed our participants to use their phones as usual.

At the end of the data collection phase, we invited participants to our lab for individual debriefing sessions. During these sessions, we downloaded the emotion and smartphone usage data and uninstalled the software from their smartphones. We also conducted semi-structured exit interviews with each participant regarding their perceptions of their emotions and smartphone usage. Every participant received a $10 gift voucher for their contribution and time.

4. Results

We collected a total of 502,851 valid observation points, each containing a likelihood estimation that the user is experiencing each of the seven emotions that the Affectiva API tracks. These observations already exclude instances where a user's face did not fully appear in the frame of the camera. We chose to only use expressions of joy, because (1) detecting changes in joy, or positive affect, has potentially strong implications for applications that are concerned with emotion modification strategies, such as Emotion Regulation, which aim at increasing positive affect (Goldin et al., 2019; Troy et al., 2018); (2) the Affectiva API reliably detects expressions of joy (in the following only "joy") unlike other emotions, *e.g.,* anger (Kulke et al., 2020; Sarsenbayeva et al., 2020a; Stöckli et al., 2018; Yang et al., 2020). Adding further emotions to our analysis could be part of future work, requiring a robust and accurate capturing technique. In our subsequent analysis we particularly focus on smartphone usage sessions where enough data points are collected (see Section 4.1). We define a smartphone usage *session* as the time between the smartphone being unlocked and subsequently locked. Simply looking at the lock screen (*e.g.,* to check time) was not considered as a session and did not yield any data.

4.1. Filtering

We further excluded additional data to improve the reliability of the analysis. First, we excluded five participants who did not substantially use their smartphone or had technical issues with their device, and 5 participants who registered less than five sessions with high (*i.e.*, joy values higher than 10% likelihood) joy values, leaving us with 20 participants (9 female, 11 male) aged between 22 and 45 years old (M = 28, SD = 5.9). Additionally, we only considered data points that were recorded between 8am and 10pm to establish a common time frame across participants. We also excluded sessions with fewer than five observation points, or sessions shorter than 1 s to avoid potential bias as this data was not descriptive enough, leaving us with a total of 266,002 observations.

4.2. Session duration

We start our analysis by considering how much time participants spent per session using their phones. In many ways, this sets a temporal boundary for our analysis. As people must use their phones to regulate their emotions with it. In this first analysis, we look at how the duration of sessions varies overall for all participants, and for each participant individually. In Fig. 1 we show the probability curve for session duration, noting that the x-axis is logarithmic. Here, we separately consider those sessions which contained *low joy* values (*i.e.*, all values for a session remain below 10% confidence) versus the remaining sessions, where *high joy* measurements (*i.e.*, all values for a session were higher than 10% likelihood) were detected.

We observe that sessions with low joy tend to be much shorter and primarily brief (typically less than 10 s) as compared to sessions with high joy (see Fig. 1. This suggests that longer usage sessions either have a stronger impact on the users' joy; ; or that participants spend more time and effort when trying to experience joy; or that or that users intentionally prolong sessions to increase the joy gained while using their phones. We note that we are interested in sessions where individuals express high values of joy while using their phones, potentially indicating a result of Emotion Regulation to increase joy, as most Emotion Regulation strategies aim at increasing happiness and dampening negative emotions.

For this reason, we decided to exclude low joy sessions (*i.e.*, all values for a session remain below 10% confidence) for the remainder of our analysis. This elimination process resulted in a new total of 266,002 data points, distributed across 489 unique smartphone usage sessions by 20 individual users. Our expectation is that if participants use their phones to modify their emotions, *e.g.*, when engaging in Digital Emotion Regulation, then the retained data would – at least partly – capture that behaviour.

The results for high-joy sessions in Fig. 1 show that the majority of sessions last less than 1000 s, with relative peaks at approximately 10, 30, and 200 s. Moreover, the majority of sessions is shorter than 100 s. These results suggest that individuals are unlikely to spend more than 15 mi in any given session, and most often the duration of a session lasts between 10 and 200 s.

While Fig. 1 shows the session duration across all participants, in Fig. 2 we visualise the behaviour of each individual participant. Here we calculate a probability curve for each participant's session duration. We observe that while some participants show a **unimodal** distribution, others present with a **polymodal** distribution. Similarly, we observe that some participants' distribution is skewed towards shorter sessions, while others' is skewed towards slightly longer sessions. For example, Participant 3 (P03) peaks at 20 s, while P23 peaks at 100 s.

[2] https://github.com/Affectiva

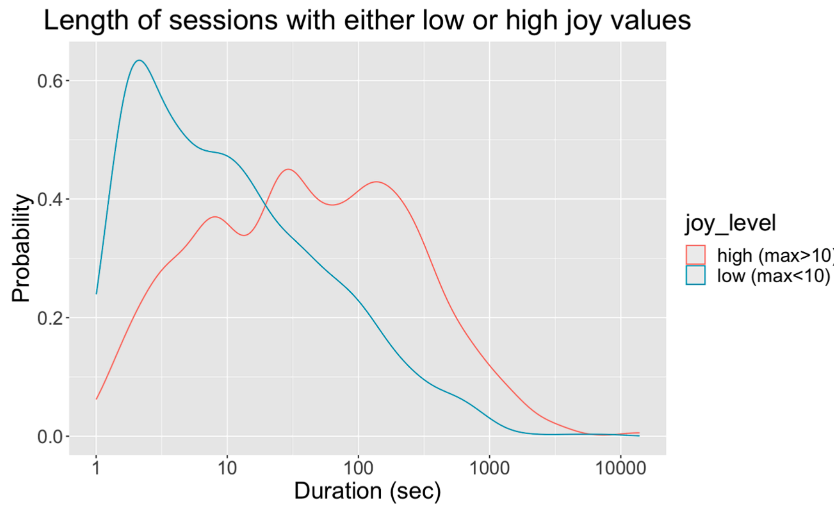

Fig. 1. Probability plot indicating the duration of sessions across all participants. Sessions with high joy are in red, and with low joy in blue.

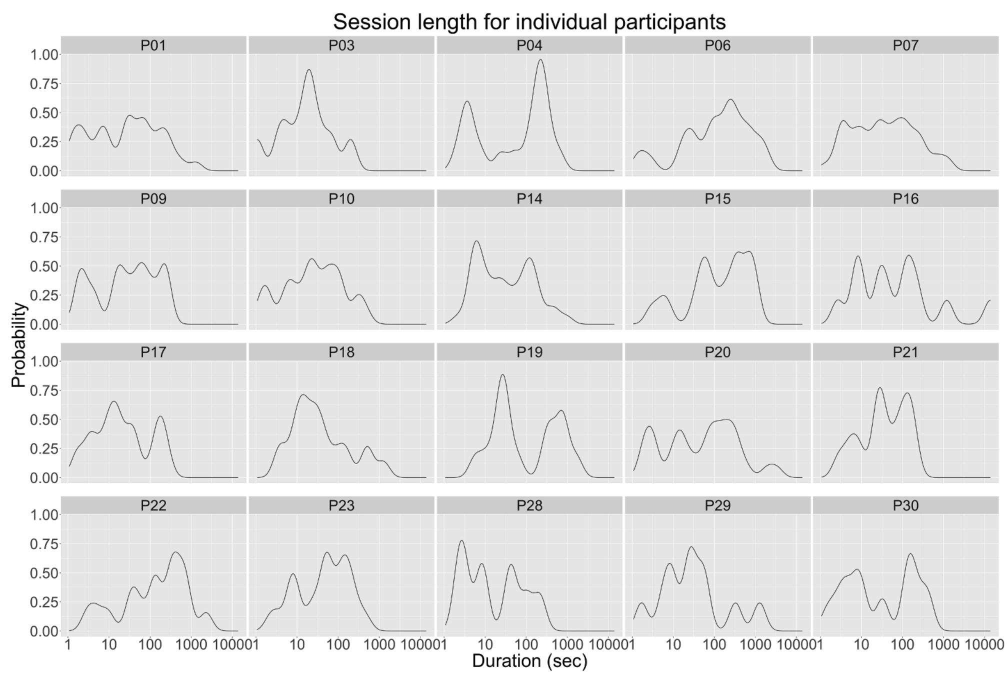

Fig. 2. Probability plot indicating the duration of sessions with high joy for each participant.

4.3. Diurnal distribution of instances of joy

To get an estimate of how instances of joy are distributed throughout the day for each participant, we calculate the *minutes of joy* that participants experience while using their phones. We identify those as 1 min periods with average joy values higher than a 10% likelihood, *i.e.*, with consistently high joy readings. We visualise the minutes of joy for each participant by identifying the time of day when these occurred, as shown in Fig. 3. In this graph, the height of each bar indicates how many minutes of joy were registered, while the color of the bar indicates, whether those minutes are spread across multiple days (*e.g.,* a person may experience 7 min of joy between 1pm and 2pm, but those could be either experienced in a single day, such as P06, or spread across many days, such as P07).

The results show that participants experienced different numbers of *minutes of joy* during the study. We also find that while for some participants these occurred relatively evenly distributed throughout the day (*e.g.,* P01, P04), for others, *minutes of joy* appeared mainly during certain hours of the day (*e.g.,* P07, P16). Moreover, some participants had a strong daily pattern with multiple readings during the same hour of day across different days (*e.g.,* P07, P10, P23), while for others the daily patterns were less prominent (*e.g.,* P03, P17).

4.4. Evolution of joy during smartphone sessions

For each participant, we collected data for multiple sessions, and in each session, we have a high-frequency assessment of their level of joy. To further analyse this data, we first calculate the mean level of joy for each participant with a granularity of one second, *i.e.*, we reduce the granularity of data to 1Hz.

As such, for each individual session, we are able to estimate the level of joy of each participant for each second of that session. However, we note that sessions have different duration, and therefore aggregating the data for each participant needs further consideration. For this reason, we

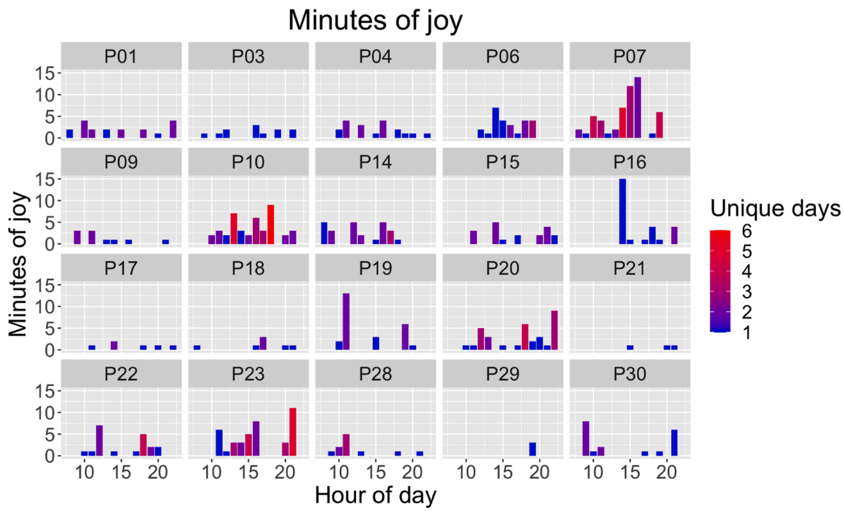

Fig. 3. Distribution of joy throughout the day. X-axis: time of day; y-axis: number of unique minutes with high joy.

choose to aggregate data in three ways.

First, we visualise the mean joy for each of the first 100 s of the sessions as shown in Fig. 4. This is calculated using conditional means and loess smoothing, while the standard error is shown as a dark grey band around the mean. We visualise the error bars based on the average joy values – not based on the raw data – to more clearly identify the signal in the noise. Some sessions are shorter than 100 s, others are longer, but regardless we calculate the mean joy for each of the first 100 s using the available data. The rationale is that this visualisation provides an assessment of how joy evolves as participants begin using their phones, but a downside is that data beyond the first 100 s is discarded. We observe that some participants experience elevated levels of joy within the first 10 s of use (*e.g.,* P01, P04, P17), while for others there is a gradual build-up that can last tens of s (*e.g.,* P09, P19, P22).

Second, we calculate the mean joy for each of the last 100 s of a session as shown in Fig. 5. The rationale is that this provides an assessment of how joy evolves leading up to participants locking their phone. Inevitably, this approach discards the first chunk of data for sessions longer than 100 seconds. We observe that some participants experience elevated levels of joy shortly before locking their phones (*e.g.,* P06, P16, P29), while for others there is a gradual wind-down that can last tens of seconds (*e.g.,* P07, P09, P21).

Third, we provide an aggregation that overcomes the limitations of the former two aggregation strategies (first 100 s vs. last 100 s) as shown in Fig. 6. Here, we normalise the duration of each session to be "1", and any measurement of joy recorded during a session is indexed to a normalised timestamp between 0 and 1. In this manner, all sessions start at 0, end at 1, and all joy readings are timestamped with a value between

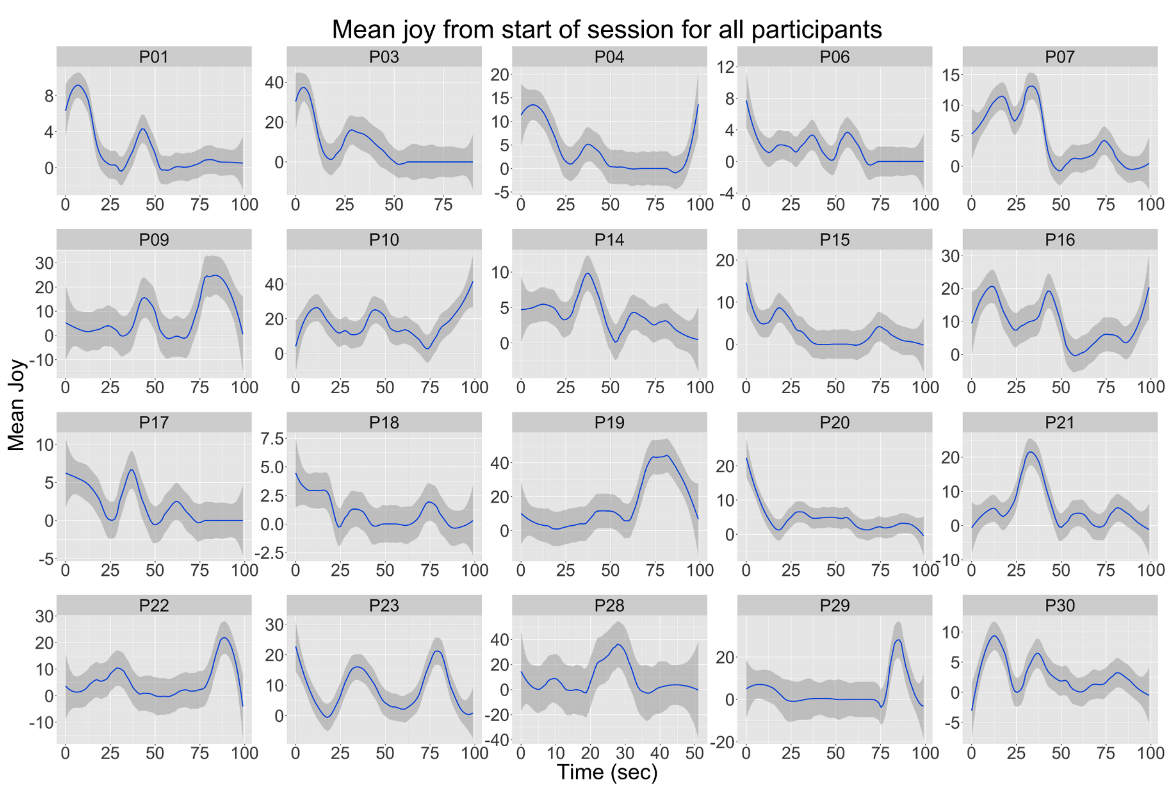

Fig. 4. Average joy for the first 100 s of sessions. The dark grey band indicates the standard error.

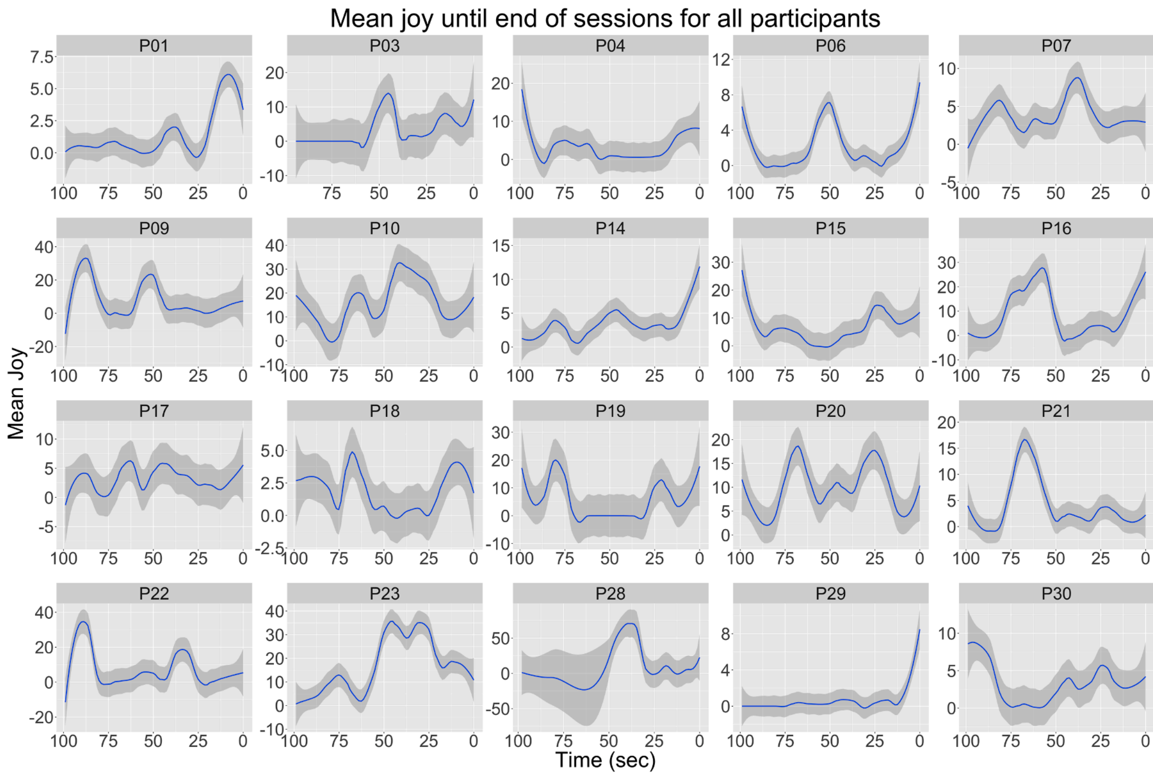

Fig. 5. Average joy for the last 100 s of sessions. The dark grey band indicates the standard error.

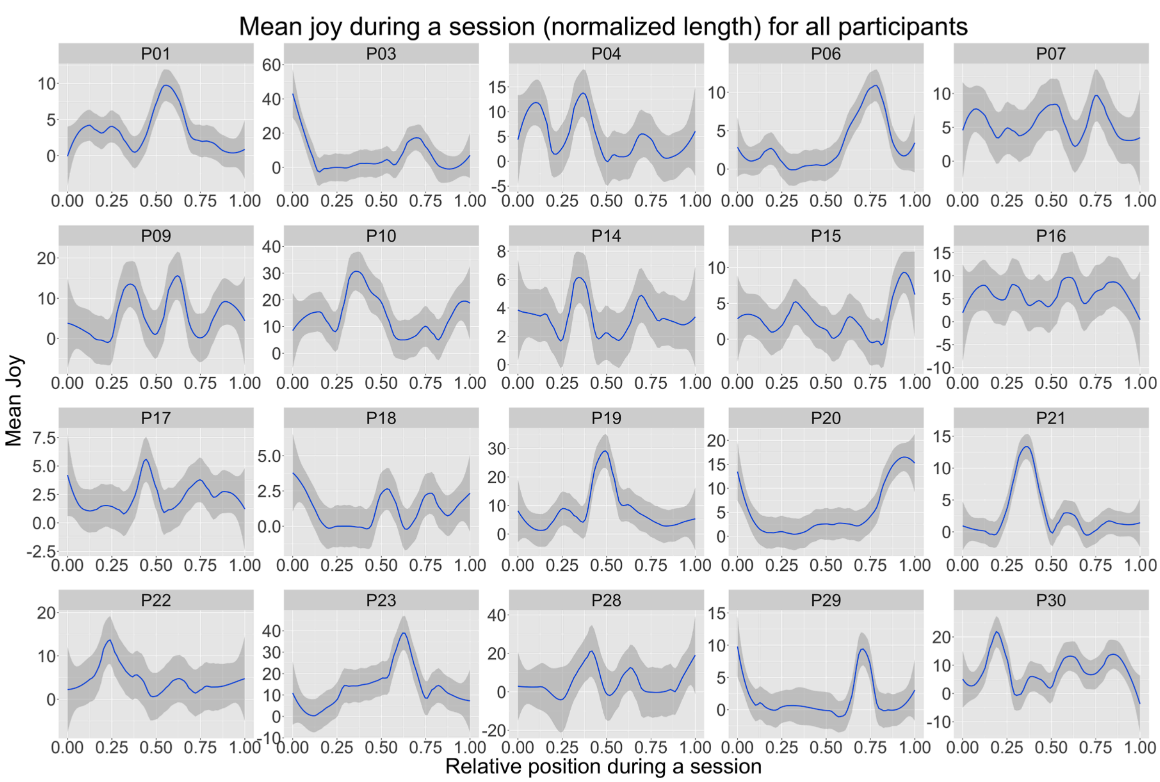

Fig. 6. Average joy for sessions, with lengths normalised to [0,1]. The dark grey band indicates the standard error.

0 and 1. This allows us to retain all our data when calculating the average joy. However, it does not capture the true magnitude (in seconds) of each session duration.

Fig. 6 provides a visual overview of different patterns of changes in joy during smartphone usage. The two major patterns we identify are **unimodal** (*e.g.,* P01, P06, P19, P21) and **polymodal** distributions (*e.g.,* P04, P07, P09, P28) of joy increases. We furthermore see that users experience changes in joy at different times during their usage sessions.

P01, P17, and P19 experience the strongest increases in joy at approximately the midpoint of a session. P04, P10, P21, and P22 on the other hand, have the most dominant increases in the first half of their smartphone sessions.

4.5. Magnitude of joy in short and long sessions

Previous work has described how users may “glance”, “review”, or “engage” with their smartphones (Banovic et al., 2014), interactions that involve spending different amounts of time with the phone. We effectively removed “glances” (of the lock screen) from our dataset through our initial filtering. Based on Banovic et al. (2014), we consider sessions with less than 60 s, short “review” sessions and sessions that last more than 60 s, long “engagement” sessions, as we illustrate in Fig. 1 (red). We repeat our previous analysis, and the results are shown in Fig. 7. These results show normalised sessions for each participant, color-coded for short “review” sessions (in blue), and longer “engagement” sessions (in red). We observe that some participants experience joy mainly in long sessions (*e.g.,* P17, P19, P20), some participants experience joy mainly in short sessions (*e.g.,* P06, P16, P22), while for some participants the results are mixed (*e.g.,* P04, P10, P21). A prevalent observation across participants is that more frequently, high joy readings happen relatively sooner in long (red) sessions than in short (blue) sessions.

4.6. Overall strategies

Finally, considering the multiple ways in which we have characterised our participants, we conduct a *hierarchical clustering analysis* of their behaviour. Our clustering follows Verduyn et al. (2009)’s emotion intensity profile definition, whereby the three defining features are the “number of peaks” (one or more), the “steepness at onset” (some profiles start with a burst of emotion), and “skewness” (experiencing emotional peaks towards the beginning or end). These features have been shown to account for over 84% of the variability in emotional profiles (Verduyn et al., 2009).

In our analysis we characterised each participant in terms of their tendency to exhibit joy near the start of a session including an initially high joy value (**onset**), peaks early in or near the end of a session (**skewness**), whether their joy distribution is unimodal or polymodal (**number of peaks**), and whether they exhibit high joy values mainly in long or short sessions. Each dimension is coded as a binary variable. The hierarchical clustering uses Euclidean distance and the ward method as it maximises the agglomerative coefficient (0.86). Using the elbow method (metric: total within sum of squares) we identified the optimum number of clusters as 3. The clustering results are shown in Fig. 8, with the three identified clusters highlighted.

We analyse the identified clusters, and summarise the main characteristics our analysis yielded as follows:

- Go-Getters (in red): participants who register high joy a few seconds before locking their phones and mainly exhibit joy in short sessions. Their behaviour suggests that they seek a quick experience of joy and then lock their phone.
- Targeters (in green): participants who mainly have a unimodal joy profile and gradually increase their joy during a session. They mainly experience a single episode of joy in their sessions, which could be the consequence of targeted use, or a side effect of their usage behavior.
- Explorers (in blue): participants who have mainly polymodal joy profiles and show gradually declining joy levels before locking their phones. They experience multiple joyful episodes in one session and lock their phones when the joy wears off.

We did not control for variables such as demographic information or smartphone notifications. However, Table 1 shows our participants’ demographic data, along with their average smartphone session length, and cluster. We found no relation between phone usage data, demographic data and clustering results. There is a tendency for female participants being more present in the Targeter cluster than male participants. However, due to the small sample size and this cluster being

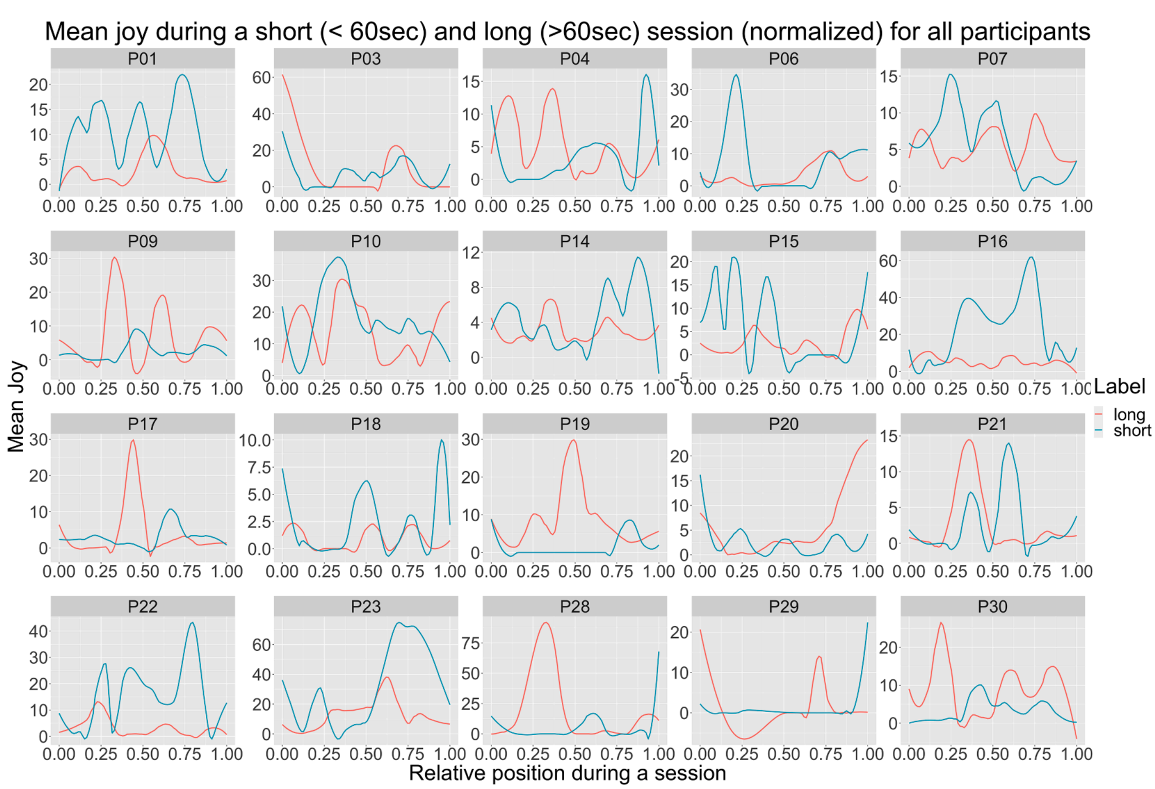

Fig. 7. Magnitude of joy during long (red) and short (blue) sessions for all participants.

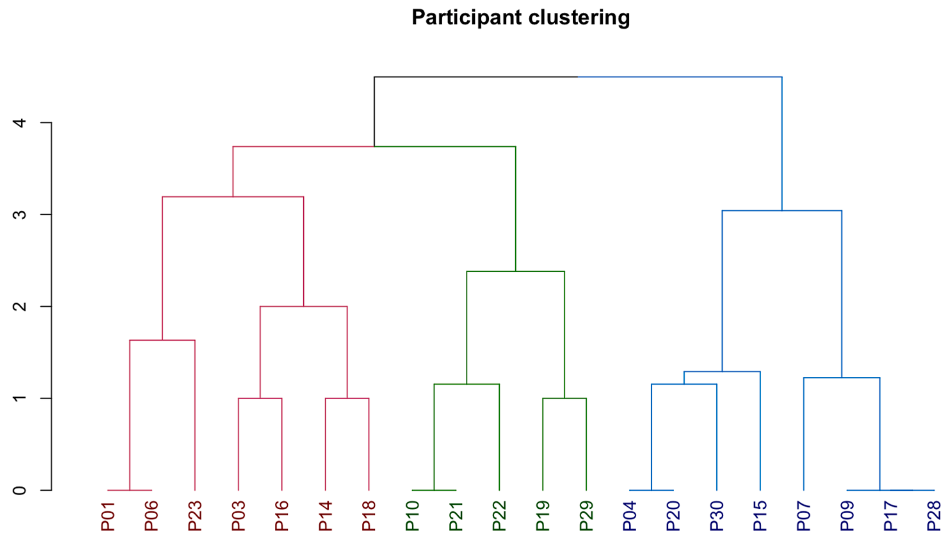

Fig. 8. Hierarchical clustering of participants based on how they exhibit joy during smartphone use.

Table 1
Summary of demographic information for all participants, average smartphone session length in seconds, and cluster.

Participant	Gender	Age	Avg. Session Length (sec.)	Cluster
P01	Male	26	112.22	Go-Getter
P03	Male	26	38.76	Go-Getter
P06	Female	33	343.64	Go-Getter
P14	Male	45	95.89	Go-Getter
P16	Male	25	1214.08	Go-Getter
P18	Male	35	148.09	Go-Getter
P23	Female	22	93.99	Go-Getter
P10	Female	31	72.33	Targeter
P19	Male	25	334.44	Targeter
P21	Female	29	64.49	Targeter
P22	Female	22	374.90	Targeter
P29	Female	38	164.28	Targeter
P04	Male	25	152.06	Explorer
P07	Male	32	138.47	Explorer
P09	Male	25	71.11	Explorer
P15	Female	25	304.36	Explorer
P17	Male	26	57.57	Explorer
P20	Male	26	263.00	Explorer
P28	Female	22	47.55	Explorer
P30	Female	25	104.53	Explorer

the smallest of the three, we recommend that future research investigates a potential impact of demographics on emotion regulation behavior in the wild. The probability curves in Fig. 2 present the smartphone session length in a more detailed format for each participant.

4.7. *Interview results*

After finishing the data collection, all participants were invited to a debriefing session. We conducted semi-structured face-to-face interviews (15min/participant, pre-covid), where we asked participants about their emotional well being, the strategies they use to respond to their emotions, and the impact of certain mobile apps on their emotional states. We used an inductive analysis approach, conducted thematic analysis with coding, and summarised our results into themes presented in the following.

4.7.1. *Response to negative emotions*

We asked about participants' responses to negative emotions. 12 out of 20 participants explicitly stated that they use their smartphone to respond to negative emotions such as sadness. Five out of these 12 spoke of distraction strategies, *e.g.*, by interacting with social media apps (P01, P21), calling people (P03), or by being rather passive and watching documentaries (at home) and listening to music (P06) (when not at home). This suggests that the patterns detected in sensor data are likely to involve emotional changes. P21 added that they would change their activity to get distracted, which does not necessarily have to include phone use, but might involve some other activity that distracts them, *e.g.,* go for a walk. One participant also mentioned mixed strategies, for example when they felt sad or depressed at night they would walk and listen to music on the phone until their *"thoughts were sorted"* (P04). P09 mentioned looking for explanations and arguments justifying how they felt, using their phone, and stated that this helped them feel better, which is a clear sign of intentional modification of their emotions. Only a small group of participants (N = 3) stated that they do not use their phones in response to feeling sad, except for when they are alone, at which time they would use their phones to get in touch with others (P29). The main applications used to respond to negative emotions were communication applications that enable talking to friends, voice calls to family, and apps that provide distraction in the form of music and videos. As we will detail in Section 5.4, this corroborates findings of prior studies that looked at app usage in relation to different session lengths of smartphone usage (Banovic et al., 2014).

4.7.2. *Response to positive emotions*

While participants showed a strong tendency to resort to smartphones in response to negative emotions, the interviews yielded that positive emotions triggered mostly non-technology responses. Nine participants explicitly stated that they would not use their smartphones in response to positive emotions, or not for any specific purpose. Partly overlapping, eight participants named engaging in offline activities, such as going into nature (P29) and meeting friends (P04, P10) as the main responses to positive emotions. P29 stated specifically that they do not use their phones much when they are happy, and P20 stressed that they just keep doing what they were doing, but did not use their smartphone. Only four out of all 20 participants mentioned responses to happiness involving phones. P17 used their phones when they felt happy to take and edit pictures as a form to act out, enhance, and sustain their happiness. P21 emphasized that they tend to continue what they had been doing when feeling happy, but sometimes use the phone to send someone a message.

4.7.3. *App usage and emotions*

17 out of 20 participants stated that rather than specific app

categories (*e.g.*, messengers, social media, entertainment), content is the important factor influencing their emotions when using the phone. However, one in four participants (N = 5) mentioned specific apps that they use to intentionally trigger certain emotions. Two participants stated that *YouTube* and *9GAG* (P16) as well as *Pinterest, WhatsApp*, and *Instagram* (P28) tend to increase their happiness. An important property of these apps is that they enable people to communicate and share content of interest with their close contacts. But it was stressed that here as well, emotions also depended on the content delivered through the app, *e.g.,* sad messages make users feel sad, happy messages make users feel happy. Communication functions of specific apps (*Instagram, Facebook*), and call and messaging functions were mentioned as important to stay in touch with friends and family, but there as well, the content of the messages is the deciding factor over positive or negative emotional outcomes. P03 stated that one never knows what is coming inside the message, unlike in other apps (*e.g.,* travel apps, weather).

The majority of participants (N = 15) mentioned specifically sadness and boredom as emotions that make them use the phone. The most frequently mentioned negative emotion was boredom (N = 10). Only three (P15, P17, P22) out of the 15 participants stated positive emotions as drivers for app choice. Sadness was not named as a motivator to use social media, it rather prompted browsing or reading on the phone. Five participants on the other hand stressed that available time rather than emotion was the driving factor for their app usage, because they check things when they have time rather than depending on their mood.

In summary, we see that negative emotions stimulate smartphone usage more often than positive emotions. While our participants mentioned using different concrete digital strategies when feeling sad or bored, responses to positive emotion are predominantly manifested in offline activities. However, online and offline activities in response to emotions primarily involve social goals, such as being in touch with friends, family, or people, which is vital for human wellbeing (Berkman and Leonard Syme, 1979; Umberson and Karas Montez, 2010).

A detailed study of the bidirectional impact of app-usage and user emotion of our sample is presented in Sarsenbayeva et al. (2020a).

5. Discussion

Our work is one of the first longitudinal studies to report individual patterns of changes in joy during smartphone use in naturalistic settings. We are able to identify and cluster characteristic usage patterns, even though characteristics of emotional responses (*e.g.,* magnitude) are highly individual (Levenson, 2014). While our analysis and discussion strongly focus on detecting and explaining non-random patterns of emotional trajectories during smartphone use, we do not claim to provide unequivocal evidence for behaviors such as Emotion Regulation. However, as sensing technology has become ubiquitous with smartphones, it is increasingly possible to sense individual activities and behaviors. Our work aims to provide a novel approach for researchers to possibly investigate and quantify intentional behaviors such as Emotion Regulation in naturalistic settings (Barrett et al., 2019; Colombo et al., 2020).

5.1. Detecting patterns of emotion changes

Reliable long term high-frequency collection of emotion ground truth is challenging, except through self-report methods such as Experience Sampling (ESM) and surveys (Tag et al., 2022). These can only be deployed a few times per day, so that long stretches of collected data do not have associated ground truth. Furthermore, using high-frequency surveys potentially disrupts the naturalistic setting of the study and changes the behavior of participants, especially in longitudinal settings. Sarsenbayeva et al. (2020a) provided a new approach to passively collecting ground truth data at a higher frequency using smartphones. They validated the robustness of Affectiva for detecting emotions from facial expressions in-the-wild using ESM data as ground truth. Based on this, and given the trade-offs of survey-based ground truth collection, our method was designed to minimise disruption and collect high-quality longitudinal data.

As the literature details, it is challenging to differentiate between emotion generation and regulation (Gross et al., 2011). We cannot capture human intention in sensor data, which by definition is a prerequisite for Emotion Regulation. Therefore, our data analysis requires further discussion. Sarsenbayeva et al. (2020a) have shown that the relationship between emotions and smartphone use is bidirectional, *i.e.*, there are instances where emotions drive smartphone use as well as there are instances where smartphone use drives emotions. Moreover, since interview data indicate that users intentionally use their smartphones to respond to emotional events, or to trigger certain emotions, we can expect that the collected data contains instances of intentional emotion modification, and thus is not random but would rather elicit trends or even patterns. Lastly, a series of studies have shown that smartphones are especially attractive for intentional use, as they serve a multitude of purposes, such as entertainment, work, information seeking, social engagement, communication (Collins and Cox, 2014; Smock et al., 2011; Wang et al., 2015).

5.2. Individual emotion trajectories

Individuals differ in the way they react to emotional events, physiologically as well as emotionally (Shallcross et al., 2013; Troy et al., 2010). In particular, people respond to emotions and express emotions differently, depending on several contextual factors (Aldao et al., 2015). One point to be addressed in this context, however, is the relative uniformity of the individual emotion trajectories. As people use their phones for different applications and purposes (*e.g.,* calls, emails, weather, social media, etc.), the individual trajectories present with striking regularity. Different research has shown that people, while picking up and using the phones multiple times a day, develop habitual use patterns. In an experience sampling and interview study, Lukoff et al. (2018) found that users often fall victim to automated checking habits. This counted especially for social media use, entertainment, and communication apps. Our participants also reported that an important purpose of smartphone use was to find relief from negative feelings, in which cases the meaningfulness of the usage session was secondary. These often quickly accessible "rewards" also contribute to the development of specific usage behaviors (Oulasvirta et al., 2012). Tran et al. (2019) have shown that certain triggers cause the start, but also end, of habitual usage. These triggers can initiate a chain of apps that is habitually used in the same order (Böhmer et al., 2011; Shema and Acuna, 2017). Nevertheless, users seem to be aware of these compulsive behaviors and have strategies to break out of them (Tran et al., 2019).

5.3. Go-Getters, targeters, and explorers

Synthesizing the aforementioned, the definitions and explanations given in the following aim to provide a first classification scheme of different smartphone use. Our analysis identified three clusters of users that show characteristic smartphone usage patterns and present with distinct patterns of joy.

5.3.1. Go-Getters

We have seen that the group of participants we call "Go-Getters" tend to express joy in the last seconds of their smartphone usage session. They also mainly express higher joy values during short phone usage sessions. Our interview findings endorse these findings: P01 and P03 mentioned accessing social media or calling friends and family in response to negative emotions. According to Banovic et al. (2014), the necessary apps are typically used in short sessions. This corroborates findings of previous studies that have investigated the differences in the impact of different Emotion Regulation strategies on positive and negative emotions (Goldin et al., 2019; Strauss et al., 2016; Troy et al., 2018) as well as on the temporal dimensions of their effects (Thiruchselvam et al., 2011), *e.g.*, distraction shows faster effects on emotional trajectories than the cognitively demanding reappraisal strategy (Thiruchselvam et al., 2011). Moreover, Suri et al. (2015) and Brans et al. (2013) show that cognitive reappraisal is actually utilized in a minority of cases, both in everyday life and in the laboratory. Considering previous work, we hypothesise that "Go-Getters" seem to be mainly adopting quick distraction strategies, which can be performed spontaneously as they require lesser cognitive effort (Troy et al., 2018) and which smartphones afford in abundance.

5.3.2. Targeters

Finally, the smallest group of "Targeters" mainly present with a gradual increase in joy values. This group tends to experience a single peak of joy (unimodal profile) in both short and long sessions. During our interviews, P21 mentioned using social media apps when feeling negative emotions, whereas P29 stated that they would get in touch with their friends when nobody was around, using their phone (see Section 4.7.3). This coincides with the work by Banovic et al. (2014), who have shown that short smartphone sessions are mostly used for fulfilling social needs (*e.g.,* communication), which are crucial for a person's physical and mental wellbeing (Berkman and Leonard Syme, 1979; Umberson and Karas Montez, 2010), whereas longer sessions are mainly used to consume entertainment content (Hoffner and Lee, 2015).

5.3.3. Explorers

"Explorers", despite experiencing several peaks of joy, show an overall gradual increase in joy throughout a session. As one of the cognitive change strategies (Gross, 2015), reappraisal requires significant cognitive effort, such as overriding a predominant initial response, actively engaging with working memory, and switching between tasks (Gan et al., 2017; Ortner et al., 2016). This corroborates findings by Verduyn et al. (2012), who argue that the expression of multiple peaks in response to a single event can be a sign of either recollecting or recalling the emotional event after successfully regulating an emotion, or that multiple peaks might be the result of overlapping processes that had different temporal onsets and resulted in emotional responses. P09 reported using their phone to "look for arguments" when they are sad, while P04 explicitly mentioned that they listen to music until their "thoughts were sorted" indicating cognitive change strategies (Gross, 2015).

5.4. Duration of use

Our analysis shows that the majority of smartphone sessions is between 10 and 200 s long. This corroborates prior findings detecting a mean smartphone usage duration of about 10-250 s (Falaki et al., 2010). Banovic et al. (2014) have classified usage sessions by their length, degree of interaction, and predominantly used application type. They classify usage sessions as "glance sessions", "review sessions", and "engage sessions".

Glance sessions are characterized by brief interactions, that do not require unlocking the phone. We removed all glance sessions from our dataset, as they do not require proactive input by the user. We deem unlocking of the phone and the need to interact with the content as an assurance that intention steers the interaction with the phone.

Review sessions are defined by an interaction duration of up to 60 s. They require users to consume content and actively input to the phone. As Banovic et al. (2014) observed, review sessions were mainly used for single-application interactions, such as checking a specific mail in the email app. The majority of our sessions fall into this category, and especially our cluster of "Go-Getters" who exhibit joy in short sessions. Ferreira et al. (2014) also state that many of these applications that are "micro-used" aim at connecting users with other people.

Engage sessions are defined by a minimum duration of 60 s. The median duration determined with 130.25 s is also reflected in our dataset, as can be seen in the third peak of the red line in Fig. 1. Engage sessions often appear when the user interacts with multiple applications, *e.g.,* when playing games, watching videos, or seeking information on the Internet. Interestingly, the study by Banovic et al. (2014) revealed that review and engage sessions are defined by targeted application launch, as user data showed very low search times for specific applications, with a median of 1s for review sessions and 4.5s for engage sessions. This is also confirmed by our participants' interview responses. None of our participants mentioned aimlessly searching for something to do on their phones, but that they rather have specific apps in mind when they are feeling sad. This also indicates intentional smartphone usage that serves specific (innate) purposes.

5.5. Towards identifying and designing for digital emotion regulation

The major hurdle on the way to detecting Digital Emotion Regulation is that Emotion Regulation involves not just a change in emotion but a goal to change emotion. While emotions can be sensed, goals cannot (yet). A series of lab studies, as well as studies in the wild (Tag et al., 2022), have compared different regulation strategies, their effectiveness, and features. However, as it is challenging to detect intention in-situ, there are no successful attempts that use sensors to quantify Emotion Regulation in naturalistic settings. We propose a first step towards quantifying Emotion Regulation and classifying distinctive features of different regulation strategies by investigating smartphone usage.

Other studies using psychophysiological measures have presented promising results, such as differing patterns in eye gaze and visual attention when comparing different strategies (Gross, 1998; Strauss et al., 2016). Others have relied on different responses in electrodermal activity (EDA) (Troy et al., 2018). Physiological sensors in smartphones, smartwatches, and other wearables promise to offer a new approach towards better categorizing (Digital) Emotion Regulation strategies (Colombo et al., 2019, 2020). However, few of these sensors are widely available, and as prior literature has shown and our analysis has corroborated, emotion profiles, responses, and their effects are highly individual. Therefore, analysing patterns will require statistical approaches, and can probably benefit from applying intelligent algorithms that learn over long periods of time, which was not possible in our study.

What our analysis has shown, though, is that recording smartphone usage data and emotion information from facial expressions in naturalistic settings enables us to categorise our sample according to features defining emotional trajectories. Our findings allow researchers and developers to begin considering designs for detecting and possibly developing interventions that foster (Digital) Emotion Regulation. For example, introducing timing interventions could stop the decreasing joy values in longer sessions. Alternatively, systems could make it easier to reach applications or services that are likely to support successful Emotion Regulation – for instance by displaying shortcuts or recommendations. Even further, there exists an opportunity for education and learning, *e.g.*, by promoting alternative strategies for Emotion Regulation that the user has not chosen in the past, or by offering instructions for specific Emotion Regulation strategies while automatically considering contextual factors, such as time available, social situation (alone, or amongst people), or location (at home, at work, or in public). Importantly, our work uses a sensor that is available on essentially all phones (the front-facing camera) and can therefore be more readily used in the design of interventions.

Future research also has to consider the impact of one usage session on the next. Interventions can support emotional well-being and prolong positive regulation effects by limiting access to applications with detrimental effects as long as users experience positive effects. Similarly, by utilizing more sensing modalities in the phone, *e.g.,* keyboard strokes to detect stress or random multitasking to detect boredom, we will be able to better understand and cater to context-dependence of emotions (Aldao et al. (2015)).

5.6. Limitations and future work

Our study has a number of limitations. First, the reliability of detecting emotions from facial expressions has been contested (Barrett et al., 2019). However, two recent studies by Kulke et al. (2020) and Sarsenbayeva et al. (2020a) have validated the robustness of Affectiva, specifically for detecting joy. Other more objective approaches are those that assess dynamic changes in the autonomic nervous system (ANS), such as cardiovascular, respiratory, or perspiration changes (measured as variations in skin conductance levels (Babaei et al., 2021)), and dynamic changes in the central nervous system, such as changes in blood flow or electrical activity in the brain (Yang et al., 2021). While these are still challenging to be deployed in naturalistic settings, future studies should adopt a multi-sensory approach to increase construct validity.

While joy alone does not reflect the complexity of human emotions, we adopt a data-driven approach to investigate if individual emotional responses (Levenson, 2014) collected in naturalistic settings exhibit non-random patterns that correlate with smartphone use. Our findings show that the quantified joy trajectories show characteristic patterns. However, a larger sample, consideration of multiple emotions, and studies that control for technical and non-technical variables (*e.g.*, demographic information, smartphone notifications, app usage, app content, personality traits) are required to increase the internal and external validity. As an exploratory approach, focusing on joy was a reasonable first step towards investigating potential use of smartphones for Emotion Regulation.

We also acknowledge that in our study we were not able to capture users' intentions in-the-moment, which is a key aspect of Emotion Regulation. We tried to assure a certain level of intention though, by only analysing sessions where users unlocked the phone. Nevertheless, our data appear to be consistent with the Emotion Regulation hypothesis, and we have made sure to clearly indicate that our findings only point to further hypotheses rather than definitive conclusions.

Additionally, our analysis has not considered the actual applications that participants used. This was intentional due to our relatively small sample size in relation to the diversity of applications and application types that exist. A study with a larger sample would be able to investigate in-depth how different applications are adopted by the different clusters of participants, and which strategies rely on which types of applications. Our interviews indicate the richness of data that application choices and usage imply for future studies.

Finally, future studies should investigate the temporal dimension of potential regulation strategies, e.g., by delivering targeted questionnaires when Emotion Regulation presumably happened. This will lower the burden on users in longitudinal studies while providing a validated ground truth. Future work can also consider instrumenting multiple devices per user, including desktop computers, tablets, smartwatches, music players, and video players. This would enable the development of high-resolution images of the emotional state of a user across devices and can provide further opportunities to support well-being through targeted interventions based on users' prior behaviour, preferences, and habits.

Declaration of Competing Interest

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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