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Research article

Positive affect state is a good predictor of movement and stress: combining data from ESM/EMA, mobile HRV measurements and trait questionnaires

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ABSTRACT

Personality describes the *average* behaviour and responses of individuals across situations; but personality traits are often poor predictors of behaviour in specific situations. This is known as the "personality paradox".

We evaluated the interrelations between various trait and state variables in participants' everyday lives. As *state* measures, we used 1) experience sampling methodology (ESM/EMA) to measure perceived affect, stress, and presence of social company; and 2) heart rate variability and 3) real-time movement (accelerometer data) to indicate physiological stress and physical movement. These data were linked with self-report measures of personality and personality-like *traits*.

Trait variables predicted affect states and multiple associations were found: traits neuroticism and rumination decreased positive affect state and increased negative affect state. Positive affect state, in turn, was the strongest predictor of observed movement. Positive affect was also associated with heart rate and heart rate variability (HRV). Negative affect, in turn, was not associated with neither movement, HR or HRV.

The study provides evidence on the influence of personality-like traits and social context to affect states, and, in turn, their influence to movement and stress variables.

1. Introduction

The study of personality and behaviour has several open issues. One of them is roughly the following: when personality itself seems to be invariant (i.e. personality remains stable for extended periods of time), the variability of behaviour of an individual with given personality across situations is large. Personality traits are often poor predictors of actual behaviours or even psychological states (e.g., affects). This is often referred to as the "personality paradox": personality trait variables seem to be independent from short-term variables measuring psychological states (Bem and Allen, 1974).

Another often-neglected issue in personality research is the lack evolutionary thinking. "Personality", that is, stable patterns of behaviour when reacting to stimuli, seems to be widespread across animal kingdom (Wolf and Weissing, 2012). For instance, some individuals are shy while others are curious and bold. Among the remaining open questions is: what are the actual mechanisms that make individuals differ in their behavioural and internal state-patterns, which are then reflected as "personality traits"?

In this study our attempt is to increase understanding in both of these issues. Specifically, we evaluate whether analysing contextual variables (such as social context) helps to bridge the gap between personality traits and affective states, and whether affective states are better predictors of and individual's behaviour and stress states than personality traits. There is some research backing the assumption of the relevance of social variables (Smillie et al., 2015).

Both state (short term) and trait (long-term) models of personality have been studied separately; and there have been several proposals on how to integrate them. Several researchers have noted that personality cannot be completely separated from the context in which it is measured. In other words, individual differences of behaviour, thinking, feeling and reacting are context-dependent. These contextualised person variables (Hong et al., 1995) focus on within-person variability and patterning of behaviour (Cervone, 2005), integrating traits with social or cognitive variables (Read et al., 2010); Fleeson & Jayawickreme, 2015) and person

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effects on situations (Snyder et al., 1997). Mischel and Shoda proposed the so-called cognitive-affective system theory (Mischel and Shoda, 1995) to explain the "personality paradox". In their model, the personality system contains mental representations that consist of "cognitive-affective units", which include the person's representations of other people, self, goals, expectations and memories of past events and people. This representational approach to the question is ambitious, but difficult to test empirically.

Evidence from long-term trait (lifespan research) and short-term state (event-sampling) studies suggest that negative and positive emotionality, as well as self-constraint, explain away most of the behavioural effects of personality and temperament (e.g. Hampson, 2012). Nevertheless, rather than explaining short-term states, personality may be better at explaining long-term outcomes such as development of expertise (Hiltunen et al., 2019), health (Ferguson, 2013; Jokela et al., 2019), mental health problems (Ormel et al., 2013; Ervasti et al., 2019) and several other long-term outcomes such as salary (Gensowski, 2018). Neuroticism and rumination, the expected key trait variables in this study, have also been found to been associated with heart rate variability (Määttänen et al., 2019).

From an evolutionary perspective, contextual, fluctuating emotions (or affects) may allow an organism to direct its behaviour and regulate its stress state in an adaptive way. Emotions can be viewed as collections of physiological changes in the organism in response to specific stimuli (such as threats or incentives), which *direct* the organism to react or behave in a specific way. Personality, in turn, may be viewed as an underlying behavioural and emotional description of how the individual feels and acts *on average*, and what kind of physiological and behavioural reactions arise. Thus, these interconnected phenomena of emotions and personality should be studied simultaneously. Contextual cues, such as immediate social environment (Bolger and Eckenrode, 1991; Fischer et al., 2003), may be relevant for individual affects and reactivity as well.

There is a clear evolutionarily understandable adaptive purpose for both positive and negative affects. According to Gray (1987) and Gray and McNaughton (2003), positive affect may be seen as part of an "approach-system" which is involved with positive reinforcement and partly dependent on hypothalamic activity. Negative affect, in turn, may be seen as a part of an "avoidance system", or, in case of anxiety, a "conflict-resolving system" responsible for a variety of behaviours such as approaching, freezing, or fight or flight -reactions. More specifically, anxiety can be seen as a distress signal caused by opposing impulses within a hesitant individual. Not only humans but also all non-human animals seem to display signs of "personality" – that is, predispositions to different behaviours across situations. For example, among non-human animals, some individuals are "shyer", and some are more explorative than others (Cole and Quinn, 2014). Animal personalities and differences in stress-reactivity have been studied across species (Carere et al., 2010).

Previous research on the relationship between the physiology of affects and behavioural predispositions has focused mainly on animal models. Human studies are limited to mostly non-invasive laboratory studies, which may lack ecological validity. It is somewhat difficult to study the interplay between psychological traits and physiological reactions in a real-life setting. One way is to collect self-reports in real-life environments with emotion sampling methods (ESM, also known as ecological momentary assessment or EMA; Csikszentmihalyi et al., 1977; Csikszentmihalyi and Larson, 2014). In ESM the person makes typically daily, or more frequent, reports on their current activity, affects and other relevant information such as social context. ESM has several strengths compared to other ways of collecting data: it is possible to collect emotions and events in real-life situations rather than in a laboratory environment or retrospectively collecting memories (Scollon et al., 2009). Using ESM, some studies have found associations with Big Five personality-traits. Neuroticism has been associated with negative affect (Geukes et al., 2017; Komulainen et al., 2014) as well as higher affect variation (Geukes et al., 2017; Komulainen et al., 2014). Komulainen et al. (2014) have linked low neuroticism with positive affect. Extraversion, in turn, has been found to be negatively associated with negative affect (Geukes et al., 2017) and positively with positive affect (Geukes et al., 2017; Komulainen et al., 2014). Finally, at Geukes et al. (2017) also found a negative association between both agreeableness and openness and negative affect, and a positive association between openness to experience and positive affect. There is an abundance of research studying affects and personality via other methods than ESM: They have revealed similar results to the previously mentioned ESM studies: extraversion is positively associated with positive affect and negatively with negative affect (Costa and McRae, 1980). In addition, state extraversion has been found to be associated with positive affect (McNiel et al., 2010).

In this study, we focused on the interplay between personality, self-reported affective states, stress physiology, overall movement, and situational social factors in the individual's current everyday environment. This was achieved by collecting a rich multi-data point dataset within the same individuals, including measures on psychological traits, affective states and physiological stress from individuals in their natural everyday environment with varying social settings. Although the variables used have been utilised in previous studies, this is among the first studies to combine multiple different types of data in such a complex way.

1.1. Expected results and preliminary structure of different analysis sections

As the study mostly explorative by its nature and it has not been done before in its current form, no strict hypotheses were proposed.

Analysis section 1 was designed to study the overall associations with multiple variables. Based on previous studies, neuroticism and rumination were expected to be associated with negative affect, and inversely associated with positive affect and heart rate variability. If the preliminary analyses in the Analysis section 1 would indicate that a variable has clear associations with positive affect, negative affect or heart rate variability, the variable would be selected for further analyses in the following analysis sections. In addition, the variables' relevance, based on the research literature, would be considered in selecting a variable to further analysis sections. Analysis section 1 would also confirm or contradict the previous studies' findings of associations between personality and affect states measured by ESM/EMA.

In the Analysis section 2, the associations between selected trait variables from Analysis section 1 and negative and positive affect will be studied further in separate analyses. Contextual variables that are known to affect the studied variables (stress state, social company) will also be utilised. No hypotheses were presented for the Analysis section 2.

In the Analysis section 3, the associations between the previously selected trait variables and heart rate, heart rate variability and movement would be studied along with several contextual variables. No hypotheses were presented for the Analysis section 3.

In addition, in general it was expected that state variables would be more strongly associated with other state variables than with trait variables.

2. Materials and methods

2.1. Study design

Participants for the study were obtained by advertising in the University of Helsinki mailing lists. More information about the participants of the online surveys can be found in Ervasti et al., 2019. For the purposes of the current study, the following criteria were used to select which participants would be invited: 1. No diagnosed conditions that might strongly influence the participation or results (e.g. severe visual impairment, depression with current medication); 2. Willingness to "certainly" or "possibly" to participate in a laboratory experiment AND to the present study that followed; and 3. Suitable mobile device that supported our data collection purposes, i.e. only android phone users were invited.

The preparation phase of the study took place in the Stress Laboratory of the Department of Psychology in the University of Helsinki after a laboratory experiment. In the laboratory, participants filled in a form asking questions on their background and mood, and then completed a series of cognitive and stress-inducing tasks. The stress-tasks have been described in Määttänen et al., 2020. Simultaneously, several physiological variables were measured from the participants.

The data collection for the present study was designed and performed following the principles of Experience Sampling Method (ESM) and Ecological Momentary Assessment (EMA; Csikszentmihalyi et al., 1977). After completing the laboratory part of the study, the participants were given a package of several physiological self-measurement devices and instructions on how to use them (details in Data collection and variables). The subjects had verbal instructions as well as a sheet of paper for the Field data collection period. Before leaving the lab, the subjects tried on the measurement devices and tested whether they would be able to get the signal working. In case the device was notifying a connectivity error, water should be spread on the electrode parts if the Bioharness chest band to increase electrical conductance. The subjects were informed to wear the chest band during the day. Participants were also informed to wear a wrist band that measures sleep quality during the night (data not included in the study). In addition, the subjects were informed that in the case of any questions or problems, they should contact the research assistant. In addition, the participants downloaded an application into their smartphones that both monitored the use of their smartphones and included a short experience-sampling questionnaire. There were two days of active measurement, during which the participants took physiological measures of themselves and, in addition, 1–3 days of passive measuring, during which the participants only carried devices that did not need their attention. During the active and passive phases the subjects used also a self-report application, answering the questionnaires, daily, for a minimum of 3 days and maximum of 5 days. The subjects received a reminder every 45 min to answer the questionnaire with their smartphones. (Further details in "Data collection and variables"-section.)

At the end of the study, the participants were sent a feedback form. Among the participants who had filled in the electronic questionnaire before the study, movie tickets were randomly allotted to some of the respondents. The participants of the study were given three movie tickets and a personal sleep quality profile that was collected during the study.

The study design was mostly exploratory because the research field on the topic is relatively new. Sample size was designed to be sufficient for reliability and statistical power, even when some of the data had to be discarded because of quality problems etc.

All of the subjects provided an informed consent and were informed that they could quit the study at any time. The Ethics Review Board in humanities and social and behavioral sciences of the University of Helsinki (Statement 10/2015) also reviewed the study.

2.2. Participants

Participants were invited to take part in the study based on their health (no clinical diagnoses which could effect the measurement), their willingness to participate and their possession of suitable smartphone for the android-based app used in the study. Out of these, 56 participants took part in the laboratory measurements. One of the participants dropped out after refusing to participate after the laboratory tasks, giving us a total number of 55 participants for the field day phase of the study. Of the participants, 44 had sufficient quality and quantity data from all of the study variables to be used in the analysis; 34 were females and 9 were males, one participant did not report their gender. There was no exclusion criterion except that the included subjects had responded to the personality questionnaires and had useable field day data from ESM/EMA questionnaire and stress from at least one day.

Average age was 25.0 (SD 5.4, range 20–47); with 24.4 years for females (SD 4.9, range 20–47) and 27.1 years for males (SD 6.9, range 21–43).

2.3. Procedure: field days

The field study consisted of two days of more laborious measurement, during which the participants took physiological measures of themselves, including saliva, and in addition, 1–3 days of passive measurement, during which the participants only carried devices and answered ESM questionnaires. The data were collected during the weekdays, although this is not considered to have significantly altered the final stress levels, as the study group consisted of relatively young subjects with active lives. The aim of the field days was to measure stress, different affective states and their valence, physiological reactions and smartphone use in daily life.

The subjects were supposed to collect data for at least three days, but were informed that they could collect data for 4 or 5 days if they chose to. The number of field days participated per subject were following: one day (3 participants); two days (6 participants); three days (18 participants); four days (12 participants); and five days (5 participants).

2.4. Data collection and variables

ESM questionnaire, that is, a short form asking questions on the participants' activities and feelings, was included in the smartphone application. The application has been previously utilised and described by Vildjiounaite et al. (2018). The aim of the questionnaire was to map the participants' physical activity, food consumption, emotional valence and stress. The questionnaire was quick to fill in (<2 min), and the interval between two consecutive questionnaire fill-ins (signalled by an alarm) was 45 min. If the subject was unable to answer, they were reminded again after 45 min. The questionnaires appeared to the subjects from 9 a.m. to 9 p.m. The average number of separate ESM/EMA-questionnaires answered was 37.51 per participant (SD 17.66, range 4–79). There were, on average, 7.5 different ESM/EMA questionnaires per day per participant (SD 4.66, range 1–22).

The ESM self-report consisted of the following items: Eight questions were about affect, including 3 items on positive-, and 5 items on negative affects. The items were inspired by PANAS (Watson et al., 1988). Positive affect was calculated as a sum of the items "Felt joyful", "Felt content" and "Felt happy", and negative affect as a sum of "Felt angry", "Felt sad" and "Felt anxious". "Felt guilty" and "felt lonely" were not used to score affect.

Answers were provided on Likert-scale ranging from 1: "not at all true"; to 7. "completely true". Three questions were about stress: "Has something stressful happened since the last report?" (yes/no; presence of stressor, later referred as *"stress state"*), "How stressful was it?" (*level* of stressor) and "Were you in control of the situation?" (*control* over stressor). The last two questions (level and control) were evaluated on Likert 1–5 scales (1 = not at all, 5 = very much). Quality of activity was calculated as sum of "I am capable of doing this activity" and "This activity does not require effort". Quality of solitude was calculated as a reverse of the item "Felt alone" when not in presence of others. Quality of sociality was calculated as a reverse of the item "Would rather be alone" when in presence of others. These answers were provided on Likert-scale ranging from 1: "not at all" true; to 7. "completely true". Subjects were also asked 1) if they were with another person at the moment; 2) about their current physical activity; and 3) whether they were eating or drinking at the moment.

Physiological stress and movement activity were measured with the Zephyr Bioharness wearable acquisition device (Annapolis, Maryland, USA), which is attached around the chest. As an overall index of total Heart rate variability (Shaffer and Ginsberg, 2017), the standard deviation of normal interbeat intervals (SDNN) was calculated using the device's own algorithm, which calculates a rolling 300 heartbeat, roughly 5 min, SDNN HRV value. This is updated once per second. For the first 300 beats of log, an invalid value will be reported. Mean values of HRV and movement were aggregated for every 45-minute segment. The device provides a null value, when data is missing.

Although additional indices of HRV might have been useful, the different indices generally correlate highly with each other and thus they are measuring the same underlying phenomenon (Massin et al., 1999).

Movement was measured by accelerometer data and it was composed to magnitude resultant vector by the algorithm of the Bioharness device, "VMU $= \sqrt{(x^2 + y^2 + z^2)}$ where x, y and z are the averages of the three axial acceleration magnitudes over the previous 1 s, sampled at 100Hz. Axial accelerometer output is band pass filtered, to remove non-human artefacts, and gravity." (Resource: www.zephyranywhere.com.) Acceleration magnitude is considered a useful parameter to describe the overall movement of a human (Godfrey et al., 2008).

The Big Five personality was assessed with Neuroticism, Extraversion, Openness-Five-Factor Inventory (NEO-FFI) (Costa and McRae, 1989). NEO-FFI is shortened version of the Revised NEO Personality Inventory. It contains 5 sub-factors: neuroticism, extraversion, openness to experience, agreeableness and conscientiousness. There are total of 60 items in this questionnaire. Responses to questions were provided with 5-point Likert scale from "strongly disagree" (1) to "strongly agree" (5).

Self-rumination (referred to as "rumination" in this study) and self-control were measured with the Self-rumination scale by Elliott & Cocker (2008). A modified Finnish version of the original scale was used (Palomäki et al., 2013). Participants provided answers to ten statements for each variable ranging from one to seven (1 = strongly disagree, 7 = strongly agree). Example items are: "Sometimes it's hard for me to shut off thoughts about myself" and "I often find myself re-evaluating something I have done".

Data from both personality (Big Five NEO-FFI) and the Self-Rumination scales were collected in the online questionnaire and recruitment phase of the study.

2.5. Descriptives for the segments

A total of 1638 separate segments (measurement occasions across participants) were included in the analyses. Of the segments, 212/1638 (13%) were reported as stressful, described as *"stress state"* in the analyses. Self-reported mean stress level during these segments was 3.53, (SD 1.41, range 1–7) and mean assessment of *"stress control"* was 5.00 (SD = 1.45 range 1–7).

Subjects reported being in company of friends or family 29 % of the time, and in company of others 19 % of the time. Being in company of a boss or a colleague constituted 13 % of the segments. The variable is referred to as *"social company"* or *"company"* in the Results.

The mean values for self-reported quality of activity, quality of social interaction when not alone, and quality of solitude when alone were 11.56 (SD 2.27, range 3–14), 6.56 (SD 1.05, range 1–7), and 6.45 (SD 1.34, range 1–7), respectively. The mean values for self-reported positive and negative affect were 14.32 (SD 3.56, range 3–21), and 4.15 (SD 2.08, range 3–19), respectively.

Mean heart rate (HR) was 76.3 (SD 18.09, range 35.13–174.94) across 1424 measured segments. Mean heart rate variability (HRV) was 1.35 (SD 1.21, range 0.00000187–8.85; 1452 segments). Mean movement (measured by accelerometer) was 0.078 (SD 0.067, range 0.01–0.89; 1483 segments). Missing values are due to data loss with the device.

2.6. Data analysis in analysis section 1

Linear mixed models were used to analyse the effects of personality traits on affect levels, other self-reported state variables and HRV. LMMs are useful when the data involve repeated measurements on the same statistical units. They also have many advantages, such as the ability to deal with missing values, over more traditional methods such as repeated measures ANOVA.

A separate model was run for every dependent and independent variable combination. *Point of measure* (time of response) was used as a level 1 predictor and personality trait as level 2 predictor. Both predictors were fixed but intercept and slope of the time variable were specified as random effects, allowing them to vary between subjects. Variables were standardised to allow comparison of the regression coefficients with each other. All models were adjusted for gender and age. Additionally, equivalent analysis without level 1 predictor was conducted using the variation (standard deviation) of the dependent variable calculated over all time points per individual.

2.7. Data analysis in analysis section 2

Based on the analyses in Analysis section 1, we selected relevant variables for Analysis section 2. We fit a series of linear mixed models using the lme4-package (Bates et al., 2015) in R (v. 3.5.2. R Core Team, 2018), separately predicting 1) *negative affect* state, 2) *positive affect* state, and 3) *heart rate variability*. *Social company* (three levels: "with family or friends", "with other people", "with no one"), and *stress state* (two levels: "stress", "no stress"), and their interaction, were entered in the models as categorical predictors. *Heart rate variability* was square rooted to normalise its distribution. *Point of measure* was entered as a repeated factor indexing the point in time during which measures were taken, approximately every 45 min during waking hours. Moreover, we fit our models separately by using trait 1) *neuroticism* scores, 2) *rumination* scores, or 3) *self-control* scores as covariates; three-way interactions between social company*stress state*neuroticism/rumination/self-control were also modelled. These individual difference measures were not entered in the models simultaneously since they diluted one another's effects if entered in the same statistical models as predictors.

Participant (numerical participant identifier) was used as a random effect allowing for variability in the intercepts but not slopes. For effect size estimates, we used the method by Nakagawa and Schielzeth (2013), which provides marginal (variance explained by fixed factors) and conditional (variance explained by both fixed and random factors) R^2-values for LMMs. For significance estimates, we used the lmerTest package in R (Kuznetsova et al., 2017), which applies Satterthwaite's method for approximating the degrees of freedom and calculating p-values for LMMs. The models satisfied the assumptions of linearity, and the residuals were near-normally distributed and homoscedastic. In the models, the residuals were also near-normally distributed across the levels of all individual predictor variables. Further, Q-Q plots indicated that the random effects were near-normally distributed for the models. Nonetheless, we reran all of our analyses using bootstrapped confidence intervals (bias corrected accelerated, with 2000 resamples), but this did not change the pattern of the results. To summarise, the results were relatively robust.

2.8. Data analysis in analysis section 3

The analyses in section 3 were identical to those in section 2, above (linear mixed models), with the exception of using *positive* and *negative affect* as predictors (instead of dependent variables), and heart-rate, HRV and movement were used as the dependent variables.

3. Results

Some of the self-reported variables were *pre-reported trait variables* (personality, including neuroticism, rumination, and self-control), whereas others were *state-variables* that were self-reported during the field days (positive and negative affect, stress state, stress level, stress control, quality of solitude, quality of sociality, with friends and/or family and with others). Heart rate (from which heart rate variability is calculated) was measured *physiologically* in real time. Description of variables can be seen in Table 1.

3.1. Analysis section 1: general associations between traits, states and context variables

Traits *neuroticism* (β = 0.24) and *rumination* (β = 0.20) were both positively associated with *negative affect level*, and negatively associated (β = -0.29 and β = -0.31) with *positive affect level*. They were also both negatively associated (β = -0.25 and β = -0.21) with the perception of *stress control* (state). Traits *openness* (β = 0.34), *agreeableness* (β = 0.24) and *self-control* (β = 0.34) were positively associated with perception of *stress control* (state). *Neuroticism* was negatively (β = -0.22), and *self-control* (trait) was positively (β = 0.15) associated with *heart rate variability*. Trait *conscientiousness* was positively (β = 0.19) associated with *positive affect level*. Rumination was negatively associated with quality of solitude (β = -0.32). (All beta-values $p < .05$.) There were multiple associations between trait-variables and quality of sociality. Complete results of the Analysis section 1 are presented in the Table 2.

The previous analyses were performed with affect state *levels*. The following analyses were made with affect *variation*. *Neuroticism* (β = 0.56) and *rumination* (β = 0.35) were statistically significantly ($p < 0.05$) associated with *negative affect variation*. *Rumination* was also significantly associated with *quality of solitude variation* (β = 0.13). There were multiple associations between trait-variables and quality of sociality variation. Details are presented in Appendix Table III.

Neuroticism was associated with heart rate variability as can be seen in Table 2. *Heart rate variability* was predicted in a separate analysis by several traits (*neuroticism*, *rumination*, *self-control*) as well as *stress state*. *Neuroticism* predicted *heart rate variability* (β = -0.10, $p = .01$). (Figure 1.).

Main effects of social company and stress state to negative affect, positive affect and HRV can be seen in Figure 2.

3.2. Analysis section 2: predicting positive and negative affect by traits, states and contextual variables

Based on Analysis section 1, we selected relevant variables for Analysis section 2. (Details of the analysis can be seen in Materials and Methods.)

The following traits and states were the strongest predictors of *positive affect* (in descending order): *stress state* (β = 0.25, $p < .001$), *neuroticism*social company*stress state* -interaction, *neuroticism*social company* -interaction, *social company*stress state* -interaction, *neuroticism*stress state* -interaction and *neuroticism* (β = -0.32, $p = .008$) (Figure 1.). The following state- and situational variables were the strongest predictors of *negative affect* (in descending order): *stress* state (β = -0.47, $p < .001$), *neuroticism* (β = 0.37, $p < .001$), *social company*stress state* -interaction and *neuroticism*stress state*-interaction (Figure 1; further details on model statistics in Appendix Tables IV and V).

In the analysis where *neuroticism* was replaced by trait *rumination*, the significant predictors of *negative affect* (in descending order) were the following: *stress state* (β = -0.46, $p < .001$), *social company*stress state* -interaction and trait *rumination* (β = 0.31, $p = .003$) (See Figure 1.). The following were significant predictors of positive affect: (in decreasing order): *stress state* (β = 0.23, $p < .001$), *rumination*social company*stress state*-interaction, *social company*rumination* -interaction and *rumination* (β = -2.9, $p = .01$). (See Figure 1, and Appendix Tables VII and VII).

Trait self-control was not a significant predictor of *negative* or *positive* affect. (Details in Table 2 and Appendix Tables IX and X).

3.3. Analysis section 3: separate analyses: predicting heart rate, HRV and movement by traits, states and contextual variables

In this analysis, *heart rate* (*HR*) was significantly associated with *positive affect* (β = 2.49, $p < 0.0001$), while *neuroticism* and *social company* remained non-significant predictors of *HR*. In the same analysis, *stress state* significantly negatively predicted *HR* (β = -1.99, $p < 0.01$). Thus, *positive affect* was strongly positively associated with physiological stress, and surprisingly, perceived stress state was negatively associated with physiological stress. In a separate analysis, where *negative affect* was

Table 1. Description of variables.

Name of the variable	Time of data collection	Type of variable	Scale	Relevance in the results
Neuroticism	**Pre-reported**	**Personality trait**	**Self-reported likert**	**High**
Extraversion	Pre-reported	Personality trait	Self-reported likert	Low
Conscientiousness	Pre-reported	Personality trait	Self-reported likert	Low
Agreeableness	Pre-reported	Personality trait	Self-reported likert	Low
Openness	Pre-reported	Personality trait	Self-reported likert	Low
Rumination	**Pre-reported**	**Personality-like trait**	**Self-reported likert**	**High**
Self-control	Pre-reported	Personality-like trait	Self-reported likert	Medium
Self-reflection	Pre-reported	Personality-like trait	Self-reported likert	Low
Positive affect	**Reported in real time**	**Perceived affect state**	**Self-reported likert**	**Very high**
Positive affect variability	Reported in real time	Perceived affects	Calculated value for each subject	Medium
Negative affect	**Reported in real time**	**Perceived affect state**	**Self-reported likert**	**Very high**
Negative affect variability	Reported in real time	Perceived affects	Calculated value for each subject	Medium
Stress state	**Reported in real time**	**Percieved state**	**Self-reported binary**	**High**
Level of stressor	Reported in real time	Percieved state	Self-reported likert	Medium
Control over stressor	Reported in real time	Percieved state	Self-reported likert	Medium
Quality of activity	Reported in real time	Percieved state	Self-reported likert	Low
Quality of solitude	Reported in real time	Percieved state	Self-reported likert	Low
Quality of sociality	Reported in real time	Percieved state	Self-reported likert	Low
Social company	**Reported in real time**	**Percieved state**	**Self-reported nominal**	**High**
Other activity and state-questions	Reported in real time	Percieved state	Self-reported nominal	Low
Movement	**Measured in real time**	**Measured acceleration**	**Accelerometer variable**	**Very high**
Heart rate variability (HRV)	**Measured in real time**	**Measured heart rate**	**HRV-variable normalised with sqrt**	**Very high**

Table 2. Associations of pre-reported trait variables (left) and state variable (top) means. Only significant and trending beta values presented.

	Positive affect	Negative affect	Quality of activity	Stress state	Stress control	Quality of solitude	Quality of sociality	HRV
Neuroticism	-0.29*	0.24*			-0.25†			-0.22*
Extraversion							0.29**	
Openness				-0.22†	0.34***		0.17†	
Agreeableness					0.24*		0.19†	
Conscientiousness	0.19†							
Rumination	-0.31*	0.20†			-0.12†	-0.32**		
Self-control					0.34**	-0.11†	0.27*	0.15†
Self-reflection								

Note: *** indicates $p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$ (trend).

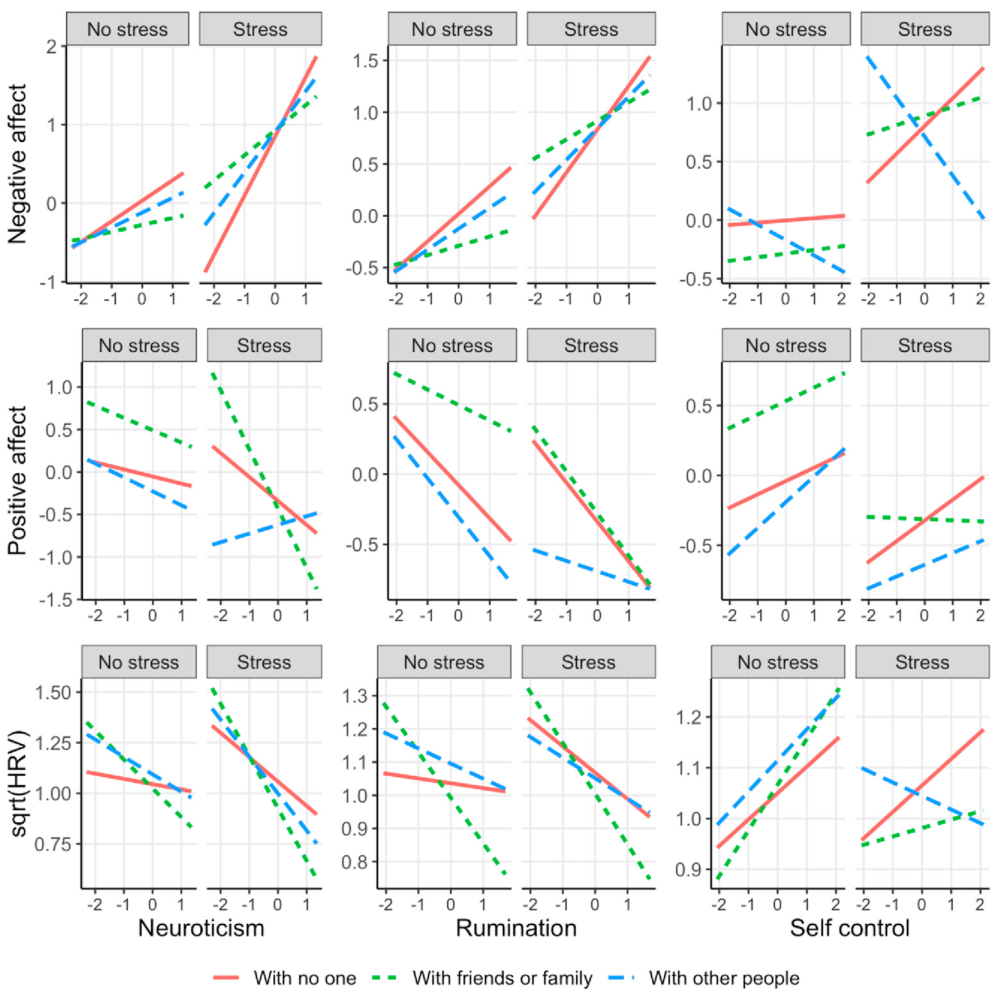

Figure 1. Associations between trait and state variables. The effects of (standardized) Neuroticism, Rumination, and Self control (trait variables measured once prior to field days) on (standardized) Negative affect, Positive affect, and (square rooted) Heart-rate variability (state variables measured on multiple occasions during field days). Slopes are plotted separately for three conditions of Social company (participants reported being i) With friends or family, ii) With no one, iii) With other people) and two conditions of Stress state (participants reported being i) Stressed or ii) Not stressed.

analysed instead of *positive affect*, no significant associations with *heart rate* were found.

Positive affect predicted *HRV* ($\beta = 0.052$, $p < 0.01$), but in a separate analysis *negative affect* did not. In the same analyses, *social company* and *stress state* were not associated with *HRV*. Details on heart rate variability associations can be seen in Appendix Tables VI, IX and XII.

Positive affect predicted *movement* ($\beta = 0.11$, $p = 0.0014$), while contextual variables (*stress state* and *social company*) and their interactions did not. *Negative affect* did not predict *movement* in a separate analysis (see Figure 3). It is worth noting that these analyses included a large number of variables, which resulted in some statistical suppression effects.

4. Discussion

We found that positive affect was in general a better predictor of outcome variables than negative affect and other state variables, contextual variables or trait variables. Specifically, positive affect was positively associated with heart rate variability, heart rate and measured movement, while the trait variables' associations with the same variables were typically weaker. Negative affect was negatively associated with HRV. The results support our assumption that affect states (although in this case mainly positive affect) are better predictors of individuals' daily movement and often also stress reactivity than personality- or personality-like traits. This may be part of the answer to why

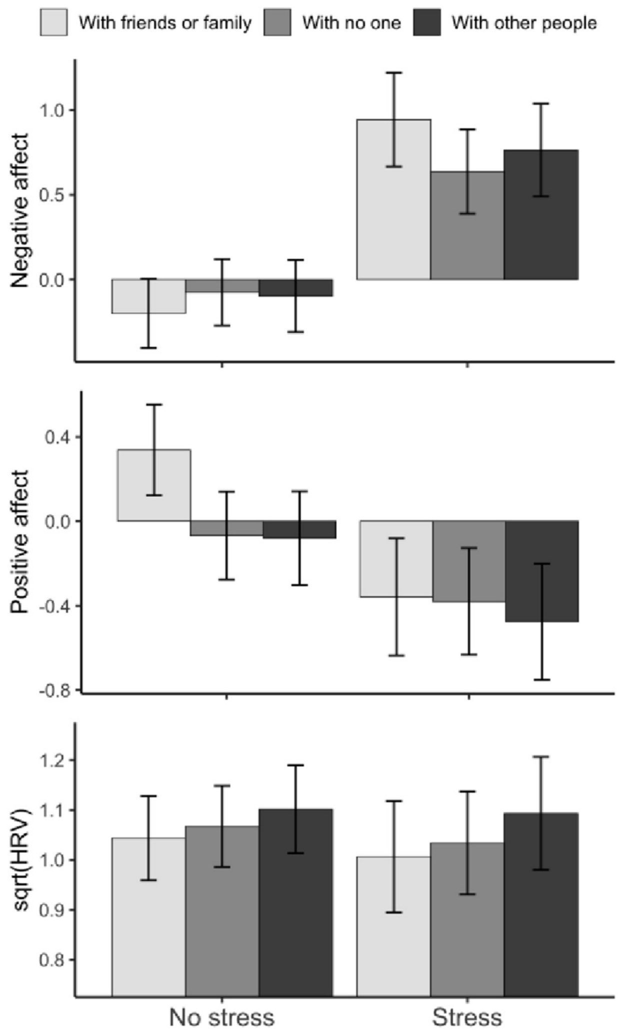

Figure 2. Main effects of Stress state and Social company. The main effects of Social company (categorical variable with three levels: participants reported being i) With friends or family, ii) With no one, iii) With other people) and Stress state (categorical variable with two levels: participants reported being i) Stressed or ii) Not stressed) on (standardized) Negative affect, Positive affect, and (square rooted) Heart-rate variability (HRV).

psychological traits are relatively poor predictors of observed behaviour in specific situations (Mischel, 2004). We have to keep in mind, that the results provided many significant associations, which would be almost impossible to discuss comprehensibly here.

As expected, neuroticism and rumination were negatively associated with positive affect, and positively associated with negative affect. These findings were not surprising in light of previous research (Slavish et al., 2018). There were also several significant interactions of both neuroticism and rumination with several contextual variables when explaining positive and negative affect. According to our results, neuroticism was negatively associated with heart rate variability, but despite this, it appears clear that trait variables are more useful in predicting affect states than they are in predicting movement or stress. Neuroticism and rumination have previously been found to be negatively associated with heart rate variability, so the lack of association between rumination and HRV was against our assumptions (Määttänen et al., 2019).

In previous studies, positive affect has been positively associated with 24 h HF-HRV (Bhattacharyya et al., 2008). Further studies have found that the relationship between HRV and trait and positive affect state is unclear (Papousek et al., 2010). Positive affect was associated with baseline respiratory sinus arrhythmia (or RSA, which is conceptually close to HRV) (Wang et al., 2013) but not with RSA reactivity or rebound. More generally, in a review by Chida and Hamer (2009), across the reviewed studies positive affect was associated with reduced HPA axis and stress reactivity, and negative affect with poorer cardiac recovery.

According to our results, positive affect state was positively and stress state negatively associated with heart rate. This finding could be considered rather surprising. It may reflect the increased movement associated with positive affect. The result emphasises the importance of knowing the context and perception of the individual before making any inferences about a stress variable.

Mischel (2004) suggests that the variability of the state variable, rather than its level, is the most meaningful correlate to other variables. Mischel and Shoda (1995) have previously argued that such variability in "state" measures does not necessarily reflect statistical "noise" or "error", but rather describes meaningful individual differences in responsiveness (see also Kosunen et al., 2018). We found several associations of trait variables and state "variability-variables": Openness, agreeableness and self-control were negatively associated with positive affect variability. Neuroticism and rumination were associated with negative affect variability. In fact, the associations with the "variability-variables" were often stronger than with the described "level-variables".

According to our results, state-variables were better predictors of affect and movement than trait-variables. Our study is among the first to have been able to simultaneously measure a large number of relevant variables in an ecologically natural every day environment. Our goal was to increase understanding on a possible pathway from background traits (personality, rumination, reflection, self-control) via contextual variables (i.e. social context) all the way to affect states and actual movement and stress. We found that especially positive affect is an important predictor of both movement and heart rate variability, which, in turn, reflects parasympathetic activity. Parasympathetic activity is believed to protect or revitalise the individual during or after stress. Negative affect was negatively associated with heart rate variability. The results describe how individuals' psychometric traits influence their real-time reactions to their surrounding environment, and how the combination of traits and social context influence perceived affect states. Affect, especially positive affect, reflecting the current self-perceived affective state of the individual, rather than psychometric "background" traits or the contextual variables, seems to be driving individual behaviour (as measured by movement) and stress-reactivity.

It is not surprising that we found positive affect to be positively associated with movement. In terms of evolutionary thinking, it can be argued that positive affect reflects the increased activity of something similar to, using Gray (1987) terminology, the behavioural activation system (BAS), as well as decreased activation of the behaviour inhibition system (BIS) and the flight, freeze and fight-system (FFFS). Positive affect state was also positively associated with HRV. These findings have been previously found with positive affect and BAS as well as BAS Reward Responsiveness and extinction in RSA responsiveness (Brenner et al., 2005). It has also been argued that there has been a shift towards understanding extraversion in terms of reward-processing (Smillie, 2013).

Perceived stress has been successfully predicted by machine learning models that included HRV, and the model was improved further by including activity data (Wu et al., 2015). In certain previous studies in cardiological contexts (e.g. congestive heart failure), the predictive accuracy of machine learning models with HRV has been even higher (Khaled et al., 2006). Relatively similar approach has also been used in the study by Vildjiounaite et al. (2018). As a whole, the previous findings combined with the results of the current study support the importance of trying to understand underlying stress phenomena instead of being interested in specific variables (See also: Okada et al., 2013.).

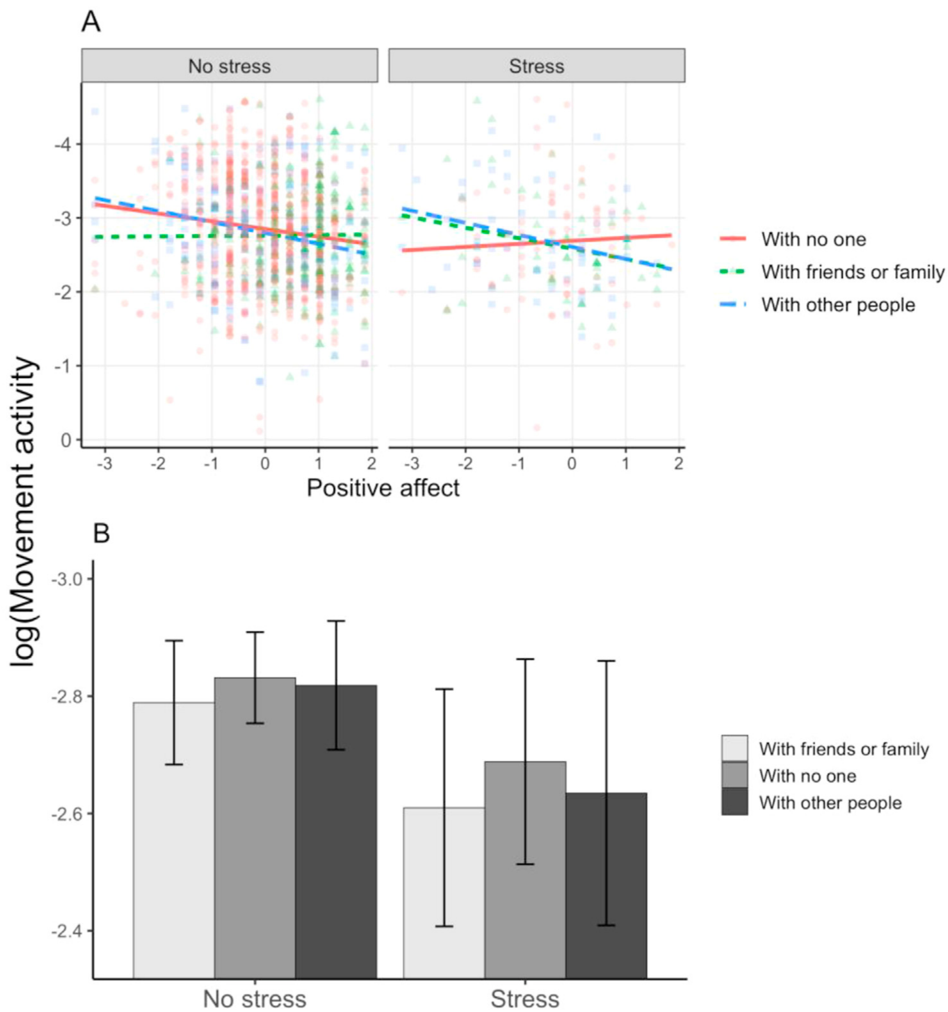

Figure 3. Main effects of Stress state and Social company when predicting movement activity. A: The effect of (standardized) Positive affect on (log-transformed) movement activity. Slopes are plotted separately for three conditions of Social company (participants reported being i) With friends or family, ii) With no one, iii) With other people) and two conditions of Stress state (participants reported being i) Stressed or ii) Not stressed). B: The effect of Stress state and Social company on (log-transformed) movement activity.

There were some limitations in our study. Firstly, our study lacked multiple behavioural outcome variables. For instance, it is unclear how the found effects and interactions would more specifically influence real-time behaviour, performance and decision-making. It is also possible that movement during, for example, exercise, may have influenced the results. Finally, missing data was an issue with some participants, as data collection during the field days may have been too laborious for them; however, linear mixed models are robust against missing data. Although much of the research literature uses different indices of HRV than this study (e.g. HF-HRV), it has been found that the associations between different indices of HRV are very strong, i.e. they are measuring the same underlying phenomenon (Massin et al., 1999).

The study limitations notwithstanding, we have presented results supporting the importance of positive affect in predicting movement and stress and proposed a theoretically reasonable way to couch this finding in existing work. Our results also underscore the importance of state variables, such as perceived stress, in predicting affective states themselves. There are no great issues with the generalisability of the results, although the subjects were recruited from a well-educated, western population.

Future studies with similar designs and with less explorative approach might provide important contribution and clarification on the results of this study.

Declarations

Author contribution statement

I. Määttänen: Conceived and designed the experiments; Performed the experiments; Analysed and interpreted the data; Contributed materials, analysis tools or data; Wrote the paper.

P. Henttonen: Analysed and interpreted the data; Wrote the paper.

J. Väliaho, M. Thibault: Conceived and designed the experiments; Performed the experiments.

J. Palomäki: Analysed and interpreted the data; Wrote the paper.

J. Kallio, J. Mäntyjärvi, T. Harviainen, M. Jokela: Conceived and designed the experiments; Contributed materials, analysis tools or data.

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Data availability statement

The data that has been used is confidential.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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