The Relationship Between Electrodermal Activity, Pulse Rate Variability, and Positive vs. Negative Emotions in Young Adults: An Experience Sampling Method Study

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M12 BSc Thesis PSY 202000384

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27.06.2024

Abstract

Background: Previous studies found associations of Electrodermal Activity (EDA) and Pulse Rate Variability (PRV) with negative emotions were limited by of being conducted in laboratory settings and primarily between-participants.

Aim: This study explored whether the digital biomarkers EDA and PRV had between- and within-person associations with positive and negative emotions in young adults, in a real-time longitudinal framework.

Methods: The study used the experience sampling method (ESM). Thirty-four young adults completed a daily questionnaire in m-Path to self-report positive and negative emotions and wore an EmbracePlus smartwatch measuring EDA and PRV over 8 measurement days. Person-centred mean analysis combined with multilevel models was used.

Results: Significant negative between-person associations were found between EDA ($p < .001$) and PRV ($p = .002$) with positive emotions, while significant ($p < .001$) positive between-person associations of EDA with negative emotions were found. Conversely, PRV had no significant positive between-person associations with negative emotions. No significant within-subject associations between EDA and PRV with positive and negative emotions were found.

Conclusion: Neither EDA nor PRV, while fluctuating daily, significantly affect within-person levels of positive and negative emotions. Significant between-person associations of EDA and PRV suggest that overall averages, rather than daily fluctuations, may be more relevant for assessing emotion valence. The findings can be used to design EDA-based mental health interventions for young adults. This study, one of the first to demonstrate significant associations between emotions and digital biomarkers using ESM, highlights the need for further exploration of real-time ecological emotion monitoring methods to improve interventions for young adults.

Keywords: *Positive / Negative Emotions, Electrodermal Activity, Pulse Rate Variability, Young Adults, Experience Sampling Method*

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Glossary

Acronym	**Term**
ANS	Autonomic Nervous System
CI	Confidence Interval
EDA	Electrodermal Activity
ESM	Experience Sampling Method
HRV	Heart Rate Variability
PPG	Photoplethysmography
PRV	Pulse Rate Variability
PNS	Parasympathetic Nervous System
SE	Standard Error
SNS	Sympathetic Nervous System

1.Introduction

Over the years, mental health issues increased significantly in young adults, with a 71% rise in major psychological distress outcomes from 2008 to 2017, a trend not found in older adults (Twenge et al., 2019). The COVID-19 pandemic further disproportionately worsened mental health conditions in young adults compared to other age groups (Foster et al., 2023). These findings highlight the necessity of research into this vulnerable demographic, which faces unique psychological challenges. Understanding the interplay between physiological reactions and emotions is important for addressing and intervening in these mental health challenges and has been a topic of interest for centuries. William James (1884) claimed that physiological reactions were not simple responses to emotional experiences but integral components of emotions. With advances in modern wearable technology, researchers can now monitor physiological and emotional indicators in real-time, a process known as personal sensing (Mohr et al., 2017; Motahari-Nezhad et al., 2022). Personal sensing involves the collection of ecological data from sensors embedded in everyday devices to identify human behaviour, emotions or traits (Mohr et al., 2017). Real-time sensing of the emotions of these individuals could be used to develop and inform targeted interventions for young adults and increase their well-being through a biopsychosocial model (Mohr et al., 2017).

Affect, Emotions and Physiological Responses

To understand physiological responses to emotions, the overarching concepts of affect, emotions, and their components must be understood. Affect is any experience of feeling or emotion, ranging from suffering to elation, from the most basic to the most intricate sensations of feeling (American Psychological Association [APA], 2018a). Affect consists of two dimensions: valence and arousal (Russell, 1980). Valence refers to how pleasant or unpleasant a stimulus is, e.g., positive excitement or negative anxiety (Berridge, 2019). Arousal refers to the intensity of affect, the level of physiological activation through the autonomic nervous system (ANS) or psychologically by e.g. feeling vigour, energy and tension (Niven & Miles, 2012). The arousal dimension can be measured through physiological sensors and used to infer the valence of an emotion. Both mood and emotion are affective states (APA, 2018a). For Rosenberg (1998), emotions and moods are distinct, while Pekrun (2009) describes moods as low-intensity emotions. Emotion describes a multifaceted response pattern that incorporates

behavioural, physiological, and sensory components through which a person deals with personally important matters (APA, 2018b). Physiological arousal, subjective perceptions, and psychological appraisal all contribute to an individual's emotional state. These collectively are referred to as the components of emotion (Lacombe et al., 2022).

Emotions profoundly influence mental and physical health. Negative emotions can lead to states of high arousal that increase blood pressure, for example, when one is feeling stressed (Mucci et al., 2016; Wibawa et al., 2019). Given these significant consequences, identifying valid markers of positive and negative emotions is crucial, as it could pave the way for tailored interventions. Young adults have higher levels of physiological arousal when experiencing negative emotions, making them suitable for non-invasive interventions (Fernández-Aguilar et al., 2020). The non-invasiveness of monitoring ensures ecological validity and minimises participant burden, making it easier to gather accurate and consistent data on their emotions (Montanari, 2024). Young adults heightened emotional arousal can be measured by so-called digital biomarkers.

Relevance of EDA and PRV in Measuring Emotions

Digital biomarkers are behavioural and physiological data obtained via digital devices, such as wearables and implants (Motahari-Nezhad et al., 2022). They can improve diagnostic precision by remotely, non-invasively, and continuously measuring physiological data, enabling ongoing monitoring. Experimental studies, e.g., by Nagai et al. (2004), have shown that distinct physiological patterns may be linked to specific emotions, underscoring the potential of non-invasive devices to identify the onset of particular emotions. Mohr et al.'s (2017) *personal sensing* framework, links behaviours and digital biomarkers to mental health outcomes. If the findings of this study validate this framework of digital biomarkers as valid markers of emotions, it can lay the foundation for future work in personal sensing, potentially leading to diagnostic and intervention tools.

Physiological arousal of the ANS is a key component of emotion and was measured by EDA and PRV in this study. (Niven & Miles, 2012). As the only autonomic psychophysiological measure unaffected by parasympathetic nervous system (PNS) activity and because of its connection with cognition, emotions, and attention, EDA is the most useful index of sympathetic nervous system (SNS) arousal. It has been employed previously in various studies e.g. assessing implicit emotional reactions (Braithwaite et al., 2013). Furthermore, EDA has been used to detect negative emotional states through positive associations with, e.g., pain, stress, and sadness (Ganapathy et al., 2021). A systematic review

found due to methodological differences an inconsistent relationship between EDA and positive emotions with moderate correlations (Horvers et al., 2021).

PRV is another relevant indicator of ANS activity (Sabour et al., 2019). PRV has been used to measure the PNS activity and the SNS activity since both nervous systems regulate the heart rate and blood pressure measured by PRV (de Geus & Goven, 2023). The majority of previous studies have focused not on PRV but heart rate variability (HRV) (Yuda, Yamamoto, et al., 2020). HRV is traditionally measured with an electrocardiogram placed on the chest and is highly accurate for ANS assessment, while PRV is measured by photoplethysmography (PPG) sensors which are feasible and convenient for wearable devices with high user acceptance (de Geus & Goven, 2023). The spread of wearable pulse wave sensors has led to the greater use of PRV to measure emotional arousal (Yuda, Yamamoto, et al., 2020). Yuda, Shibata, et al. (2020) proposed that PRV should be recognised as a distinct biomarker from HRV, showing promise as a new indicator of emotional arousal. Additionally, PRV was found to be more sensitive in measuring changes in blood pressure states than HRV (Mejía-Mejía et al., 2021). Blood pressure states are another indicator of negative emotions since anxiety and stress have been found to be related to hypertension, a condition characterised by high blood pressure in multiple studies (Mucci et al., 2016; Ostir et al., 2006). However, former studies of the related biomarker HRV found positive correlations of HRV and positive emotions, since also positive emotions such as excitement can lead to increased arousal and thus blood pressure (Ballesio et al., 2023). Meanwhile, Sabour et al. (2019) found that PRV has an approximate accuracy rate of 60% in experimental conditions of assessing emotions in young adults, but its effectiveness in naturalistic settings remains underexplored. In sum, EDA and PRV sensor data collected in real-life situations may offer new insights into the capacity of digital biomarkers to monitor emotions outside the laboratory.

The Present Study

Several researchers have already examined the use of digital biomarkers in connection with emotion valence (Bodenstein et al., 2023; Feng et al., 2018). Some have also highlighted the importance of understanding and being able to monitor emotions in young adults in light of a significant increase in mental health issues, a phenomenon exacerbated by factors such as cultural shifts and the COVID-19 pandemic (Foster et al., 2023; Twenge et al., 2019). Digital biomarkers offer a promising avenue as proxies for positive or negative emotions because they allow for the continuous and non-invasive monitoring of physiological responses

(Motahari-Nezhad et al., 2022). For instance, EDA has proven effective as a measurement of implicit emotional reactions over several studies, while PRV has shown a high degree of accuracy in the prediction of emotions (Braithwaite et al., 2013; Sabour et al., 2019).

However, the previous studies have been limited in certain respects. The hypothesis that emotions and physiological responses are linked was based on intraindividual variability but has largely been studied using interindividual variability, rather than capturing longitudinal variations outside laboratory settings. (Institute of Medicine (US), 2004). Differences in body features and bodily reactions can affect results, thus studies measuring organ (e.g., heart or skin) responses to assess ANS activity have been more effective when focusing on changes within the same person rather than between people (de Geus & Gevonden, 2023). Previous studies, often conducted in controlled settings, did not capture daily fluctuations in emotions and physiological responses and had irregular survey intervals (Hernandez et al., 2016; Sabour et al., 2019). According to Stemmler and Wecker (2010), individual differences in physiological responses to emotions can vary over time within individuals and cannot be predicted from inter-subject research findings. Disentangling between-person and within-person effects is increasingly recognised as essential for understanding physiological and psychological processes since psychological theories often aim to understand processes occurring within individuals (Kraiss et al., 2022). Collecting longitudinal data, using the experience sampling method (ESM), is one way of realising such an aim.

The present study addresses these limitations of previous research by employing ESM and wearable technology to monitor between- and within-participants' emotional and physiological responses in a real-time, ecological, longitudinal framework. The ESM overcomes the limitations of traditional cross-sectional and lab-based studies by actively assessing participants' behaviour, emotions, and thoughts in daily life (Larson & Csikszentmihalyi, 1983). Unlike conventional methods (e.g., surveys and diaries), ESM requires participants to answer the same questions several times, reducing recall bias and increasing the ecological validity of the results (Hernandez et al., 2016). In the present study, a daily questionnaire was used to assess participants' positive and negative emotions over eight days. Advances in mobile technology (such as wearables) made this approach feasible because detailed contextual data like EDA and PRV can be measured and collated through onboard sensors (Van Berkel et al., 2017). By combining digital biomarkers and the ESM, data on emotional and physiological responses (and the associated fluctuations) can be gathered in naturalistic settings daily (Hernandez et al., 2016). In the present instance, inter-

and intra-individual variations were used to evaluate PRV as a proxy for assessing emotions, filling a gap in the literature.

Research Aim and Hypotheses

The study will explore whether EDA and PRV show between- and within-person associations with positive and negative emotions in young adults aged 18 to 27 years. The negative and positive emotions experienced by the participants were self-reported through a daily questionnaire via the platform m-Path (m-Path, 2024). The EDA and PRV biomarkers were measured using the medical-grade wearable EmbracePlus, equipped with EDA and PPG sensors, over eight days to ensure a week-long collection of physiological data. Most studies have focused on between-person associations, and to maintain comparability, this study also emphasises between-person associations. This led to the first research question: "How are fluctuations in EDA and PRV associated with positive and negative emotions among young adults?" Based primarily on studies in experimental contexts, it was hypothesised that EDA would be positively associated with negative emotions such as sadness, while PRV would be positively associated with negative emotions such as anxiety and stress (Hovers et al., 2021; Mejía-Mejía et al., 2021; Mucci et al., 2016).

Distinguishing between- and within-participant variability was also important because understanding the latter would provide deeper insights into individual processes and help validate the personal sensing framework and the intraindividual hypothesis of the link between emotions and physiological reactions (Institute of Medicine (US), 2004; Kraiss et al., 2022; Mohr et al., 2017). The current study follows this framework as deemed relevant, aiming to better understand individual physiological and psychological processes, leading to the second research question "Do EDA and PRV have significant within-person association with positive and negative emotions?".

2. Methods

2.1 Study design

This 8-day longitudinal study focused on the relationship between positive and negative emotions and EDA and PRV in young adults between the ages of 18 and 27. The measurement period length was based on the median duration of ESM studies (Yearick, 2017). The study collected physiological data using wearables for 7 days and self-reported data via m-Path for 8 days, encompassing an overall measurement period of eight days. Daily ESM-based questionnaires on participants' positive and negative emotions were sent via the m-Path platform (m-Path, 2024) while their physiological arousal, as evidenced by EDA and

PRV, was measured using the medical-grade wearable EmbracePlus (Empatica, 2024). The Ethics Committee of the University of Twente's Faculty of Behavioural Sciences approved this study (project 240133, obtained on 23/02/2024). This thesis was written according to STROBE guidelines to enhance transparency and replicability of its findings (Vandenbroucke et al., 2007).

2.2 Setting

The data were collected between 18 March and 12 May, 2024 as part of a broader research project examining the physiological and emotional responses of young adults. The data were collected by three researchers in the context of conducting psychological studies for the bachelor thesis, the present study. The data collection started with an intake session where participants met with one of the researchers to review the study's design, procedures, and to set up the necessary mobile applications. Participants received a comprehensive manual of instructions (Appendix B) and were provided with an EmbracePlus wearable and charger. During the intake session, the researcher described the study's design and clarified the minimum duration for which the wearable device needed to be worn. Researchers assisted participants in downloading and setting up the m-Path and Care Lab mobile applications.

The m-Path app was used to obtain participants' informed consent and distribute the daily questionnaire form (Appendix A). Participants completed a one-time landing survey (Appendix C) to collect sociodemographic information. For 8 consecutive days, between 6:00 p.m. and 12:00 a.m., participants received a questionnaire probing their positive and negative emotions and other variables (Table 1). The questionnaire, which included each three items of positive and negative emotions, had to be completed between these designated time slots. Reminders were sent through the app every 2 hours and via personal messages from the researchers to ensure participants' adherence.

Following this, the researchers set up the EmbracePlus equipment such as the Care Lab app (Empatica, 2023). The integration of the EmbracePlus with the Care Lab app enabled real-time synchronisation of the collected data. Participants were instructed to install the "Care Lab" mobile application and to enable Bluetooth and have an internet connection as much as possible. The app facilitated data synchronisation and provided access to basic measurements such as heart rate and temperature. The researcher's ensured participants were familiar with the indicators that signified their devices were connected and that they were recording data. Participants wore an EmbracePlus, which passively sensed several digital biomarkers continuously, e.g. EDA and PRV. The digital biomarker data was firstly stored in

the Care Lab Portal, and then moved and stored pseudo anonymously to the University of Twente server. Participants in the eight-day data collection period were required to wear the EmbracePlus continuously, except during showers and charging times. The data collection of EDA and PRV and the daily questionnaires took place in the daily life of the participants and was thus not bound to a fixed location. After the data were collected, participants returned the EmbracePlus to the researcher. No follow-up study was conducted.

2.3 Participants

The participants were recruited through snowball sampling within the circle of friends and family of the researchers. The inclusion criteria for the participants were being as follows: able to speak English, being within the age range 18- 30, and in possession of an Android 11 or more recent reversion or an iPhone to connect the wearable and fill out the questionnaires via m-Path. Furthermore, all participants had to be able and willing to wear the EmbracePlus most of the time.

2.4 Variables

2.4.1 Covariates

The sensors of the EmbracePlus measured digital biomarkers such as physical activity, sleep detection, skin temperature, respiratory rate, and blood oxygen saturation (Empatica, 2023). Relevant for this study were EDA measured with a ventral EDA sensor and PRV with a PPG sensor.

2.4.2 Electrodermal Activity: Skin Conductance Level

To measure and quantify EDA, a specific component has to be selected. The term EDA refers to electrical phenomena observable on the skin (Amin & Faghih, 2022). Sweat secretion caused by activation of the ANS causes variations in skin conductance as a measure of EDA. Skin conductance level as a measure of EDA is considered a 'time-tested metric'; it has been extensively validated and employed in tracking SNS activity for several decades (Braithwaite et al., 2013). Skin conductance level represents the total level of arousal, declining with physiologically relaxing activities like rest and sleep (Malmo, 1959). A shift in the body's psychophysiological and metabolic states occurs in reaction to emotional stimuli, allowing the body to deal with them, e.g., flight or fight response (Amin & Faghih, 2022). The ANS may activate sweat glands, thereby increasing skin conductance. Researchers can investigate how emotional arousal-associated ANS activation fluctuates by analysing skin conductance. Skin conductance responses, which reflect peripheral bodily signals associated

with emotions, have been used to further investigate the emotional experiences and mental health (Christopoulos et al., 2019).

To measure the data of the digital biomarkers EDA and PRV, the EmbracePlus wearable by Empatica was utilised (Empatica, 2023). The EmbracePlus devices were provided to the researchers by the BMS Lab of the University of Twente (BMS Lab, 2024). The EmbracePlus contains several sensors such as the Ventral EDA sensor, which detects changes in electrical conductance on the skin. The EDA sensor provides high-precision data, ensuring the reliability and validity of the measurements according to the company Empatica (2023), however in literature the EDA sensor has only been validated in the previous wearable model the E4 (Borrego et al., 2019). The EmbracePlus and the Care Lab app in combination allowed for continuous real-time monitoring of physiological biomarkers. Through the Care Lab application, the researchers were able to check the adherence of the participants to the study and check if the data synchronisation worked for every participant.

2.4.3 Pulse Rate Variability

Objective physiological data regarding participants' ANS activity were continuously gathered using the EmbracePlus smartwatch, which contains an advanced PPG sensor to measure PRV (Empatica, 2023). A PPG sensor uses a non-invasive signal that transmits light through the skin and measures the reflection of the light from the capillaries to evaluate physiological information (Mao et al., 2021). Thus, PPG sensors capture the pulse waves generated by heart contractions and their transit through the arteries (Wibawa et al., 2019). Due to its sensitivity to variations in blood pressure and autonomic neural activity, PRV was used in the present study (Mejía-Mejía et al., 2021; Yuda, Shibata, et al., 2020). As the pulse wave travels through the arteries, its timing can be affected by factors such as respiration and autonomic nervous activity. Thus, PRV reflects changes in the time intervals between pulse waves, influenced by both the SNS and PNS (de Geus & Goven, 2023). This makes PRV a useful measure for monitoring physiological responses to emotions. The PRV measurements reflect the shorter pulse transit times resulting from higher blood pressure and by extension, the cardiovascular response to stress and other emotional stimuli (Mejía-Mejía et al., 2021).

A PPG sensor is not as reliable as an electrocardiogram sensor (ECG) measuring HRV, though it can be integrated into wearables (de Geus & Gevonden, 2023). Using a PPG sensor in a wearable offers convenience, feasibility, and increased user acceptance for continuous monitoring but with potentially more variability due to external influences (de

Geus & Gevonden, 2023). Unfortunately, PPG sensors in wearables are very sensitive to motion, resulting in missing data (Mao et al., 2021).

2.4.4 Negative and Positive Emotions

Daily questionnaires via the m-Path platform assessed participants' positive and negative emotions, providing subjective assessments of affective experiences. The self-reported measures of positive and negative emotions consisted of six items (Table 1), based on the PERMA Profiler's Positive and Negative Emotions items (Butler & Kern, 2016). The phrase "How often" in the original items was removed, the items were changed to the first person, and the word "today" was added (Table 1). The items were reformulated to fit the format of a daily questionnaire; the original PERMA questionnaire was designed to ask participants about the previous 2 weeks. To minimise workload and allow participants to complete the questionnaire in a few minutes, only a set number of questions were included (Hasselhorn et al., 2021). The participants rated the items on a scale from 0 (*not at all*) to 10 (*completely*) on the Visual Analogue Scale (VAS) via the m-Path app. Three items each assessed positive and negative emotions, and the responses were then averaged (Table 1).

The responses to the daily questionnaires were captured by the m-Path app, which was developed for use in psychological research by KU Leuven (m-Path, 2024). It allows researchers to collect real-time data on participants' emotions in their natural environment, ensuring ecological validity. Participants used their smartphones to respond to the daily questionnaire via the m-Path app, simplifying the process.

Table 1

Altered Items Based on the PERMA Questionnaire

Construct	Emotion	Formulation Presented to Participant
Positive Emotions	Joy	I felt joyful today
	Positive Attitude	I felt positive today
	Contentedness	I felt content today
Negative Emotions	Anger	I felt angry today
	Anxiety	I felt anxious today
	Sadness	I felt sad today

2.5 Bias

To limit response variability and poor adherence, participants received explicit instructions on data collection via the manual and during the meeting with researchers

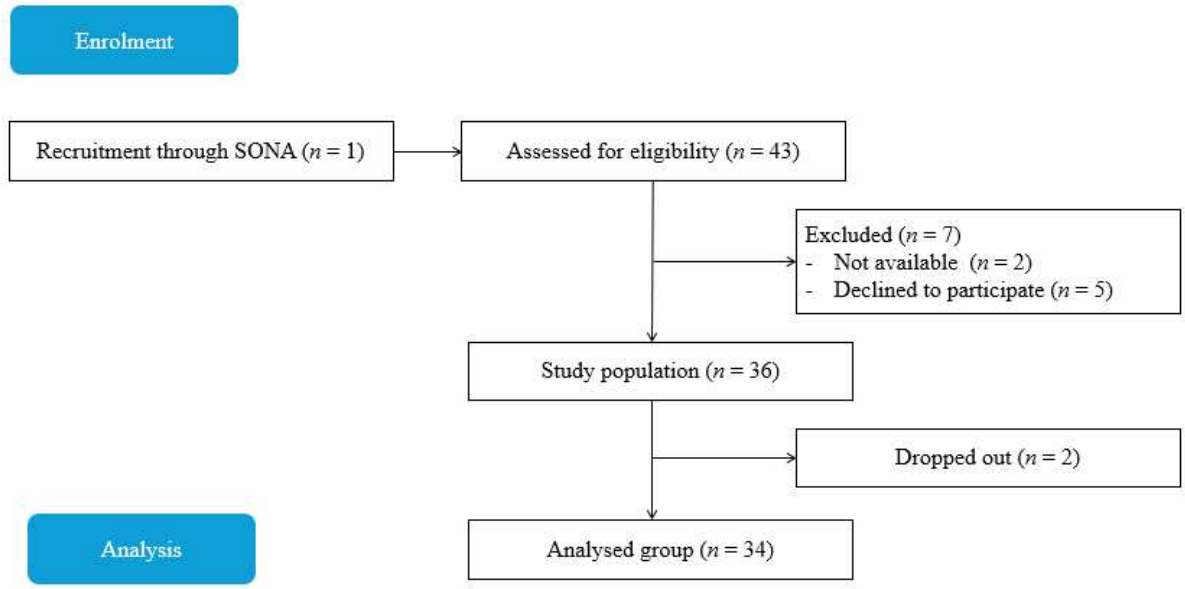
(Appendix B). Additionally, the participants received messages from the researchers reminding them to adhere to the study. Participants who adhered to the protocol, wearing the smartwatch for > 80% of the time and completing > 80% of the daily questionnaires, were entered in a raffle for a 50€ Amazon gift card. Participants recruited through SONA received 2.5 SONA points for their participation.

2.6 Study Size

Forty-two participants were contacted by the researchers. Five declined because they were not interested in the subject of the study and two others were unavailable during the allotted timeframe, which left 35 participants. Another participant was recruited through the SONA system for students at the University of Twente. Two participants dropped out during the study, leaving a final number of 34. Participants had to wear the EmbracePlus and complete the daily questionnaires at least 50% of the time to be in line with common ESM practice and thus be included in the final sample (Conner & Lehman, 2012). Figure 1 provides an overview of the recruitment process.

Figure 1

Flowchart of the Recruitment Process



2.7 Statistical Methods

2.7.1 Multilevel Modelling

First, the m-Path data were downloaded into Excel from the researchers' m-Path website (https://m-path.io/). The EmbracePlus data were downloaded via an access key from

the Care Lab portal (Empatica, 2023). Both sets of data were then uploaded to a university OneDrive server with pseudonymised IDs. To conduct the statistical analysis, RStudio-2023.12.1-403 was used. The raw physiological EDA and PRV data were processed hourly. EmbracePlus has a one-minute sampling rate, and to better capture fluctuations over the day and avoid overfitting of the models, EDA and PRV was resampled to hourly measurements. The hourly data for each participant were derived by summarising mean or count values for each hour. Additionally, each participant's Excel file with the necessary column names was read from m-Path, and the data were combined into a single data frame. After being properly parsed into a date-time format, the timestamp field was adjusted to the closest hour. The final dataset, after cleaning and merging, contained hourly measures of physiological and self-reported negative and positive emotion items for each participant. The adherence rate for each participant were calculated to remove participants with an adherence rate below 50% on both measures. Afterwards, the items for positive emotions (Joy, Positive Attitude, Contentedness) and negative emotions (Anger, Anxiety, Sadness) were combined, and the means for each of these three items were used per day.

Person-centred mean multilevel models are widely employed to disaggregate between- and within-person relations (Dao et al., 2021). The person- and person-centred means for EDA and PRV were examined using linear mixed-effects models. The person-centred mean is calculated by subtracting the overall mean of the variable from each individual's mean of the variable (Kraiss et al., 2022). The person means for EDA and PRV represented the between-participant effects, while the centred person means were used to examine the within-person effects. Multilevel models enable accounting for the structure of the data (observations nested within days within person) and have been widely used in ESM (Curran & Bauer, 2011; Kraiss et al., 2022).

The coefficient of fixed-effects, standard error (*SE*), confidence interval (CI), *p* values and standardized beta were calculated and reported. Standard error quantifies how accurately a sample can depict a population (Lee & Cerin, 2023). Confidence intervals are computed by the standard error and provide a potential range of values for a population. Standardised beta (β) is a standardised version of the raw beta coefficient, meaning that the variables have been rescaled to have a mean of 0 and standard deviation of 1 (Bring, 1994). This allowed the comparison of the effects of the variables EDA and PRV which are measured in different units. The *p* values below the threshold of 0.05 are statistically significant, so the null hypothesis can be rejected (DiLeo & Sardanelli, 2020).

2.7.2 Handling Missing Data

Missing data were systematically addressed to ensure the integrity of the dataset. Firstly, any *NaN* (Not a Number) entries were removed in cases when both EDA and PRV measurements were absent at the beginning or ending of participant measurement since these missing values are likely due to the starting and the ending of the measurement. To manage missing questionnaire data, the last observation carried forward (LOCF) approach was applied to the m-Path item data (Overall et al., 2009). This procedure involves inserting missing values for each participant for every hour; the missing values are replaced by the last observed value of that variable for each individual regardless of when it occurred. The missing values were completed upwards of every hour to minimise the temporal bias in reporting emotional states and maximise the use of available data, which is necessary for a longitudinal study design (Ji et al., 2018).

3. Results

3.1 Descriptive Statistics

The final sample consisted of 34 participants. Half of the participants were male (n = 17) and the other half female. The average age was 21.45 years (SD = 2.05, range = 18-27). Most participants (94.1 %, n = 32) were German, with one participant reporting as Dutch and another participant reporting as Vietnamese. Half of the participants reported being a full-time student (n =17), 12 working students (35.3%) and 5 working (14.7%). Table 2 displays the sociodemographic characteristics of the participants.

Table 2

Sociodemographic Characteristics of Participants

Baseline characteristic	**Participants**	
	n	*%*
Gender		
Female	17	50.0
Male	17	50.0
Age		
Mean **(SD)**	21.45 (2.05)	
Occupation		
Student	17	50.0
Student &Working	12	35.3
Working	5	14.7
Nationality		
German	32	94.1
Dutch	1	2.9
Vietnamese	1	2.9

The overall adherence rate was 90.47%, with the m-Path adherence rate at 93.06% and the (smart)watch-wearing adherence at 87.88% (Appendix D).

3.2 Visualisations of the Variables

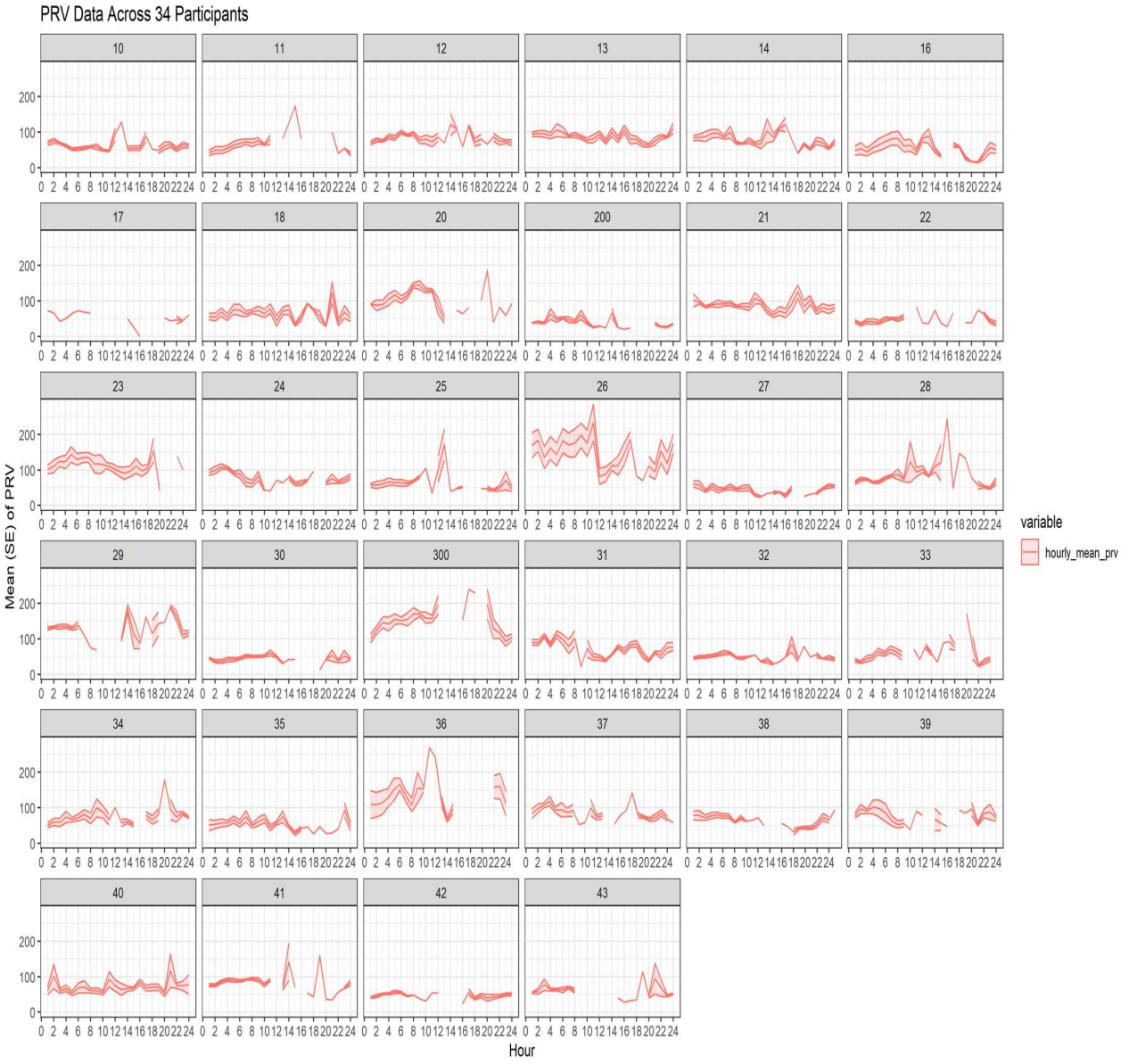
This section displays the mean values and standard errors for each variable across the 34 participants. For the physiological measures EDA and PRV, the measures are presented with their mean values across the 24 hours of the day (Figures 2 and 3). The m-Path graph in Figure 4 shows the fluctuations in positive and negative emotions throughout the 8 days.

Figure 2 presents the mean and *SE* of PRV for each hour across the 34 participants. The participants with larger ribbon areas are likely to have had greater variability in their hourly PRV measurements. The particular patterns in each participant's PRV data suggest significant individual differences in physiological responses influenced by factors such as time of day, daily activities, and personal physiological characteristics. Some participants showed noticeable spikes in PRV values at specific times, e.g., higher PRV values in the afternoon, while others exhibited more stable values with fewer fluctuations. At the same

time, the plot reveals missing values, particularly in the afternoon, likely due to excessive motion affecting the PPG sensor. In particular, participants 17 and 11 had very few PRV measurements leading to fewer observations being available for the analysis.

Figure 2

Hourly PRV Data per Participant



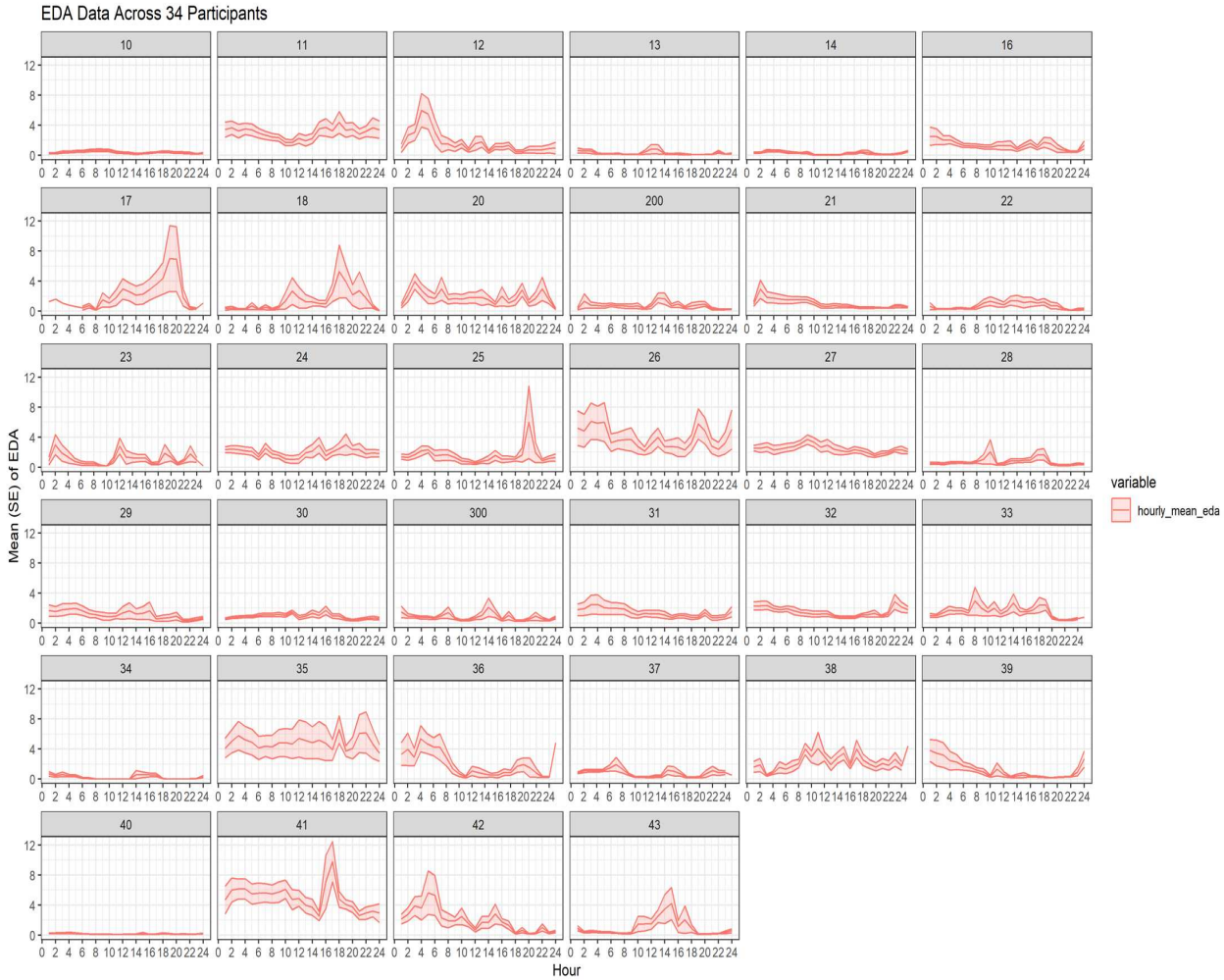
Note. hourly_mean_prv (red line) represents the mean value of the hourly PRV for each day. The x-axis (Hour) represents the hours of the day (from 0 to 24). The y-axis represents the mean value of the PRV for each hour. Each small plot corresponds to an individual participant, identified by a pseudonymised number at the top of each plot. PRV can only be calculated in the absence of movement; explains the gaps in the graph (section 2.4.2). The middle line represents the mean, the ribbon around it indicates the *SE*.

Figure 3 presents the hourly EDA data for the mean and *SE* for each participant. The ribbon around the middle line, representing the *SE* varied widely, some participants showed

almost no ribbon, indicating little variability, while others had large ribbon areas, indicating more variability. Other participants generally displayed low EDA patterns with low arousal levels, whereas other participants showed high levels of activity. Some participants had mean EDA spikes in the evening indicating high arousal activities in the evening, while others showed multiple smaller spikes throughout the day showing relatively stable arousal levels throughout the day. This suggests regular routines or activities could be affecting their EDA values. Participants 10, 14, and 40 showed almost no EDA measurement values or very low ones, suggesting potential measurement bias or stable emotions resulting in minimal fluctuations.

Figure 3

Hourly EDA Data per Participant

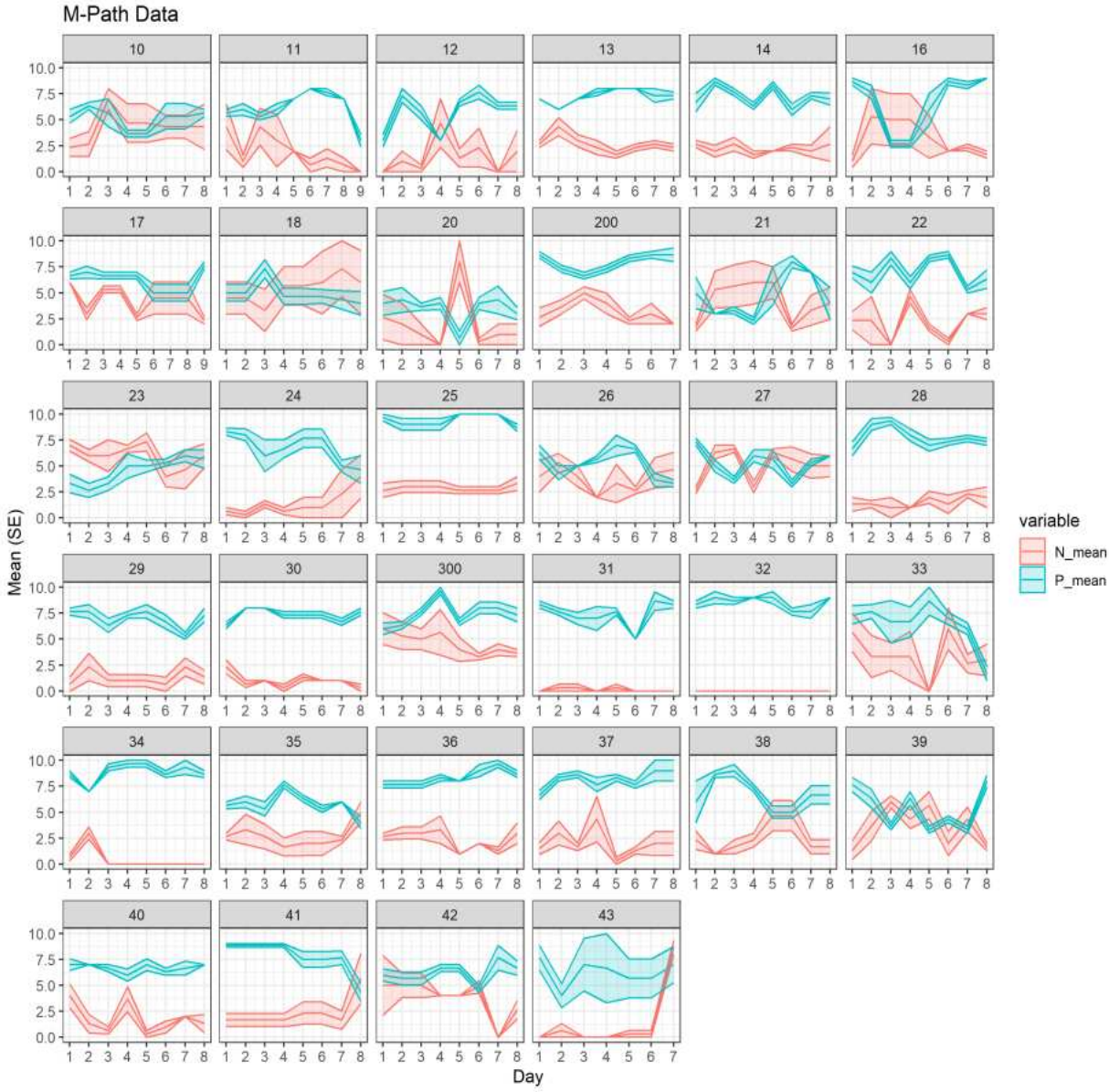


Note. The variable hourly_mean_eda stands for the mean of EDA on the hour; the x-axis represents the hours of the day (from 0 to 24). The y-axis represents the mean values of the EDA for each hour. Each small plot corresponds to an individual participant, identified by a pseudonymised number at the top of each plot. The middle line represents the mean, the ribbon around it indicates the *SE*.

In figure 4, the means and *SE*s of the variable's positive emotions and negative emotions for all 34 participants are displayed. The *y*-axis mean values ranged from 0 to 10. On the *x*-axis the day is indicated, showing the fluctuating levels of positive and negative emotions over the study's duration. There were clear differences between participants. Some participants showed stability in their emotional states with minimal fluctuations and reported higher positive emotion values (means of 6 or higher) and lower negative emotion values (means of 3 or lower). Participants whose emotions fluctuated largely often experienced more negative and less positive emotions compared to those with stable emotional states. Furthermore, these participants exhibited more variability, with different levels of positive and negative emotions each day. Overall, the data illustrate the different emotional experiences of participants, with some showing consistent emotional states and others showing significant daily variations. This highlights the importance of considering individual differences and assessing within-participant variability, when examining the relationship between physiological indicators and emotions.

Figure 4

M-Path Data of the 34 Participants With Mean and SD



Note. N_mean = mean value of the negative emotion items (Anger, Anxiety, Sadness) for each day; P_mean = mean value of the positive emotion's items (Joy, Positive Attitude, Contentedness) for each day. The middle line represents the mean, the ribbon around it indicates the *SE*. Each participant has a pseudonymised number at the top.

3.3 Multilevel Modelling with Person-Mean Centring

To address the first research question regarding how PRV and EDA are associated with positive and negative emotions and the second research question whether PRV and EDA have within-person associations with positive and negative emotions, a multilevel model with person-centred mean was used to distinguish between and within-participants. Two models were calculated to predict the two response variables positive and negative emotions.

3.3.1 Positive Emotions

Table 3 provides an overview of the model for positive emotions. The average level of positive emotions when all predictors are at their mean values was 7.08, which is statistically significant (*SE* = 0.20, CI [6.68–7.47], $p < .001$). When considering the β value 0.01 of the intercept, the intercept had a relatively weak effect on positive emotions. The EDA person mean value, representing the between-person effect of EDA had an estimate of -0.12 and *p* value of less than 0.001 and was therefore significant (*SE*= 0.02; CI [[−0.16–−0.08]). Although it was not hypothesised before, EDA had significant negative between-person association on positive emotions. The PRV person mean, the between-person effect for PRV, had a small negative effect size with an estimate of −0.00. This was significant, *SE* = 0.00; CI [−0.00–−0.00]; $p = .002$. Thus, PRV had a significant negative between-person association with positive emotions, which was not hypothesised, thus further significant relationships were also found. In summary, PRV and EDA had both non-significant within-person associations with positive emotions, and EDA and PRV had both significant negative between-person relationships with positive emotions.

Table 3

Person-Centred Mean and Multilevel Model for Between- and Within-Participant Relationships Between EDA, PRV, and Positive Emotions

	Positive Emotions						
Predictors	Estimates	*SE*	β	Standardised error	CI	Standardised CI	*p*
(Intercept)	7.08	0.20	0.01	0.11	6.68 – 7.47	-0.20 – 0.22	**<0.001**
EDA (Person Mean)	-0.12	0.02	-0.12	0.02	-0.16 – -0.08	-0.15 – -0.08	**<0.001**
EDA (Person Mean Centred)	0.01	0.00	0.01	0.00	-0.00 – 0.02	-0.00 – 0.02	0.063
PRV (Person Mean)	-0.00	0.00	-0.06	0.02	-0.00 – -0.00	-0.09 – -0.02	**0.002**
PRV (Person Mean Centred)	0.00	0.00	0.00	0.00	-0.00 – 0.00	-0.00 – 0.01	0.476

Note. There were 3,109 observations. EDA (Person Mean) = EDA mean of person; EDA (Person Mean Centred) = the mean-centred EDA of the person; PRV (Person Mean) = PRV mean of person; PRV (Person Mean Centred) = the mean-centred PRV of the person.

3.3.2 Negative Emotions

Table 4 provides an overview of the model for negative emotions. The intercept coefficient of 2.40 was the negative emotion value when all other variables (e.g., EDA and PRV) were at their mean. The intercept was statistically significant (*SE* = 0.22; CI [1.96–2.84]; $p < .001$). In contrast with positive emotions, negative emotions had a rather low intercept value of 2.40, while positive emotions had an intercept value of 7.12 (Table 3). The EDA person mean had a coefficient of 0.10 and was statistically significant (*SE* = 0.02; CI [0.06–0.15], $p < .001$). Thus, in line with the hypothesis, EDA had a significant positive between-person association with negative emotions. The EDA person mean-centred value, showing the within-participant value, was not statistically significant. Contrary to the hypothesis, PRV showed no evidence for a significant positive between-person association

with negative emotions. Thus, no evidence for the second research question was found that EDA and PRV have within-person associations with positive and negative emotions.

Table 4

Person-Centred Mean and Multilevel Model for Between- and Within-Participant Relationships Between PRV and EDA and Negative Emotions

				Negative Emotions			
Predictors	Estimates	*SE*	β	Standardised error	CI	Standardised CI	*p*
(Intercept)	2.40	0.22	-0.02	0.10	1.96 – 2.84	-0.23 – 0.18	**<0.001**
EDA (Person Mean)	0.10	0.02	0.09	0.02	0.06 – 0.15	0.05 – 0.12	**<0.001**
EDA (Person Mean Centred)	-0.00	0.01	-0.00	0.01	-0.02 – 0.01	-0.01 – 0.01	0.422
PRV (Person Mean)	0.00	0.00	0.02	0.02	-0.00 – 0.00	-0.02 – 0.05	0.420
PRV (Person Mean Centred)	0.00	0.00	0.00	0.00	-0.00 – 0.00	-0.01 – 0.01	0.851

Note. There were 3,109 observations. EDA (Person Mean) = EDA mean of person; EDA (Person Mean Centred) = the mean-centred EDA of the person; PRV (Person Mean) = PRV mean of person; PRV (Person Mean Centred) = the mean-centred PRV of the person.

4. Discussion

In this study, EDA and PRV were used to examine the association between physiological arousal with positive and negative emotions in young adults. The first research question, how EDA and PRV are associated with positive and negative emotions among young adults, was answered with the confirmation of one of the two hypotheses. Aligning with the hypothesis, a significant positive between-person association of EDA and negative emotions was found. Contrary to the hypothesis, PRV was not significantly positively between-person associated with negative emotions. Additionally, significant negative between-person associations of EDA and PRV on positive emotions were found. However,

significant within-person associations between EDA and PRV on positive and negative emotions were not found, providing no evidence for the second research question, that fluctuations in EDA and PRV were significantly associated with within-participant negative and positive emotions.

The results align with findings from previous studies indicating that EDA is a reliable indicator of physiological arousal (Braithwaite et al., 2013). EDA's ability to only measure SNS activity and be unaffected by PNS activity makes EDA a direct and consistent measure of arousal indicating negative emotions (Braithwaite et al., 2013). The results supported the significant negative between-person relationship between EDA and negative emotions highlighted by Horvers et al. (2021), and the significant negative between-person relationship between EDA and positive emotions, indicating that heightened arousal levels are often associated with heightened stress or anxiety, which can detract from positive emotions and increase negative emotions (Ganapathy et al., 2021). Thus, participants with higher average EDA levels reported fewer positive emotions and more negative emotions.

Moreover, there were no significant within-person associations between EDA and positive and negative emotions. The complexity and rapid changes in emotional states can result in fluctuations in EDA readings that do not align precisely with the emotions reported in the evening (Aldao, 2013). Therefore, while EDA may indicate overall arousal levels, it cannot be used to precisely identify emotions experienced at particular times.

The relationship between PRV and emotions was less consistent. The small but significant negative between-person relationship between PRV and positive emotions suggests that participants with higher average PRV were more prone to experience slightly fewer positive emotions. However, Zhou et al. (2023) found PRV to have positive associations with positive emotions such as amusement and furthermore able to detect amusement and sadness, a negative emotion. The common denominator between these emotions was their high arousal levels. The negative association with positive emotions may have been because PRV is sensitive to physiological stress and blood pressure changes (Mejía-Mejía et al., 2021). Higher PRV might indicate a more reactive or stressed physiological state, such as hypertension, which can detract from an individual experiencing positive emotions (Mucci et al., 2016).

The lack of a significant relationship between PRV and negative emotions suggests PRV might not be as reliable in detecting negative emotions as EDA. PRV is influenced by both the SNS and PNS, which independently affect heart rate and blood pressure (de Geus & Gevonden, 2023). The PNS, responsible for rest and digestion, slows heart rate and lowers

blood pressure, while the SNS, responsible for fight or flight, increases them. Both can independently activate and influence PRV. Since both systems influence PRV simultaneously, it can reflect a mix of stress and relaxation signals, making it less precise in indicating clear positive or negative emotion. EDA's specificity to the SNS means it directly measures physiological arousal associated with stress and anxiety, clearly indicating negative emotions in moments of high arousal measurement. Additionally, this contention is reinforced by the fact that PRV is highly sensitive to movement (Mao et al., 2021). Sahroni et al. (2022), who used stable PPG sensors in a setting where movement was minimised, found a significant between-person association between PRV and negative emotions.

The present study showed no significant within-person relationship between PRV and positive and negative emotions. In contrast, Jang et al. (2019) concluded that skin conductance level (measure of EDA), heart rate, and blood volume pulse (measured by PRV) were reliable within-participant physiological indices of emotions. Their findings supported the intraindividual hypothesis that physiological reactions to emotions are participant-specific (Institute of Medicine [US], 2004). However, Jang et al.'s (2019) study involved the presentation of emotion-provoking films in a controlled setting and measuring with an electrocardiogram. In contrast, the current study's naturalistic setting introduced more noise and used more feasible but less accurate wearable sensors such as the PPG sensor of PRV to increase user acceptance (de Geus & Goven, 2023). This impacted the detection of these associations. Thus, significant evidence could not be found for the second research question of within-person associations and, therefore no support for the longstanding intraindividual hypothesis (Institute of Medicine (US), 2004).

In summary, the results seem to confirm EDA as a reliable indicator of emotional arousal, particularly for identifying negative or positive emotions at the between-participant level through arousal averages. While physiological measures such as EDA and PRV showed consistent daily arousal fluctuations within participants, these fluctuations were not significantly associated with the levels of positive and negative emotions in individual participants. This contrasts with the between-person results where significant associations were found, indicating that overall averages rather than daily fluctuations of measured arousal may be more relevant for understanding positive and negative emotions. Meanwhile, although, PRV provides valuable insights into the autonomic regulation of emotions, it is not a precise standalone measure for assessing negative emotions of individuals, e.g., because of its sensitivity to movement.

4.1 Implications of the Study

The findings indicate that digital biomarkers should still complement self-reported emotions, as they cannot yet fully replace subjective measures due to their unreliability in assessing within-person variability. EDA sensors should be used in everyday wearables to assess the arousal levels of young adults in their daily lives, and to compare them to other users, as increased average EDA may suggest a tendency to experience negative emotions (Stifter & Augustine, 2019). Developing ecological emotion regulation and monitoring programmes for young adults require methods that mitigate recall bias, prioritise non-invasiveness, and offer practical applications such as digital biomarkers (Beames et al., 2021; Stifler & Augustine, 2019). So-called ecological momentary interventions could offer immediate support based on increased EDA readings over several hours, prompting clients to do breathing or movement exercises to regulate the ANS and thereby the positive and negative emotions (Balaskas, et al., 2021). These interventions could enhance emotional awareness among young adults, leading to favourable outcomes such as less stress, better emotion regulation, and fewer health risks (Yoon et al., 2018). If proven reliable, EDA could be used for clinical applications, such as real-time monitoring to support mental health interventions. Real-time monitoring could help therapists understand their clients' emotional patterns and triggers, allowing for more personalised and timely support (Tao et al., 2023). Additionally, researchers might use the present findings to develop more sophisticated ecological emotion monitoring methods to better support young clients in managing their emotional well-being.

4.2 Strengths and Limitations

4.2.1 Strengths

This study has several strengths. First, the study has large ESM sample size of 34 participants with a high levels of questionnaire adherence and high wearable adherence (Table 2). Secondly, ESM, in the form of a daily questionnaire, minimised recall bias and researcher bias (Hernandez et al., 2016). The recording of real-time data in a daily life context not bound to an experimental design increased the generalisability of the results. Furthermore, the ESM longitudinal framework allowed for disaggregating between- and within-participants associations (Kraiss et al., 2022). Thirdly, the Embrace Plus wearable allowed for passive and unobtrusive recording of PRV and EDA, thus the device did not impact participants' daily activities (Motahari-Nezhad et al., 2022). Fourth, the present study is the first to investigate associations of EDA, PRV with positive and negative emotions by distinguishing the

between- and within-subject effects in the context of ESM. Furthermore, PRV is in its infancy in psychological research and has not found significant negative between-person associations with positive emotions in studies thus far.

4.2.2 Limitations

However, it is important to consider several limitations when interpreting the study's findings. EmbracePlus's PRV measurements are of research and not medical grade (Empatica, 2023). The PPG sensor is sensitive to motion, leading to missing data as be seen in figure 2 (Mao et al., 2021). Because participants were physically active during the day, the reliability of the PRV measurements may be called into question (Figure 2). Next to that, the LOFC was used to fill in the missing values of the day for the variables positive and negative emotions since the participants only reported one time a day. The idea behind the method is that the emotions participants recollect at the end of the day match the emotions they would report throughout the day if asked multiple times (Cao & Fine, 2019). But participants might have reported the most intense emotion they remembered, while neglecting other emotions they experienced throughout the day due to only being asked once a day. Increasing sampling frequency might have increased accuracy, but it might also have increased participants' perceived burden and lessened adherence (Hasselhorn et al., 2021). Furthermore, this study used the *Root of the Mean Squared of Successive Difference* feature, the consecutive pulse-to-pulse time intervals, of the PRV measurement (Sabour et al., 2019). However, due to no standardised method for pre-processing data and multiple other features of PRV that can be computed, this can lead to reproducibility issues across studies (Föll et al., 2021). Additionally, no behavioural or contextual factors that might change EDA, PRV and positive and negative emotions were taken into account such as caffeine consumption (Schwerdtfeger & Gertreis, 2014). Finally, the sample consisted primarily of German university students with a personal connection to the researchers due to the nature of the sampling method. Thus, the generalisability to other age groups, cultural backgrounds, or populations with different occupations might be limited.

4.3 Recommendations

More research is needed to obtain a fuller understanding of the extent of the relationship between the digital biomarkers EDA and PRV and positive and negative emotions. Future research might focus on validating the PERMA items to ensure their reliability and validity in the ESM context. As discussed before, participants' trajectories of emotion likely fluctuated throughout the day, possibly resulting in self-reports of only the

most intense ones. This would indicate that a study with multiple assessments throughout the day can be a better design to capture putative within-person variability. Research could examine the balance between the potential burden of asking participants about their emotions multiple times a day and the possible improvement in the accuracy and reliability of the data collected. Furthermore, researchers can work on improving wearable sensor technology to reduce noise and increase accuracy, especially for PRV, enhancing its reliability for real-world applications. Otherwise, advanced machine learning techniques should be researched which could help overcome the limitations of PPG sensors by detecting and correcting movement artifacts. Furthermore, these machine learning techniques could be used to extract the complex patterns of EDA and PRV to analyse them more in-depth, a technique already used for atrial fibrillation (Xie et al., 2024). New technologies should be used to make more accurate inferences concerning momentary changes and assess a greater range of physiological and emotional factors (Gross & Malzhacker, 2023). With the development of context sensors, event-contingent triggering could be used to assess specific emotional states and physiological reactions to specific events in daily life.

4.4 Conclusion

The present study aimed to explore the between-person relationship of PRV and EDA with positive and negative emotions, finding clear support for the significant negative between-person associations of both EDA and PRV with positive emotions and a significant positive between-person association of EDA with negative emotions. For the second research question whether additionally within-person associations exist, no significant within-participant associations were found for EDA and PRV on positive and negative emotions, highlighting the importance of averages rather than daily fluctuations for understanding positive and negative emotions. The study successfully leveraged ESM and wearables to capture real-time data on physiological responses and positive and negative emotions over 8 measurement days in a naturalistic setting, addressing the limitations of previous studies through both the decomposition of between- and within-subject effects and the ESM approach. This study is one of the first to demonstrate significant associations between EDA, PRV, and positive and negative emotions using ESM, highlighting the need for further research into and development of real-time emotion monitoring methods to improve mental health interventions in young adults.

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During the preparation of this work the author(s) used ChatGPT in order to correct grammar/spelling, summarise and get an overview. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the work.

Appendices

Appendix A

This was provided in a digital format in the mPath application

Consent Form for *BioMean*- Digital Biomarkers of Meaning in Everyday Life

Researchers: Carolina Annabell Klingebiel (s2704161), Leonie Döhrmann(s2682818), Sophie Spierenburg(s2664682)

Introduction:

You are invited to participate in a research bachelor thesis study exploring the use of digital biomarkers for exploring the connection to the variables of positive and negative affect, self-esteem and meaning in life. Before you decide whether to participate, it is important that you understand the purpose, procedures and potential risks.

Study Purpose:

The purpose of this study is to investigate the meaning of digital biomarkers in everyday life. In particular, the variables of positive and negative affect, self-esteem and meaning in life will be assessed through daily questionnaires and correlated with the assessment of the biomarkers. The examination of these relationships allows for a deeper understanding of the role of digital biomarkers in everyday human experience and provides valuable insights into the dynamics between psychological states and biological markers.

Duration:

Your participation in this study is expected to last eight days.

Procedures:

If you agree to participate, you will be asked to wear the Embrace Plus watch which measures physiological and behavioural parameters. In detail the watch will measure:

- *Blood Oxygen Saturation (SpO2)*
- *Sleep Detection*
- *Electrodermal Activity (EDA)*
    - *Skin Conductance Level (SCL)*

- *Temperature*
- *Pulse Rate*
- *Respiratory Rate*
- *Pulse Rate Variability*
- *Wearing Detection*
- *Actigraphy Measures:*
    - *6MWT*
    - *Advanced Gait Analysis*
    - *Raw 3-axis Accelerometer Data*
    - *Wearing Detection*
    - *Sleep Detection*
    - *Activity Counts*
    - *Energy Expenditure*
    - *Body Position*

No harms are expected from this experiment and participants can contact the researchers in case of expected side effects or questions (contact information are listed below).

Please tick the appropriate boxes	**Yes**	**No**
Taking part in the study		
I have read and understood the study information dated [08/04/2024], or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	□	□
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	□	□
I understand that taking part in the study involves wearing the Embrace Plus watch all day (except when being in the water) and filling in a questionnaire once a day.	□	□

Use of the information in the study

I understand that information I provide will be used for a bachelor thesis… □ □

I understand that personal information collected about me that can identify me, such as [e.g. my name or where I live], will not be shared beyond the study team. □ □

Future use and reuse of the information by others

The data will be anonymised. If future publications utilise this study's data only groups estimates (e.g., mean, median, standard deviations, max, min, etc) will be reported. By clicking this box, I give permission for the questionnaire data and biomarker data that I provide to be archived in the UT data storage so it can be used for future research and learning. □ □

Signature

I understand what taking part in this study will involve. I agree to take part in this study □ □

Study contact details for further information:

Sophie Spierenburg, s.c.spierenburg@student.utwente.nl

Carolina Annabell Klingebiel, c.a.klingebiel@student.utwente.nl

Leonie Döhrmann, l.dohrmann@student.utwente.nl

Contact Information for Questions about Your Rights as a Research Participant

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Secretary of the Ethics Committee/domain Humanities & Social Sciences of the Faculty of Behavioural, Management and Social Sciences at the University of Twente by ethicscommittee-hss@utwente.nl

Appendix B

Manual for Participants

Everything you require to participate in this research should be covered in this manual. Take your time going over everything, and don't hesitate to get in touch with the researchers if you have any questions, are experiencing technical problems or if you want to withdraw from the study:

Sophie Spierenburg, s.c.spierenburg@student.utwente.nl
Carolina Annabell Klingebiel, c.a.klingebiel@student.utwente.nl
Leonie Döhrmann, l.dohrmann@student.utwente.nl

What is the purpose of the study?

The purpose of this study is to investigate the meaning of digital biomarkers in everyday life. In particular, the variables of positive and negative affect, self-esteem and meaning in life will be assessed through daily questionnaires and correlated with the assessment of the biomarkers. The examination of these relationships allows for a deeper understanding of the role of digital biomarkers in everyday human experience and provides valuable insights into the dynamics between psychological states and biological markers.

What is to be expected during the research?

Every day for 7 days you will be asked to answer a questionnaire via the app ***mPath*** on your mobile phone. The daily questionnaire will appear every evening at 18-21.00.
During these 7 days you will additionally be asked to wear the ***EmbracePlus*** watch **day and night**.
You will additionally be asked to download the ***EmpaticaCareLab app*** *f*or the upload of your watch's data. Ensure that your phone always has an internet and Bluetooth connection and ensure the watch is connected, which can be checked through the EmpaticaCareLab app, this will ensure a continuous synchronisation of data.
When you are requested to set up an account using your email but prefer not to use your personal email, you have the option to utilize *Proton Email* service at no cost (link on

last page). This allows you to quickly establish a secure, anonymous, encrypted email account.

If you adhere to the protocol (wearing the watch for > 80% of the time and completing > 80% of daily diaries) you will go to a pool (of all participants of this study) where a 50-euro Amazon gift card will be raffled.

How does *mPath* work?

MPath is a mobile application through which questions can be sent to you.

1. First you download the mPath app
2. You are then asked to provide a nickname (you do not have to provide your real name, to protect your privacy you can also provide numbers or an alias)
3. After accepting the terms, you can connect to our study through clicking on "Your practitioner" and then on the plus symbol, where you can then look for **@zcfp9** to add us as your practitioner.
4. Enable notifications for this app on your phone
5. For this study, you will be sent a consent form and a landing survey once at the start the study.

After these first steps you will receive a daily questionnaire between 18.00-21.00 (at the time you prefer in the landing survey) consisting of 18 items for 8 days. You can click on the notification or go to the app manually within this time frame. You will see "start the questionnaire"on the bottom of the page. We ask you to answer each question as truthfully as possible. Your answers are automatically and securely processed and stored in the researcher's dashboard.

How does the *EmpaticaCareLab app* work?

The EmpaticaCareLap app is part of the monitoring system of the EmbracePlus. Through this application you as a participant can check if the data is synchronising and if you are wearing the watch correctly. Please, activate the Bluetooth function of your device to connect the app to the EmbracePlus wearable. Additionally, your wearing time, pulse rate and skin temperature are displayed in the app.

The charge of the watch lasts approximately two days, so please recharge the wearable for about 1 ½ hours, when necessary, with the included charger.

Please do not wear the EmbracePlus during showers and when swimming. It is advised against to use it in water (despite the IP67 certification).
If the EmbracePlus **gets damaged** at any point, please notify the researchers **immediately,** there will be **no repercussions** for you, but we are required to inform the lending institutions of its damage.

How does the *EmbracePlus* work?
The EmbracePlus is a smartwatch designed for continuous health monitoring.
Place the EmbracePlus wristband top-down on a surface. Wrap the band around the wrist while making sure that the button is on the outside of your wrist. For reference look at the picture below. The EmbracePlus should be worn behind the knuckle. Make sure it is fixed and can't wriggle back and forth. Wear it on your non-dominant hand with a finger-width from your wrist bone. Check the underside if you want to make sure the wearable is recording, you should be able to see a green light.

How can I be sure the EmbracePlus is correctly recording?
Look out for the following signs

CARE LAB APP

Open the application and check that:

- ☑ The background is teal;
- ☑ The Status card reads 'Care is running smoothly';
- ☑ Wearing time is increasing;
- ☑ The Participant has the correct EmbracePlus. You can check this by looking at the serial number on the EmbracePlus, and comparing it to the serial number in the Settings menu of the Care Lab App

EMBRACEPLUS

Check the EmbracePlus and verify that:

- ☑ The display is light;
- ☑ The Empatica heart icon is visible;
- ☑ The sensor is on (there is a green light from the bottom of the device)

The Empatica heart icon tells you if the watch is connected to the app. If the watch is momentarily not connected to the app (no heart icon) the watch will upload the missing data when you are connected to the app again. Make sure your device with the Care Lab App has Bluetooth activated and is close to the EmbracePlus wearable.

What does the *EmbracePlus* measure?

In detail the watch will measure:

- Blood Oxygen Saturation (SpO2)
- Sleep Detection
- Electrodermal Activity (EDA)
    - Skin Conductance Level (SCL)
- Temperature
- Pulse Rate
- Respiratory Rate
- Pulse Rate Variability
- Wearing Detection
- Actigraphy Measures:
    - 6MWT
    - Advanced Gait Analysis
    - Raw 3-axis Accelerometer Data
    - Wearing Detection
    - Sleep Detection
    - Activity Counts
    - Energy Expenditure
    - Body Position

Links:

For more information about the applications and EmbracePlus:

EmbracePlus and EmpaticaCareLab: https://www.empatica.com/en-gb/

MPath: https://m-path.io/landing/

Proton E-mail free account: Proton Mail: Registrierung

Appendix C

Landing Survey Items

Welcoming text (ethics approved, researchers, what the study is about, informed consent form (first page study description, duration, randomized price voucher send by email, second page consent-only can continue when boxes are checked))

Landing survey items:

1. What is your gender Identity?
    a. Male
    b. Female
    c. Other

2. How old are you?

3. What is your nationality?
    a. Dutch
    b. German
    c. Other

4. What is your current occupation?
    a. Student
    b. Working
    c. Student and working
    d. other

5. What time in the day would be suitable for you to answer the daily survey?

Appendix D

Total Adherence, Questionnaire Adherence and Watch Adherence

Participant	m-Path adherence (%)	Watch adherence (%)
30	100	90.1
20	100	89.6
21	100	85.4
31	100	88.0
32	100	87.5
10	86	85.4
11	100	95.3
12	100	92.2
13	100	88.5
33	100	83.9
22	100	84.9
34	100	84.4
23	100	85.4
24	88	89.6
35	100	88.0
26	100	87.5
36	88	87.5
37	100	87.0
38	75	87.0
25	50	87.0
27	100	88.5
28	100	94.4
14	100	85.4
39	100	87.5
29	100	93.3
300	100	87.0
200	88	85.7
16	88	90.1

Participant	m-Path adherence (%)	Watch adherence (%)
17	50	88.5
18	100	92.2
40	100	87.0
41	75	88 .0
42	88	85.7
43	88	87.5
Overall adherence: 90.47%	**Total m-Path:** 93.06%	**Total Watch:** 87.88%