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The Impact of Wearable Stress Feedback on Individuals' Challenge-Threat Appraisals in Daily Life: The Moderating Role of Extraversion

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Abstract

Experts continue to explore innovative approaches involving technology to support individuals in managing stress, as stress-related problems become more prevalent in everyday life. Furthermore, cognitive appraisals significantly influence subjective responses and reactions to stress and are influenced by personality characteristics, such extraversion, which has repeatedly shown its positive effects on stress views. This study examines the effect of real-time stress feedback from wearable devices on stress appraisals in daily life, with extraversion as a moderating factor. A repeated-measures design with 75 participants (M age = 27.59, 63% female, 37% male) compared the stress appraisals across three questionnaires, during the baseline, after a week wearing and one without a stress feedback device. Participants wore a Garmin smartwatch that provided real-time stress feedback and stress appraisals were measured using an eight-item scale administered after each condition. Extraversion was evaluated using a three-item scale during baseline. The findings showed that wearable stress feedback did not significantly affect stress appraisals in this sample, as participants' scores remained stable across all conditions. Additionally, although individuals low in extraversion tended to perceive stressors as more threatening, extraversion did not significantly moderate the impact of the wearable. Future research could benefit from exploring and understanding further factors or interventions that may boost the effectiveness of wearable stress feedback in managing stress in daily life.

The Impact of Wearable Stress Feedback on Individuals' Challenge-Threat Appraisals: The Moderating Role of Extraversion

Chronic stress is a serious health concern that affects the cognitive functions of the brain and makes one more susceptible to mental disorders (Marin et al., 2011). In response, wearable stress monitoring devices, such as smartwatches, can be proposed as a way to help individuals manage their stress in everyday life. According to a report from Future Market Insights Inc. (2025), the adoption of such devices is expanding globally and is expected to grow even more in the next ten years. Asia is the region indicating the fastest growth in the use of such devices, while America and Europe follow with equally important and strong adoption rates. Nevertheless, despite their relevance and growing popularity, research on their real-world effects remains rare. Moreover, since stress is a subjective experience, individual differences might have an influence on how people perceive stress. Some individuals may interpret certain stressors as challenges, while others view them as threats. Personality traits, like extraversion may influence the feeling and response to stress one has, which raises the question of what effect it might also have on responses to stress feedback. This study aims to explore how wearable stress monitoring devices affect how people perceive stressors, as either challenges or threats and whether extraversion as a personality trait moderates this outcome. Unlike many controlled experiments, this research takes a different approach by allowing individuals to directly experience and report on stress feedback in their everyday life.

Stress and Stress Appraisal

Stress is a globally prevalent experience that affects people in their daily life. More importantly, stress is a major public health concern in the current years (Gallistl et al., 2024). According to APA (2022), over 75% of adults claim to have experienced health implications on the account of stress. Stress is defined by the APA Dictionary of Psychology (2018) as *"the physiological or psychological response to internal or external stressors and involves changes affecting nearly every system of the body, influencing how people feel and behave".*

Specifically, typical levels of stress can be characterised as part of daily life and experience. During regular levels of stress, the human nervous system automatically reacts to situations which are perceived as possibly threatening, with stress hormones that are necessary for survival (McEwen, 2007). Moreover, according to Lazarus and Folkman (1984, as cited in Epel et al., 2018) stress is the view that environmental expectations outperform a person's perceived ability to accomplish them. Nonetheless, continuous and intense stressors are damaging to humans and can cause disruptions in healthy functioning (Cohen et al., 2007). Accordingly, chronic stress is alarming and by definition is the physiological or psychological persistent reaction to internal or external stress-inducing events (APA, 2018). Early identification of stress could reduce the damage caused and keep it from growing into chronic (Can et al., 2019). Although scientists agree on general definitions and similarity in what individuals experience as stressful situations, every person perceives stress differently.

Stress Appraisal Theory

Individuals may evaluate and experience the same stressful event differently (Conner & Barrett, 2005). This process, scientifically known as appraisal, refers to the cognitive assessment of an event. Studies indicate that cognitive appraisals play a key role in shaping individuals' subjective experiences, physiological reactions, and behavioural responses to stress (Penley & Tomaka, 2002). Lazarus and Folkman (1984) first developed the Stress Appraisal Theory, and it suggests that people evaluate stressors based on either their capability for damage (threat appraisal) or personal growth (challenge appraisal). A threat appraisal may impact a person's quality of life, mental state, and health and trigger emotional and unhealthy coping reactions (Lazarus and Folkman, 1984). Challenge appraisals emerge when individuals interpret a stressor as an opportunity for personal growth or skill enhancement, fostering optimism and expectations of favourable outcomes (Chen et al., 2024). According to Jamieson et al (2018), stress can be advantageous when it is reappraised by the individual as helpful in achieving a goal. Based on that, appraisal of the stressor can be seen as a moderator on the effect it has on individuals.

Extraversion

The Big Five personality traits are widely recognised as the main dimensions of personality and are strongly linked to stress appraisal and management (Ringwald et al., 2024). Extraversion is one of those traits and is characterised by sociability and assertiveness

(Barrick & Mount, 1991). Based on research, extraversion has been associated with viewing stressors as opportunities and endorsing more adaptive stress responses (Ebstrup et al., 2011; Schneider et al., 2011). A systematic review by Kilby et al (2018) highlighted extraversion as a potential predictor of stress appraisals and showed the strong connection between high extraversion and challenge appraisals. In another context, a study by Yan et al (2024) assessed how extraversion moderated the relationship between job stress and positive well-being and found that individuals high in extraversion had more adaptive responses to stress. Overall, given these positive associations, it would be both interesting and valuable to investigate how extraversion might influence appraisals in the current real-life context study.

While many studies suggest a general positive trend between extraversion and stress responses or views (Tohver, 2020), findings of other research indicate no influence of extraversion on perceived stress (Luo et al., 2023). This mixed evidence highlights the lack of unanimity in existing recent literature regarding the effect of extraversion on stress appraisals. Moreover, the exploration of the effect of the trait extraversion on how an individual perceives and reacts to stress when using a stress monitoring device are very limited. Much of the existing work focuses on controlled laboratory settings, which may not fully capture the complexity of stress in daily life. Additionally, there is a little research on the impact of wearable devices on stress appraisals in general. In light of these gaps, this study aims to explore how extraversion may influence the effect of wearable devices on stress appraisals.

Wearable Technologies and Stress Management

Over recent years, wearable devices have gained immense popularity, with millions of people adopting them for various purposes, ranging from fitness to everyday convenience (Lunney et al., 2016; Smith et al., 2020; Chong et al., 2020). They also represent a type of wearable technology that individuals use to track and manage their health and well-being (Lu et al., 2020). The general definition can be viewed as devices that are worn on the body, wrist, fingers, legs or head, which contain very small and unobtrusive sensors that detect and quantify the individual's physiological activity (Canalli et al., 2022; Mukhopadhyay, 2015).

Within wearable devices, watches have become prevalent in remote monitoring of the vital signs of wearers. Wearable devices are also perceived positively by users and are relatively quick and easy to comprehend and use (Maher et al., 2017). Specifically, wearable devices that provide stress feedback have been found to be a promising tool to measure and manage stress effectively, as worn reminders have been found to increase the effectiveness of the intended procedure (Santoro et al., 2020). Wearable-based health interventions generally aim to enhance self-regulation by increasing individuals' awareness of their stress responses (González Ramírez et al., 2023). The devices provide real-time physiological feedback, aspiring to help users recognize and understand their stressors more effectively. In turn, this increased awareness may encourage individuals to re-evaluate their initial appraisal of a stressor, potentially leading to a more adaptive view of the situation. As a result, individuals may perceive the stressor as less threatening or more manageable. An illustration of this is a study by Gjoreski et al (2016), which found that wearable devices tracking Heart Rate Variability, among others, helped participants recognise stress patterns and adopt coping strategies.

More importantly, van den Berg et al. (2025) emphasise in their recent work the importance of understanding user experiences outside of experimental settings. Their extensive review shows that existing studies primarily assess the effectiveness of wearable devices in controlled environments, and this creates a significant gap in how these devices fit into the fluctuations and complexities of everyday life. This neglected area is a challenge for the design and implementation of wearable stress management technologies. Beyond the need to measure stress effectively, the use of these devices should also integrate into users' daily life. This calls for further exploration into the factors users encounter when engaging with stress feedback devices in real-world settings, which could lead to more effective and personalized stress management solutions.

Current Study

This study aims to contribute to the underexplored topic of the impact of wearable stress feedback on individuals' stress appraisals in daily life, while exploring the moderating role of extraversion on this effect. To investigate this, the study used a repeated measures quantitative design. Participants were exposed to two conditions, one week wearing a smartwatch providing stress feedback and one week without it, completing questionnaires after each condition.

As noted previously, most existing studies have been conducted in controlled laboratory settings, which are informative, but do not fully capture the dynamic and multidimensional nature of stress as it occurs in daily life. In response to this research gap, the present study adopts an exploratory approach to investigate how wearable stress feedback affects users' stress experiences in real-life settings. Furthermore, it aims to examine whether individual personality traits, particularly extraversion, play a moderating role in this process. Accordingly, the following research questions were addressed:

(RQ1): *Does real-time stress feedback from a wearable device influence individuals' appraisal of stressors as challenges or as threats?*

(RQ2): *Does extraversion moderate the effect of real-time stress feedback from a wearable device on individuals' appraisals of stressors as challenges or threats?*

Methods

Research Design

Figure 1

Graphical Overview of Current Study and Its Data Collection Points

This study was approved by the ethics committee of the Faculty of Behavioural, Management and Social Sciences (BMS) at the University of Twente with project number 250419 . A repeated-measures quantitative design was implemented to assess how participants' stress appraisals differ across two conditions, a week wearing a stress feedback device and one without. At the beginning of the study, participants met with the researchers for an introduction and explanation of the experiment and to complete the initial questionnaire. This process was repeated after each condition. During all meetings, the researcher explained the study details and was open to any clarifications. The current study was conducted in collaboration with another bachelor student from the University of Twente and several others from the University of Tilburg. The fellow researchers followed the same design but focused on different variables. The data were collected individually and later merged into a single dataset from which all researchers received a copy and pursued their own research focus.

Participants

After clearing the data and omitting participants who did not fit the requirements or left questions unanswered, the sample of this study included 75 subjects. Most participants represented a convenience sample, while some were recruited through SONA, an online research participation credit system in the University of Twente, from which participants could receive 3.75 credits for their involvement. Participants aged between 18 and 67 (M= 27.59, SD=11.69), 28 identified as male (37%) and 47 identified as female (63%). The sample included participants from varied nationalities, with the most representatives being German (n=4), Dutch (n=61) and Greek (n=5). Other nationalities included Belgian, Moroccan, Peruvian and Irish. The eligibility requirements for the study included being at least 18 years old and not having worn a wearable providing stress feedback in the last months. Furthermore, to ensure the safety of all participants, those suffering from serious psychological conditions were advised not to participate in the experiment.

Materials

The materials utilized in this study include an information brochure, a wearable device that provides stress feedback, questionnaires and digital platforms to distribute those and observe the response rate.

Psychoeducation

A brochure was provided to the participants, either in the intake or second meeting depending on the condition they were placed. This entailed of important concepts, including the summary of the study, instructions for participants, stress, stress feedback and stress management through wearables. The detailed version can be found in Appendix (A).

Wearable device

The Garmin Forerunner 255 (https://www.garmin.com/nl-NL/p/780139/pn/010-02641-10) was used as the wearable device that was worn by and provided stress feedback to participants. The BMS Lab of the University of Twente provided the researchers with five of these devices. The fixed watch display (Figure 2) was created by the researcher and participants were instructed not to change this watch face. It shows the exact time (11:44:24), battery life of the watch, stress level of user (5, bottom of display), heart rate (first heart icon top right, 69) and HRV (second heart with graph top right). However, the participants reported that HRV did not always show a score, unless they had slept while wearing it, which was not required of them.

Due to high cost of equipment, some participants had to perform the experiment with a different wearable, namely the Garmin Vivosmart 5 (https://www.garmin.com/nl-NL/p/782585). The Vivosmart had a smaller screen which consisted of three interactive faces, where the user could navigate between (see Figure 3). Subjects wearing the Vivosmart watch were required to perform an additional action, by sliding two times in order to view the stress score and one time to view the heart rate. Compared to the first device, this watch had the same features available. However, the opportunity to omit irrelevant features such as step count and burned calories was available and was done so by the researchers before handing out the watches to participants. This ensured that users would only be exposed to the wanted features, specifically the heart rate, time, watch battery and stress levels

Figure 2

Garmin Forerunner 255 Display

Figure 3

Garmin Vivosmart 5 Display

Digital platforms

The questionnaires relevant to the other researchers were administered to participants through M-Path (https://m-path.io/landing/), a survey platform for repeated assessment. The questionnaires of this study were provided via Qualtrics (https://www.qualtrics.com), an online survey platform, where participants received a link to each questionnaire. The M-path questionnaires made use of numerous concept variables, none of which were used in the analysis of this study. Even so, they are visualised in Appendix D for transparency purposes.

Questionnaires

The study carried out by all researchers employed several questionnaires. However, not all were relevant to this research's focus and therefore were not further analysed. As the current study is part of a larger research project, "Stress in Action" (https://stress-in-action.nl/), the questionnaires were provided to researchers complete, without any need for further modifications.

The Qualtrics questionnaires were three in total. The first questionnaire provided background information as well as data on perceived stress, stress mindset, personality and other variables outside the scope of this research. The second and third ones were administered depending on the condition, wearable or no, however both entailed questions regarding stress mindset and perceived stress. The detailed questions can be found in Appendix E. Participants who completed the first week with a wearable received the "Follow-up wearable" questionnaire and the "Follow-up No wearable" questionnaire at the end of the second week. Correspondingly, participants starting with no device followed the opposite procedure.

Stress Appraisal Measure

Participants' appraisal of stress was measured using the Stress Mindset Measure (SMM), which is an eight-item scale designed to capture the extent to which individuals view stress as either enhancing or debilitating (Crum et al., 2013). An enhancing view reflects the belief that stress could promote growth and performance, whereas a debilitating view involves the belief that stress can harm health and productivity. Participants completed the SMM at three different time points: in the beginning of the study, No Wear (Follow-up after no wearable), and the Wear (Follow-up after wearable) condition. Responses were recorded on a 5-point Likert scale ranging from 0 (completely disagree) to 4 (completely agree), with higher scores indicating a positive appraisal. The internal consistency of the current scale was calculated using Cronbach's alpha and was found to be 0.94 (95% CI = 0.92 to 0.96). This aligns with previous research demonstrating the SMM's reliability, in broader but still stress and health related contexts. Färber and Rosendahl (2022) utilized this scale to examine psychological responses during the COVID-19 pandemic and found the overall SMM scale to have good internal consistency, with Cronbach's alpha of 0.88. Moreover, the original scale demonstrated good internal consistency, with a Cronbach's alpha of 0.86 (Crum et al., 2013). This further supports the reliability of this questionnaire for measuring positive or negatives views on stress and is closely related to the idea that stress arises from perceived demands and coping ability (Lazarus & Folkman, 1984).

Extraversion Measure

In this research, extraversion was measured using the Big Five Inventory-2 Extra-Short Form (BFI-2-XS) questionnaire developed by Soto and John (2017). It is a scale built around a well-supported hierarchical model, where each domain includes three underlying facets and strengthens the predictive accuracy of the measure across the numerous variables beyond self-report (Soto & John, 2017). The questionnaire was translated from Dutch, therefore the statements may not be identical to the original scale but convey the same meaning. The questionnaire entailed of 15 statements ranging from "completely agree" to "completely disagree" in a 5-point Likert scale.The extraversion subscale consisted of three items which were used in this study and the Cronbach's alpha for this scale was 0.62.

Participants completed the questionnaire during the initial meeting, along with others mentioned in different sections of this paper. The values from each item were on a 5-point Likert scale, with values ranging from 1(completely disagree) to 5 (completely agree), with a possible range of score from 3 to 15.

In previous research, the extraversion scale has been applied to various health-related studies. For instance, Willroth et al (2021) used the BFI-2-XS questionnaire to examine personality predictors during the 2019 pandemic and extraversion was found to be positively associated with health behaviours. Yet, the context of daily life represents a gap in health-related research that looks at personality effects. For this reason, it is chosen as a variable in the current study to further explore.

Procedure

The participants from the convenience sample were called and agreed upon an intake meeting with the researchers. Similarly, participants recruited through SONA signed up for an administered timeslot to meet with the researchers for the intake meeting. Upon ask or sign up, participants received a detailed email of general information about the study and procedure (see Appendix B). During the intake meeting, participants were asked to sign a consent form (seen in Appendix C), received details and instructions about the study and were ensured they could withdraw from it at any point. Afterwards, subjects completed the first questionnaire, and the experiment began.

Following the initial meeting,participants were assigned to one of the two conditions based on availability. The available smartwatches were distributed between the researchers, who then handed them out to some participants. The remaining participants started with the condition without the wearable. This approach ensured that half of the participants started with one condition and half with the other, resulting in a balanced design.Participants starting with the watch received a brochure containing important concepts of the study. The researchers then helped participants download M-path and set up an account, with an encrypted unique nickname used throughout the whole study and completed the intake questionnaire via Qualtrics. After that, for two weeks, participants received four questionnaires daily, which will not be analysed further as they are not relevant in this study.

Following the end of the first week, participants had a second meeting with the researchers, to exchange devices, receive the information brochure if they had started without a device. Additionally, they completed the follow-up Qualtrics questionnaire and shared some insights if they were comfortable on their experience so far. At the end of the last week, participants met for a final time with a researcher to return the equipment and complete the last follow-up Qualtrics questionnaire. Moreover, participants provided if wanted further insights into their experience during participation and received a debrief and further information upon ask. The data was then collected, shared along all researchers and prepared for analysis.

Data Analysis

Once collection was complete, all data were exported from Qualtrics in a SPSS file and loaded in RStudio (version 2025.05.0 + 496) using R (version 4.2.1), where all the necessary analysis was conducted. The corresponding script can be found in Appendix H. Prior to the analysis, the dataset was cleaned through item transformation, reliability testing, and descriptive statistics for each condition. The dataset was first screened for completeness and demographic eligibility. Any participants under the age of 18 were excluded to comply with ethical requirements. Additionally, any participants with missing responses in the stress appraisal and extraversion questions were removed to ensure consistency. Approximately 22% of the data needed to be removed.Following the cleaning process the data was left with participants (n=75) and all unrelated variables were omitted.

Stress Appraisals

The Stress Mindset Measure (SMM) consisted of eight items measured 3 times, four of which were negatively worded (items 1, 3, 5, 7). These items were reverse coded to ensure that higher values consistently reflect more positive stress mindset across all items and conditions. All labelled variables were converted to numeric format, appearing as values 0-4 per question. For each participant, challenge or threat appraisal scores were calculated by calculating the mean of eight appraisal items within each of the three measurements. This resulted in three total appraisal scores per participant, one per timepoint. This design choice was based on the original study by Crum et. al (2013), in which participants' stress views were displayed as the mean of the eight items to investigate overall patterns.

Personality Trait

The trait extraversion was measured using three items (item 1, 6, 11) from the BFI-2-XS baseline personality questionnaire. One negatively worded item (item 1) was reverse coded to ensure consistency, and the three scores were summed to create a total extraversion score. This approach followed the procedure of the original study by Soto and John (2017b). To divide participants into extraversion groups, a median split was applied to the total extraversion scores, creating high and low extraversion groups. This process facilitated a clear comparison between groups. Moreover, scholars have acknowledged that such approach improves the clarity and interpretability of findings, which in turn improves communication among researchers and experts (Farrington & Loeber, 2000).

Analysis

To investigate the two research questions, statistical analyses were conducted. The analysis focused on comparing participants' stress appraisals across the three measurements, as well as examining whether extraversion moderated the outcome. The dataset was reshaped into long format to support both fixed and random effects.

To address the first research question, a linear mixed-effects model was fitted with appraisal score as the dependent variable and condition as a fixed effect. A time variable was incorporated to reflect the repeated measurements across the three timepoints. The model also included random intercepts and slopes for condition to account for individual variability in participants' responses. Moreover, an AR(1) correlation was included to account for dependencies between repeated measurements. This allowed for a more accurate estimation of the effect of each condition on appraisal scores and the difference from the Baseline measure.

For the second research question, a similar model was applied to a filtered dataset that included only the two experimental conditions (No Wear and Wear), excluding the baseline. The fixed effects included both condition and extraversion group as well as their interaction. Similarly to the first, this model included the time variable and an AR(1) correlation to account for the repeated observations, as well as random slopes and intercepts exhibited by participant ID. Using a subset, direct examination of the effect of wearing the device between participants was possible. Collectively, the second model aimed to assess whether the effect of condition (Wear vs No Wear) on appraisal differed across extraversion groups (High vs Low).

All mixed models were fitted using the "lme()" function from the "nlme" package with p-values calculated via the "lmerTest" package. In addition, visualisations for both research questions were created using package "ggplot". The analysis aimed to identify patterns and relationships within the data that could inform future hypothesis-driven research.

Parametric assumptions were also assessed. Q–Q plots and the Shapiro-Wilk test were used to evaluate normality. Additionally, Levene's test was applied to test homogeneity of variances, while linearity between variables was analysed from scatterplots. During preliminary analysis, z-scores were calculated for appraisal scores to check for potential outliers. Two observations exceeded $z > 3$. A sensitivity check excluding these values showed minimal impact on the model, therefore no data points were omitted.

Results

Descriptive statistics

The descriptive statistics for appraisal scores across the three conditions and for extraversion during baseline are shown in *Table 2*. The appraisal scores showed a consistent central tendency across all conditions and no condition appeared to produce remarkably higher or lower scores than the others. Similarly, extraversion showed moderate uniformity across participants, with no indication of extensive spreading.

Table 2

Descriptive Statistics of SMM and BFI-12 scores Across All Measurements

Measure	Condition	Min	Max	Scale range	Mean	SD
Appraisal	Baseline	0	28	0-32	15.89	**5.20**
	No Wear	0	24	0-32	15.96	**4.92**
	Wear	2	27	0-32	15.75	**5.14**
Extraversion	Baseline	4	15	3-15	9.8	2.47

Preliminary analysis

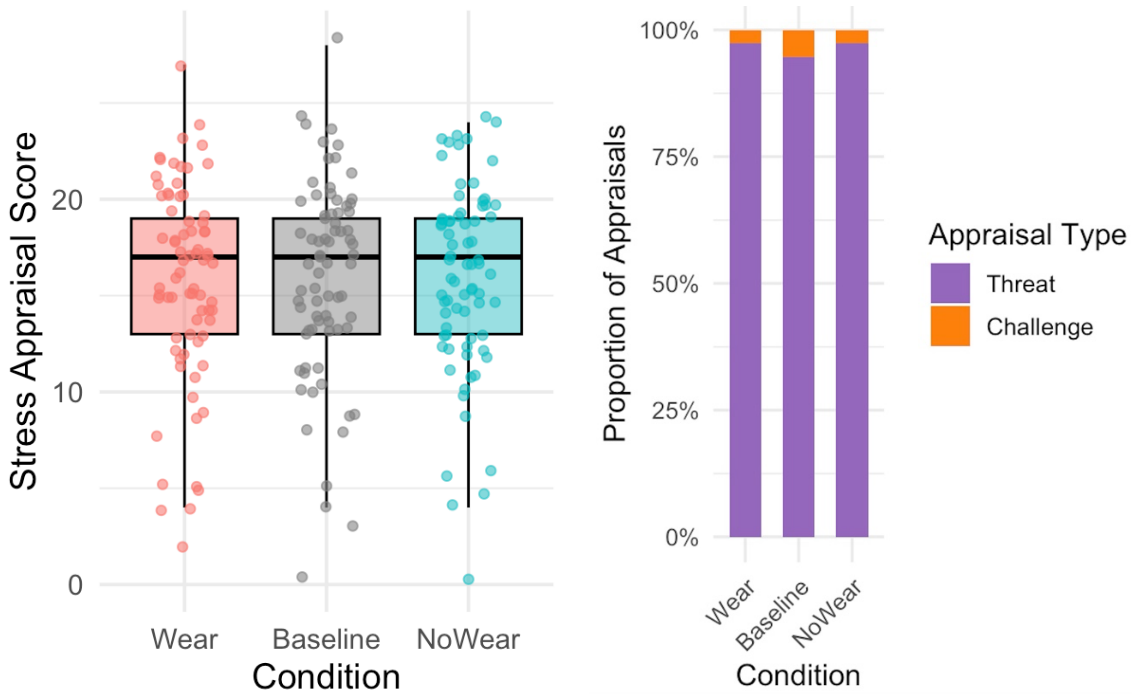
Before the main analysis, parametric assumptions were tested. Visual assessment of Q–Q plots (found in Appendix H) indicated that the distribution of appraisal scores was normal across all three conditions. Although Shapiro–Wilk tests were statistically significant for the Wear and No Wear conditions, the deviations from normality were minor and not considered problematic for the intended mixed model analysis. In order to assess for homogeneity, Levene's test for equality of variances was conducted and was not significant, F (2, 222) = 0.04, p = 0.97. Visualisations through scatterplots (found in Appendix H) confirmed a linear relationship between Extraversion scores and Appraisal scores across conditions.

Main analysis

A linear mixed-effects model was used to assess the effect of condition on stress appraisal scores and the difference from baseline. The results showed no statistical significance of the fixed effect of condition on appraisal scores. Relative to the Wear condition, neither the Baseline (β = 0.15, SE = 0.37, t(148) = 0.40, p = 0.69) nor the No Wear condition (β = 0.21, SE= 0.35, t(148) = 0.61, p = 0.54) showed significant changes in appraisal scores. The distribution of stress appraisal scores across the three measurements are displayed in Figure 4.

Figure 4

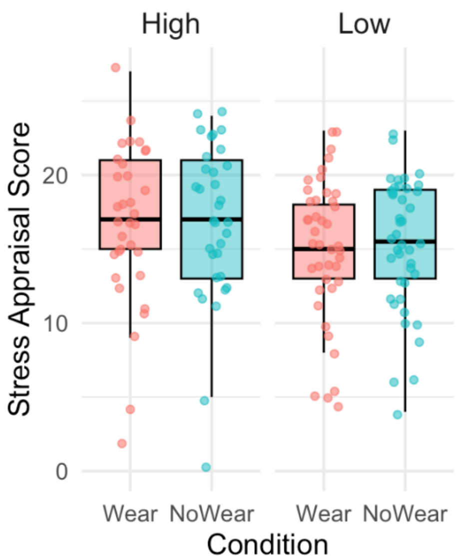
Stress Appraisals and Appraisal Type Across All Timepoints



A second linear mixed-effects model examined whether the effect of condition on stress appraisal was moderated by extraversion group. The analysis was conducted on a subset of the data containing only the Wear and No Wear conditions. In this second model, Wear condition and High extraversion group served as the reference categories. The results indicated that participants in the No Wear condition did not differ significantly from those in the Wear condition ($\beta = 0.12$, SE = 0.53, $t(73) = 0.23$, $p = 0.82$). Similarly, the differences between Extraversion Groups scores were not significant ($\beta = -1.64$, SE = 1.19, $t(73) = -1.38$, $p = 0.17$). The interaction between Condition and Extraversion Group was also not significant ($\beta = 0.16$, SE = 0.71, $t(73) = 0.23$, $p = 0.82$). Figure 5 illustrates stress appraisal scores across both conditions, separated by extraversion group.

Figure 5

Stress Appraisal Scores across Wear and No Wear Conditions Divided by Extraversion Group



Discussion

This study aimed to investigate the potential effect of real-time stress feedback provided through a wearable device on stress appraisals of participants in daily life. While focusing on real-time context and individual differences, this study attempted to expand both theoretical and practical understanding of how wearable technologies interact with psychological processes. To explore this, participants' responses to stress appraisal questionnaires were compared across three timepoints: a measurement before the start of the experiment, one after a week receiving stress feedback and one after a week without feedback. Additionally, the role of extraversion in influencing this relationship was examined, to determine if individuals with different levels of extraversion would respond differently to stress feedback in their appraisals. To test this moderation, the measurement before the experiment was not used, to directly test any possible effects. According to recent research by Yan et al (2024), extraversion had previously shown a positive effect on stress appraisals, therefore was assessed as a moderator in this study to investigate how it may influence participants' reactions on stress feedback. The study adopted an exploratory approach to investigate any possible effects of the wearable device, thus hypotheses or directionality were not predetermined.

The findings of the analysis indicate that the feedback (Wear) condition did not substantially alter appraisals from threat to challenge across the three timepoints. Participant scores remained consistent across the baseline, the week wearing the stress feedback device and the week without it. Moreover, the proportion of challenge appraisals remained low and was mostly evident in the pre-experiment measure, as the current sample was largely dominated by threatening views of stress. The sample consisted of mixed aged participants, primarily consisting of young adults with some middle-aged adults, therefore it is difficult to determine with accuracy what is expected. However, there are some possible explanations for this observation. Even though stress is so prevalent, there is a lack of awareness in coping with stress across all age groups. Psychoeducation on the symptoms could be a promising tool, as identifying signs of stress allows individuals to set stress management techniques into action (Ernstmeyer & Christman, 2022). Furthermore, extraversion did not significantly moderate the effect of real-time stress feedback on stress appraisals, suggesting that this personality trait did not have a big influence on how participants in the current sample responded to the feedback condition.

Previous research suggests that stress feedback devices can facilitate effective stress management (Santoro et al., 2020). However, the results of the current study indicated no significant effect. While stress score feedback can be informative and a useful tool to some, it may not be sufficient alone to alter individual's threat appraisals. There are many possible reasons for that. Firstly, stress scores represent part and not the whole equation. While they provide a measure of physiological arousal, they do not directly address the cognitive processes behind stress appraisals. Appraisals are complex, change in response to different situations and rely on experiences and coping resources (Lazarus & Folkman, 1984). Such complex and multifaceted construct should be treated accordingly.

Moreover, to effectively change threat appraisals to more positive views of stress, reappraisal techniques may be necessary. A study by Troy et al. (2010) demonstrated that individuals with a higher ability to use reappraisal, manage stress more effectively and experience fewer depressive symptoms. Reappraisal allows individuals to better regulate their emotion and reduce the overall psychological impact of stressors (Gross, 1998). Accordingly, such approach, along with use of real-time stress feedback may provide more substantial effects on individuals' appraisals.

The findings of the second research question contrast with the findings of Ebstrup et al (2011), who suggested that extraverted individuals are more likely to reshape stressors as challenges due to higher perceived control. However they partially align with recent research, which shows that while extraversion may foster greater adaptability in stress responses it does not certainly moderate responses to specific stress-related situations (Luo et al., 2023). Even so, visualisations showed individuals low in extraversion reporting somehow lower appraisal scores across the two experimental conditions, highlighting the need for further and deeper exploration to understand any potential impact.

Strengths

This study may not have yielded any statistically significant results, yet it still may offer important insights to the field of health psychology. It showed that awareness of stress, through a werable device, did not positively nor negatively affect stress appraisals, with the latter potentially addressing concerns regrading the negative effects of the presence of such device. This study was exploratory, as it investigated the underexplored relationship between stress appraisals, extraversion and stress feedback. Moreover, it served also as a short-term, naturalistic self-management intervention, as it tested the effect of a werable device on participants stress views and provided a more ecologically valid understanding of stress in relation to personality.

One strength of the study is the context of daily life in each condition, which allows for a more representative understanding of stress experiences. Real-life setting is crucial to produce applicable findings, as stress is inherently subjective and context-dependent (Epel et al., 2018). Moreover, the study drew upon the growing popularity and accessibility of wearable devices (Jerath et al., 2023), providing a detailed analysis of their role in stress appraisal and management. While some scepticism exists regarding the effectiveness of wearables (Ferguson et al., 2022), recent evidence suggests that integrating such technology into stress management interventions may improve stress responses and provides a significant breakthrough in health research (Ciccarelli et al., 2025; Smith et al., 2020).

Limitations

Nonetheless, several limitations of this study need to be considered for replicational and transparency purposes. First, the Qualtrics questionnaires used to measure stress appraisals were not randomized. Some participants reported after the experiment that they found questions repetitive. While the questions themselves were not identical (see Appendix E), the wording was similar, only varying to reflect positive or negative feelings, which may have caused confusion or fatigue and potentially influenced their responses. Future studies could incorporate more accessible and easier to understand questionnaire items to diminish such effects. Second, although participants wore the device for a week, the study did not explicitly assess whether participants interacted with the device. Including a sanity check or brief reminders to confirm whether participants viewed and reflected on their stress scores could help ensure better engagement.

Future Directions

The expected interactions between real-time stress feedback and stress appraisals may not have been as distinct in the current sample or may require additional tools to display significance. Nevertheless, the findings highlight the need for further exploration of the factors examined in this study or additional variables in the context of daily life. It provides a foundation for future studies to refine approaches and strategies of real-time stress management and investigate the dynamics behind these constructs. Additionally, future research should also delve deeper into the most suitable device for similar experiments.

In general, this study showed that the Vivosmart was more efficient in terms of the focus on the lifestyle, as the Forerunner models are more focused on running features. The latter involved higher costs, and included many additional features, mostly focused on tracking physical health, which would make it more suitable for such setting.

The incorporation of reappraisal techniques proposed earlier could serve as an additional important tool to transform stress views to more positive ones. Future research should also consider integrating stress measures that capture both cognitive appraisals and physiological responses in real-time. Even though both were technically measured, the physiological scores were accessible only by the participants and solely for observation purposes, and appraisals were assessed after and not during each condition. Epel et al. (2018) emphasize the importance of combining self-reported and physiological data to provide a thorough understanding of stress in health research. This approach, alongside continued use of real-world settings, would allow for an exhaustive assessment of stress processes and the effectiveness of wearables in everyday life.

Conclusion

The aim of the study was to explore the possible effects of real-time stress feedback on appraisals of stress as threatening or challenging. Additionally, the role of personality traits, specifically extraversion, was assessed to explore underlying possible moderators of this effect. The findings suggest no significant effect or interaction between stress feedback, stress appraisals and extraversion. Nevertheless, the overall patterns observe in the current sample could serve as a starting point of future research. Future research of health psychology and stress management should explore strategies and additional tools to effectively assist individuals in shifting their views of stress to more positive ones, thus creating more manageable experiences. Additionally, future stress management interventions should shift their focus on the context of daily life and the fundamental constructs rooted in everyday experiences, to produce and encourage lasting, real-world solutions.

References

American Psychological Association. (2018). *Chronic stress*. In *APA Dictionary of Psychology*. Retrieved May 19, 2025, from https://dictionary.apa.org/chronic-stress

American Psychological Association. (2022). Stress in America 2022: Concerned for the future, beset by inflation. Retrieved May 19, 2025, from https://www.apa.org/news/press/releases/stress/2022/concerned-future-inflation

Barrick, M. R., & Mount, M. K. (1991). The Big Five Personality Dimensions and Job Performance: A meta-analysis. *Personnel Psychology*, *44*(1), 1–26. https://doi.org/10.1111/j.1744-6570.1991.tb00688.x

Can, Y. S., Arnrich, B., & Ersoy, C. (2019). Stress detection in daily life scenarios using smart phones and wearable sensors: A survey. *Journal of Biomedical Informatics*, *92*, 103139. https://doi.org/10.1016/j.jbi.2019.103139

Canali, S., Schiaffonati, V., & Aliverti, A. (2022). Challenges and recommendations for wearable devices in Digital Health: Data Quality, interoperability, health equity, fairness. *PLOS Digital Health*, *1*(10), 1–13. https://doi.org/10.1371/journal.pdig.0000104

Chen, Q., Chen, M., Lin, L., & Bai, X. (2024). The Challenge–Hindrance–Threat Appraisal Framework and the Differential Effects on Employees' Work Well-Being and Behaviors. *Behavioral Sciences*, *14*(9), 734. https://doi.org/10.3390/bs14090734

Chong, K. P., Guo, J. Z., Deng, X., & Woo, B. K. (2020). Consumer perceptions of wearable technology devices: Retrospective Review and analysis. *JMIR mHealth and uHealth*, *8*(4), 1–5. https://doi.org/10.2196/17544

Ciccarelli, M., Pesaresi, A., Papetti, A., & Germani, M. (2025). Wearable devices for stress detection: Insights on exploring generalizability in controlled laboratory settings. *Procedia Computer Science*, *253*, 2014–2023. https://doi.org/10.1016/j.procs.2025.01.263

Cohen, S., Janicki-Deverts, D., & Miller, G. E. (2007). Psychological Stress and Disease. *JAMA*, *298*(14), 1685. https://doi.org/10.1001/jama.298.14.1685

Conner, T., & Barrett, L. F. (2005). Implicit self-attitudes predict spontaneous affect in daily life. *Emotion*, *5*(4), 476–488. https://doi.org/10.1037/1528-3542.5.4.476

Crum, A. J., Salovey, P., & Achor, S. (2013). Rethinking stress: The role of mindsets in determining the stress response. *Journal of Personality and Social Psychology*, *104*(4), 716–733. https://doi.org/10.1037/a0031201

Ebstrup, J. F., Eplov, L. F., Pisinger, C., & Jørgensen, T. (2011). Association between the Five Factor personality traits and perceived stress: is the effect mediated by general self-efficacy? *Anxiety, Stress & Coping*, *24*(4), 407–419. https://doi.org/10.1080/10615806.2010.540012

Epel, E. S., et al. (2018). More than a feeling: A unified view of stress measurement for population science. Frontiers in Neuroendocrinology, 49, 146–169. https://doi.org/10.1016/j.yfrne.2018.03.001

Ernstmeyer, K., & Christman, E. (2022). *Stress, coping, and crisis intervention* (Chap. 3). *Nursing: Mental health and community concepts*. Chippewa Valley Technical College. https://www.ncbi.nlm.nih.gov/books/NBK590037/

Farrington, D. P., & Loeber, R. (2000). Some benefits of dichotomization in psychiatric and criminological research. Criminal Behaviour and Mental Health, 10, 100-122. https://doi.org/10.1002/cbm.349

Ferguson, T., Olds, T., Curtis, R., Blake, H., Crozier, A. J., Dankiw, K., Dumuid, D., Kasai, D., O'Connor, E., Virgara, R., & Maher, C. (2022). Effectiveness of wearable activity trackers to increase physical activity and improve health: a systematic review of systematic reviews and meta-analyses. *The Lancet Digital Health*, *4*(8), e615–e626. https://doi.org/10.1016/S2589-7500(22)00111-X

Future Market Insights Inc. (2025). *Stress Tracking Devices Market Analysis 2025 to 2035*. Future Market Insights. https://www.futuremarketinsights.com/reports/stress-tracking-devices-market?.com

Gallistl, M., Linz, R., Puhlmann, L. M. C., Singer, T., & Engert, V. (2024). Evidence for differential associations of distinct trait mindfulness facets with acute and chronic stress. *Psychoneuroendocrinology*, *166*. https://doi.org/10.1016/j.psyneuen.2024.107051

Gjoreski, M., Gjoreski, H., Luštrek, M., & Gams, M. (2016). Continuous stress detection using a wrist device. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*, 1185–1193. https://doi.org/10.1145/2968219.2968306

González Ramírez, M. L., García Vázquez, J. P., Rodríguez, M. D., Padilla-López, L. A., Galindo-Aldana, G. M., & Cuevas-González, D. (2023). Wearables for Stress Management: A Scoping Review. *Healthcare*, *11*(17), 2369. https://doi.org/10.3390/healthcare11172369

Gonzalez, R. (2017). *Science says fitness trackers don't work. wear one anyway*. Retrieved May 19, 2025, from https://www.wired.com/story/science-says-fitness-trackers-dont-work-wear-one-anyway/

Gross, J. J. (1998). The emerging field of Emotion Regulation: An integrative review. *Review of General Psychology*, *2*(3), 271–299. https://doi.org/10.1037/1089-2680.2.3.271

Iwanaga, K., Schiferl, J., Sampath, S., Chan, F., & Rumrill, P. D. (2024). Psychometric validation of the stress appraisal measure in a sample of individuals with multiple sclerosis. *Journal of Applied Rehabilitation Counseling*, *55*(1), 51–61. https://doi.org/10.1891/jarc-2023-0019

Jerath, R., Syam, M., & Ahmed, S. (2023). The future of stress management: Integration of Smartwatches and HRV Technology. *Sensors*, *23*(17), 1–14. https://doi.org/10.3390/s23177314

Kilby, C. J., Sherman, K. A., & Wuthrich, V. (2018). Towards understanding interindividual differences in stressor appraisals: A systematic review. *Personality and Individual Differences*, *135*, 92–100. https://doi.org/10.1016/j.paid.2018.07.001

Lazarus, R. S., & Folkman, S. (1984). Stress, appraisal, and coping, 464. Sprinter

Lieberman, B. (2015). *The 4 Biggest Problems With Your Fitness Tracker, Accoring To Scinetists.* Retrieved May 19, 2025, from https://www.self.com/story/fitness-tracker-accuracy-wearables

Lu L., Zhang J., Xie Y., Gao F., Xu S., Wu X., Ye Z. (2020). Wearable health devices in health care: Narrative systematic review. JMIR mHealth uHealth. https://doi.org/10.2196/18907

Lunney, A., Cunningham, N. R., & Eastin, M. S. (2016). Wearable Fitness Technology: A structural investigation into acceptance and perceived fitness outcomes. *Computers in Human Behavior*, *65*, 114–120. https://doi.org/10.1016/j.chb.2016.08.007

Luo, J., Zhang, B., Cao, M., & Roberts, B. W. (2023). The Stressful Personality: A Meta-Analytical Review of the Relation Between Personality and Stress. *Personality and Social Psychology Review*, *27*(2), 128–194. https://doi.org/10.1177/10888683221104002

Maher, C., Ryan, J., Ambrosi, C., & Edney, S. (2017). Users' experiences of wearable activity trackers: A cross-sectional study. *BMC Public Health*, *17*(1), 1–8. https://doi.org/10.1186/s12889-017-4888-1

Marin, M.-F., Lord, C., Andrews, J., Juster, R.-P., Sindi, S., Arsenault-Lapierre, G., Fiocco, A. J., & Lupien, S. J. (2011). Chronic stress, cognitive functioning and mental health. *Neurobiology of Learning and Memory*, *96*(4), 583–595. https://doi.org/10.1016/j.nlm.2011.02.016

McEwen, B. S. (2007). Physiology and Neurobiology of Stress and Adaptation: Central Role of the Brain. *Physiological Reviews*, *87*(3), 873–904. https://doi.org/10.1152/physrev.00041.2006

Newman, D. B., Gordon, A. M., O'Bryan, J., & Mendes, W. B. (2024). Stress reduction experiments in daily life: Scaling from the lab to the world. *Journal of Experimental Psychology: General*, *153*(4), 1076–1092. https://doi.org/10.1037/xge0001546

Penley, J. A., & Tomaka, J. (2002). Associations among the Big Five, emotional responses, and coping with acute stress. *Personality and Individual Differences*, *32*(7), 1215–1228. https://doi.org/10.1016/S0191-8869(01)00087-3

Ratanasiripong, P., Ratanasiripong, N., & Kathalae, D. (2012). Biofeedback intervention for stress and anxiety among nursing students: A randomized controlled trial. *ISRN Nursing*, *2012*, 1–5. https://doi.org/10.5402/2012/827972

Ringwald, W. R., Nielsen, S. R., Mostajabi, J., Vize, C. E., van den Berg, T., Manuck, S. B., Marsland, A. L., & Wright, A. G. C. (2024). Characterizing stress processes by linking big five personality states, traits, and day-to-day stressors. *Journal of Research in Personality*, *110*, 104487. https://doi.org/10.1016/j.jrp.2024.104487

Schneider, T., Rench, T., Lyons, J., & Riffle, R. (2011). The influence of neuroticism, extraversion and openness on stress responses. *Stress and Health*, *28*(2), 102–110. https://doi.org/10.1002/smi.1409

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology*, *4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Smith, E. N., Santoro, E., Moraveji, N., Susi, M., & Crum, A. J. (2020). Integrating wearables in stress management interventions: Promising evidence from a randomised trial. International Journal of Stress Management, 27(2), 172 182. https://doi.org/10.1037/str0000137

Soto, C. J., & John, O. P. (2017). Short and extra-short forms of the big five inventory–2: The BFI-2-S and BFI-2-XS. *Journal of Research in Personality*, *68*, 69–81. https://doi.org/10.1016/j.jrp.2017.02.004

Soto, C. J., & John, O. P. (2017b). The next big five inventory (BFI-2): Developing and assessing a hierarchical model with 15 facets to enhance bandwidth, fidelity, and predictive power. *Journal of Personality and Social Psychology*, *113*(1), 117–143. https://doi.org/10.1037/pspp0000096

Stone, J. D., Ulman, H. K., Tran, K., Thompson, A. G., Halter, M. D., Ramadan, J. H., Stephenson, M., Finomore, V. S., Galster, S. M., Rezai, A. R., & Hagen, J. A. (2021). Assessing the accuracy of popular commercial technologies that measure resting heart rate and heart rate variability. *Frontiers in Sports and Active Living*, *3*, 1–16. https://doi.org/10.3389/fspor.2021.585870

Tohver, G. C. (2020). Extraversion, Personality Correlates of. In *The Wiley Encyclopedia of Personality and Individual Differences* (pp. 161–166). Wiley. https://doi.org/10.1002/9781119547174.ch204

Troy, A. S., Wilhelm, F. H., Shallcross, A. J., & Mauss, I. B. (2010). Seeing the silver lining: Cognitive reappraisal ability moderates the relationship between stress and depressive symptoms. *Emotion, 10*(6), 783–795. https://doi.org/10.1037/a0020262

Willroth, E. C., Smith, A. M., Shallcross, A. J., Graham, E. K., Mroczek, D. K., & Ford, B. Q. (2021). The Health Behavior Model of personality in the context of a public health crisis. *Psychosomatic Medicine*, *83*(4), 363–367. https://doi.org/10.1097/psy.0000000000000937

Yan, S., Ping, L., Feng, X., & Jin, X. (2024). Highest order moderation of extraversion and neuroticism into the relationship between job stress and flourishing: Mediated by readiness to change among Chinese Medical Teachers. *Heliyon*, *10*(13), 1–11. https://doi.org/10.1016/j.heliyon.2024.e33405

Appendices

Appendix A- Psychoeducation

Information Sheet Psychoeducation Group English Version

Study on Stress Wearables

Summary	We are using wearables smartwatches that are worn on the wrist, to gain insight into the influence that stress feedback has on perceived stress, health anxiety and challenge threat appraisals.
Instructions	We would like you to wear the wearable for one full week. You can choose which wrist you would like to wear it on, and you should feel slight pressure when you wear it. Please check your stress level multiple times throughout the day. The smartwatch has many other features, which we would like you to not pay attention to nor use. The watch may run out of battery at some point, so you are also provided with a charger. We would like you to wear the watch all day, however you are allowed to exercise, to sleep and shower without it, besides the fact that it is waterproof.
Stress	Stress can be good, describing manageable levels that promote growth, and bad, describing chronic stress that can cause diseases and mental issues. Stress can be measured in different ways, but for the sake of this study we will focus on physiological stress, which describes the body's reactions to stress demonstrated in high heart rate.
Stress feedback	The wearable indicates stress via four different levels: -Resting State: 0-25 -Low Stress: 26-50 -Medium Stress: 51-75 -High Stress: 76-100

	Please be aware that those stress levels can indicate either good or bad stress and the wearable cannot measure that. If the wearable indicates for instance high stress it would be a good time to check with yourself how you feel about this and if you are ready for more challenges or a small break.
Stress management through wearables	Wearables measure physiological signals through an optical sensor, at the back of the watch. However, measurements are often inaccurate. Keep in mind that stress measurement through wearables is not perfect BUT it can also be a helpful tool to self-check and manage your stress.
Contact researchers	Anna Fyntiki: a.fyntiki@student.utwente.nl Toya Ropers: t.ropers@student.utwente.nl

Appendix B - Email

Dear participant,

You have signed up for the study exploring the stress feedback from wearables on different individuals, great! In this email, you can find information about the purpose of this study, the planning, m-Path and questionnaires, the smartwatch and the intake meeting.

Purpose of study

The effect of stress feedback from smartwatches on perceived stress is currently underexplored and could help people manage their stress better. In this study, we will explore the effects of stress feedback from smartwatch devices on perceived stress, health anxiety, and challenge-threat appraisals. The study starts with an intake meeting during which the details of the study are explained again, and participants are helped to set up the app used for questionnaires. The study will last 2 weeks, during which participants fill in five very short daily questionnaires using the app. Participants will receive a wristwatch capable of providing stress feedback during one of these two weeks, which they are to return at the end of that week. During the intake, after one week, and after two weeks participants will be asked to fill out an additional questionnaire.

Planning

This study will take two weeks and will include two to three short meetings (on campus). These meetings are intended to hand out or hand in the smartwatch and to fill out a questionnaire. In the first meeting or intake meeting, we will also discuss the psychoeducation which can also be found in the attachment. The psychoeducation includes information about the stress measurement of smartwatches. In one of the two weeks, you will receive a smartwatch. Whether you will receive a smartwatch in the first or second week will be disclosed during the first meeting. Furthermore, each day you will receive five short questionnaires via m-Path.

m-Path and questionnaires

m-Path is a digital platform designed to help participants track their emotions, thoughts, and behaviours in real time. It allows you to complete short questionnaires at various points during the day, helping you and the researchers gain insights into your daily experiences and patterns. m-Path can be downloaded to your phone and will be configured during the intake meeting. m-Path will send a notification when a questionnaire is due, you are expected to fill in all questionnaires. A questionnaire is only available between the following timeframes.

The first and second questionnaire (together) are the morning questionnaire which is available from 7:00 until 10:00.

The third and fourth questionnaires are dailycore questionnaires which are available from 12:00-14:00 and 16:00-18:00. The final questionnaire is the evening questionnaire which is available from 20:00 until 22:00.

Garmin Forerunner 255 smartwatch

During the study, you will make use of a Garmin Forerunner 255 smartwatch. Some practical information about this watch:

- The battery lasts roughly one week, and you will be provided with a charger cable and a USB-A adapter.
- The watch is waterproof.
- While the watch can be worn in most situations, it is okay if you would prefer to sometimes take it off, like during sports, sleeping or showering.
- The watch has settings that enable additional functionality, but you are requested not to change any settings.

Intake meeting

Now, to plan the intake meeting. The intake meeting takes place on campus, the exact building and location will be communicated to you a few days prior to the meeting. The intake meeting you signed up for takes place on ……

We are grateful for your participation!

If you have any questions during or after the study please contact us via our email:

Toya Ropers: t.ropers@student.utwente.nl

Anna Fyntiki: a.fyntiki@student.utwente.nl

Appendix C - Informed Consent

Informed Consent

Thank you for participating in our study. This study investigates the relationship between stress feedback from wearables, perceived stress, personality and health anxiety. Participating in this study is voluntary and it is possible to withdraw at any time during the study without providing a reason. The questionnaires consist of several questions about stress, relaxation, interoception, health anxiety, emotion regulation and personality. In the first questionnaire, there will be some questions about demographics. Please answer all questions as honestly as possible.

Your participation will take two weeks in which you are expected to fill out five questionnaires daily. With an additional questionnaire at the start of the first week, at the start of the second week and the end of the second week.

All data collected will be anonymised and will only be seen by the researchers, but cannot be traced back to you. This study is part of a bigger research project. Therefore, your anonymised data could also be used in other studies regarding stress feedback from wearables. The data will be stored following the guidelines of the University of Twente. If there are any questions or remarks, feel free to contact the researchers:

Anna Fyntiki: a.fyntiki@student.utwente.nl

Toya Ropers: t.ropers@student.utwente.nl

Supervisor:

Matthijs Noordzij: m.l.noordzij@utwente.nl

I read the informed consent and agree to participate in this study. My results can be used for the purpose of the study and the research project of which this study is part.

○ *Yes* ○ *No*

Appendix D – M-path questionnaires

Morning questionnaire

1.1. Approximately how long did you sleep

1.1.1. 00 to 23 hours can be chosen on one axis and 00 to 59 on another.

1.2. How would you rate the quality of your sleep

1.2.1. A rating from 0 to 100 can be indicated using a slider. On the left side is very bad, on the right side very good.

1.3. Yesterday I used the following products:

1.3.1. Caffeine

1.3.2. Nicotine

1.3.3. Alcohol

1.3.4. Cannabis

1.3.5. Other drugs, namely: ...

1.3.6. None of the above

Daily core

1.1. At the moment my positive feelings are

1.1.1. A rating from 0 to 100 can be indicated using a slider. On the left side is not strong at all, on the right side is very strong.

1.2. At the moment my negative feelings are

1.2.1. A rating from 0 to 100 can be indicated using a slider. On the left side is not strong at all, on the right side is very strong.

1.3. At the moment I feel stressed

1.3.1. A rating from 0 to 100 can be indicated using a slider. On the left side it says not at all, on the right side it says very much.

1.4. At the moment I feel tense

1.4.1. A rating from 0 to 100 can be indicated using a slider. On the left side it says not at all, on the right side it says very much.

1.5. Right now I feel energized

1.5.1. A rating from 0 to 100 can be indicated using a slider. There is no text on the sides. In the middle is a battery that gets fuller as a higher energy score is indicated.

1.6. Since the previous questionnaire, to what extent have you been mentally overloaded by too much information? (e.g., during a call at home or work, while multitasking, etc.)

1.6.1. A rating from 0 to 100 can be indicated using a slider. On the left side it says not at all, on the right side it says very much.

Evening questionnaire

1.1. At the moment my positive feelings are

1.1.1. A rating from 0 to 100 can be indicated using a slider. On the left side is not strong at all, on the right side is very strong.

1.2. At the moment my negative feelings are

1.2.1. A rating from 0 to 100 can be indicated using a slider. On the left side is not strong at all, on the right side is very strong.

1.3. At the moment I feel stressed

1.3.1. A rating from 0 to 100 can be indicated using a slider. On the left side it says not at all, on the right side it says very much.

1.4. At the moment I feel tense

1.4.1. A rating from 0 to 100 can be indicated using a slider. On the left side it says not at all, on the right side it says very much.

1.5. Right now I feel energized

1.5.1. A rating from 0 to 100 can be indicated using a slider. There is no text on the sides. In the middle is a battery that gets fuller as a higher energy score is indicated.

1.6. Since the previous questionnaire, to what extent have you been mentally overloaded by too much information? (e.g., during a call at home or work, while multitasking, etc.)

1.6.1. A rating from 0 to 100 can be indicated using a slider. On the left side it says not at all, on the right side it says very much.

1.7. How was your day today?

1.7.1. A rating from 0 to 100 can be indicated using a slider. On the left side it says not at all, on the right side it says very much.

1.8. How was your day today

1.8.1. A rating from 0 to 100 can be indicated using a slider. On the left side is relaxed, on the right side is stressful.

1.9. Describe your day: What was the most unpleasant situation?

1.9.1. Do you want to type or record this?

1.9.1.1. Type in

1.9.1.2. Recording

1.10. Describe your day: What was the most pleasant situation?

1.10.1. Do you want to type or record this?

1.10.1.1. Type in

1.10.1.2. Recording

1.11. Today I felt physical discomfort (e.g. fatigue, flu, headache, back pain, ringing in the ears, tension, hay fever, period pain)

1.11.1. Yes

1.11.2. No

1.12. Today I felt that I had control over the important things in my life

1.12.1. A dotted line with five dots can be seen with options 0 through 4. On the left is never said, on the right it says very often.

1.13. Today I felt confident to deal with personal problems

1.13.1. A dotted line with five dots can be seen with options 0 through 4. On the left is never said, on the right it says very often.

1.14. Today I had the feeling that things were going the way I wanted them to

1.14.1. A dotted line with five dots can be seen with options 0 through 4. On the left is never said, on the right it says very often.

1.15. Today I felt like difficulties were piling up so high that I couldn't handle them anymore

1.15.1. A dotted line with five dots can be seen with options 0 through 4. On the left is never said, on the right it says very often.

1.16. Did you experience anything else stressful today that you were unable to indicate? For example, because it was not an unpleasant or pleasant situation?

1.16.1. A large white compartment in which you can type

1.16.2. Skip this question...

Appendix E- Stress Appraisal & Personality Questions

BFI-12 Ultra-short version

I see myself as someone who...

1	Is Usually quiet	1 2 3 4 5
2	Is involved, empathetic	1 2 3 4 5
3	Prone to sloppiness	1 2 3 4 5
4	Worries a lot	1 2 3 4 5
5	Is fascinated by art, music or literature	1 2 3 4 5
6	Sets the tone, when a leader acts	1 2 3 4 5
7	Sometimes is rude to others	1 2 3 4 5
8	Has difficulty starting tasks	1 2 3 4 5
9	Tends to feel depressed, gloomy	1 2 3 4 5
10	Has little interest in	1 2 3 4 5

	abstract ideas	
11	Energy theft is	1 2 3 4 5
12	Assume the best in people	1 2 3 4 5
13	Is reliable, always lives up to expectations	1 2 3 4 5
14	Is emotionally stable, not easily upset	1 2 3 4 5
15	Is original, comes up with new ideas	1 2 3 4 5

Domain Scales

Extraversion (alpha .62): 1K, 6, 11

Agreeableness (alpha .56): 2, 7R, 12

Conscientiousness (alpha .64): 3R, 8R, 13

Negative Emotionality (alpha .72): 4, 9, 14R

Open-Mindedness (alpha .66): 5, 10R, 15

SMM- Stress Appraisal

Below are some eight statements that you can agree or disagree with. Please indicate on the following scale from "completely disagree" to "completely agree" to what extend you agree or disagree with each stament.

	Completely disagree	Disagree	Neutral	Agree	Totally Agree
1.The effects of stress are negative and should be avoided					
2.Experiencing stress promotes my learning and growth					
3.Experiencing stress drains my health and vitality					
4.Experiencing stress improves my performance and productivity					
5.Experiencing stress hinders my learning and growth					

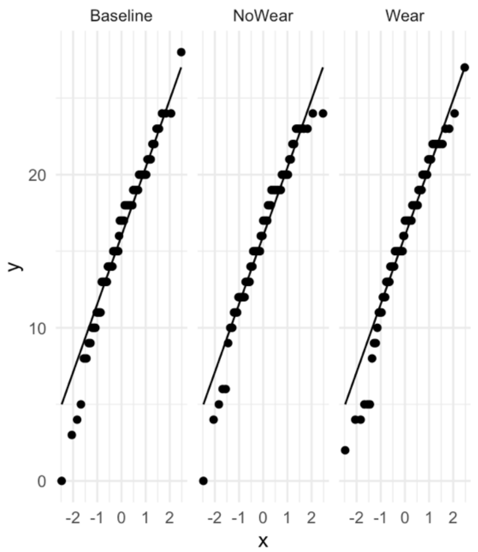
6.Experiencing stress improves my health and vitality					
7. Experiencing stress hinders my performance and productivity					
8.The effects of stress are positive and should be utilized					

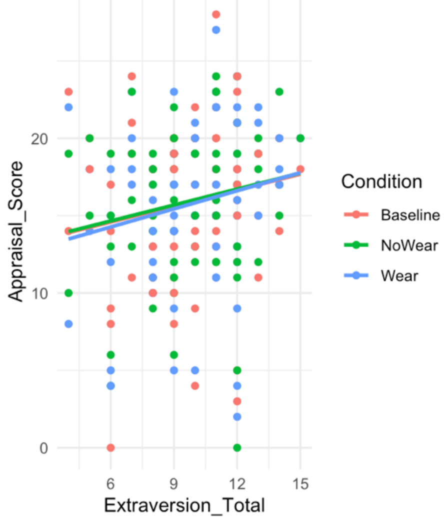
Appendix F- AI statement

During the preparation of this thesis, I the author used ChatGPT-4 Mini (OpenAI) to repair and refine some R codes, especially for plot visualisations and receive additional feedback on sentence clarity, grammar, and alignment with APA guidelines (e.g. prompt: "I am an academic student conducting my thesis and I want feedback on how to improve parts of my paper to be more reader-friendly, clear, and grammatically correct. Be critical, avoid assumptions, follow APA guidelines and follow the following rubric"). After receiving these AI-generated suggestions, I the author reviewed, edited, and revised the material and take full responsibility for the final content of my work.

Note: Rubric refers to the thesis assessment form, found in the graduation web, excluding names and source.

Appendix G - Assumption check





Appendix H- RStudio Script

```
#install necessary packages

install.packages("janitor")

install.packages("tidyverse")

install.packages("dplyr")

install.packages("ltm")

install.packages("psych")

install.packages("ggplot2")

library(janitor)

library(tidyverse)

library(dplyr)

library(ltm)

library(psych)

library(ggplot2)



#import baseline qualtrics questionnaire

install.packages("haven")



library(haven)

df <- read_sav("Wearables_allmerged_050525.sav")
```

```
# how many female and male

my_data$Gender <- as.numeric(my_data$Gender)

table(my_data$Gender)


#rename dataset

dataset <- df


#clear data

dataset$Status <- NULL

dataset$IPAddress <- NULL

dataset$Progress <- NULL

dataset$Duration__in_seconds_ <- NULL

dataset$RecordedDate <- NULL

dataset$StartDate <- NULL

dataset$EndDate <- NULL

dataset$Gender_3_TEXT <- NULL

dataset$Education <- NULL

dataset$Education_3_TEXT <- NULL
```

```
dataset$Education_7_TEXT <- NULL

dataset$Finished <- NULL

dataset$UserLanguage <- NULL

#delete NA



dataset <- dataset[dataset$ID != 270354, ]

dataset <- dataset[dataset$ID != 611717, ]

dataset <- dataset[dataset$ID != 231109, ]



#age range

range(dataset$Age, na.rm = TRUE)



#delete people <18

my_data <- my_data[my_data$Age >= 18, ]

#M and SD for age

mean(dataset$Age, na.rm = TRUE)

sd(dataset$Age, na.rm = TRUE)

#convert age to numeric

dataset$Age <- as.numeric(dataset$Age)

#dutch nationality
```

```
sum(dataset$Nationality_1 == 1, na.rm = TRUE)

#omit unrelated measures

dataset$UserLanguage <- NULL



#own dataset

my_data <- df[, c("ID", "Age", "Gender", "SMM_1", "SMM_2", "SMM_3", "SMM_4",
    "SMM_5",
    "SMM_6","SMM_7","SMM_8","Personality_1_Er","Personality_2_A","Personality_3_
    Cr","Personality_4_N", "Personality_5_O", "Personality_6_E", "Personality_7_Ar",
    "Personality_8_Cr", "Personality_9_N", "Personality_10_Or", "Personality_11_E",
    "Personality_12_A", "Personality_13_C", "Personality_14_Nr", "Personality_15_O",
    "SMM_1_FUW","SMM_2_FUW", "SMM_3_FUW", "SMM_4_FUW",
    "SMM_5_FUW", "SMM_6_FUW", "SMM_7_FUW", "SMM_8_FUW",
    "SMM_1_FUNO", "SMM_2_FUNO", "SMM_3_FUNO", "SMM_4_FUNO",
    "SMM_5_FUNO", "SMM_6_FUNO", "SMM_7_FUNO", "SMM_8_FUNO")]

View(my_data)

my_data <- na.omit(my_data)

nrow(my_data)



#demographics

my_data$Age <- as.numeric(as.character(my_data$Age))

mean(my_data$Age, na.rm = TRUE)

sd(my_data$Age, na.rm = TRUE)

range(my_data$Age, na.rm = TRUE)
```

```
#make all numeric

non_numeric <- sapply(my_data, function(x) !is.numeric(x))

names(my_data)[non_numeric]



#recode negative items

my_data[c("SMM_1", "SMM_3", "SMM_5", "SMM_7", "SMM_1_FUW", "SMM_3_FUW",
        "SMM_5_FUW", "SMM_7_FUW", "SMM_1_FUNO", "SMM_3_FUNO",
        "SMM_5_FUNO", "SMM_7_FUNO")] <-

  lapply(my_data[c("SMM_1", "SMM_3", "SMM_5", "SMM_7", "SMM_1_FUW",
        "SMM_3_FUW", "SMM_5_FUW", "SMM_7_FUW", "SMM_1_FUNO",
        "SMM_3_FUNO", "SMM_5_FUNO", "SMM_7_FUNO")], function(x) 6 - x)

#extravesrion

my_data$Personality_2_A <- NULL

my_data$Personality_3_Cr <- NULL

my_data$Personality_4_N <- NULL

my_data$Personality_5_O <- NULL

my_data$Personality_7_Ar <- NULL

my_data$Personality_8_Cr<- NULL

my_data$Personality_9_N <- NULL

my_data$Personality_10_Or <- NULL

my_data$Personality_12_A <- NULL
```

```
my_data$Personality_13_C <- NULL

my_data$Personality_14_Nr <- NULL

my_data$Personality_15_O <- NULL



# reverse code q1 of extraversion


my_data$Personality_1_Er_rev <- 6 - my_data$Personality_1_Er


#divide into extraversion groups

median_extrav <- median(my_data$Extraversion_Total, na.rm = TRUE)


# Create labeled grouping variable

my_data$Extrav_Group <- ifelse(my_data$Extraversion_Total > median_extrav, "High",
    "Low")


# Reshape the data to long format

my_data_long <- my_data %>%

  pivot_longer(cols = c(Appraisal_Baseline, Appraisal_FUNO, Appraisal_FUW),

               names_to = "Condition",

               values_to = "Appraisal")
```

```
#descriptive statistics for extraversion

summary(my_data[, c ("Extraversion_Total",
          "Total_Baseline",
          "Total_FUNO",
          "Total_FUW")])

table(my_data$Appraisal_Baseline)
table(my_data$Appraisal_FUNO)
table(my_data$Appraisal_FUW)
table(my_data$Extrav_Group)

fisher.test(table(my_data$Appraisal_Baseline, my_data$Extrav_Group))
fisher.test(table(my_data$Appraisal_FUNO, my_data$Extrav_Group))
fisher.test(table(my_data$Appraisal_FUW, my_data$Extrav_Group))
#moderation # High Extraversion
friedman.test(as.matrix(my_data[my_data$Extrav_Group == "High",
                c("Total_Baseline",
                 "Total_FUNO",
```

```
                        "Total_FUW")]))


# Low Extraversion

friedman.test(as.matrix(my_data[my_data$Extrav_Group == "Low",

                        c("Total_Baseline",

                          "Total_FUNO",

                          "Total_FUW")]))


#reshape data to long to create condition


library(tidyr)


long_data <- pivot_longer(

  my_data,

  cols = c(Appraisal_Baseline, Appraisal_FUNO, Appraisal_FUW),

  names_to = "Condition",

  values_to = "Appraisal"

)


#make appraisal numeric
```

```
long_data$Appraisal_numeric <- ifelse(long_data$Appraisal == "Challenge", 1, 0)

#convert condition to factor

long_rq1$Condition <- factor(
  long_rq1$Condition,
  levels = c("Appraisal_Baseline", "Appraisal_FUNO", "Appraisal_FUW")
)
#recreate own data set due to errors
library(dplyr)

data_1 <- df[, c("ID", "Age", "Gender", "SMM_1", "SMM_2", "SMM_3", "SMM_4",
    "SMM_5",
    "SMM_6","SMM_7","SMM_8","Personality_1_Er","Personality_2_A","Personality_3_
    Cr","Personality_4_N", "Personality_5_O", "Personality_6_E", "Personality_7_Ar",
    "Personality_8_Cr", "Personality_9_N", "Personality_10_Or", "Personality_11_E",
    "Personality_12_A", "Personality_13_C", "Personality_14_Nr", "Personality_15_O",
    "SMM_1_FUW","SMM_2_FUW", "SMM_3_FUW", "SMM_4_FUW",
    "SMM_5_FUW", "SMM_6_FUW", "SMM_7_FUW", "SMM_8_FUW",
    "SMM_1_FUNO", "SMM_2_FUNO", "SMM_3_FUNO", "SMM_4_FUNO",
    "SMM_5_FUNO", "SMM_6_FUNO", "SMM_7_FUNO", "SMM_8_FUNO")]

#make values numeric
```

```
data_1[c("SMM_1", "SMM_3", "SMM_5", "SMM_7",
         "SMM_1_FUW", "SMM_3_FUW", "SMM_5_FUW", "SMM_7_FUW",
         "SMM_1_FUNO", "SMM_3_FUNO", "SMM_5_FUNO", "SMM_7_FUNO")] <-
  lapply(data_1[c("SMM_1", "SMM_3", "SMM_5", "SMM_7",
                  "SMM_1_FUW", "SMM_3_FUW", "SMM_5_FUW", "SMM_7_FUW",
                  "SMM_1_FUNO", "SMM_3_FUNO", "SMM_5_FUNO", "SMM_7_FUNO")],
       function(x) as.numeric(unclass(x)))


#recode negative SMM (0-4 scale)


data_1[c("SMM_1", "SMM_3", "SMM_5", "SMM_7",
         "SMM_1_FUW", "SMM_3_FUW", "SMM_5_FUW", "SMM_7_FUW",
         "SMM_1_FUNO", "SMM_3_FUNO", "SMM_5_FUNO", "SMM_7_FUNO")] <-
  lapply(data_1[c("SMM_1", "SMM_3", "SMM_5", "SMM_7",
                  "SMM_1_FUW", "SMM_3_FUW", "SMM_5_FUW", "SMM_7_FUW",
                  "SMM_1_FUNO", "SMM_3_FUNO", "SMM_5_FUNO", "SMM_7_FUNO")],
       function(x) 4 - x)


#recode negative extraversion
# Convert to numeric
```

```
data_1$Personality_1_Er <- as.numeric(unclass(data_1$Personality_1_Er))


# Reverse code (1–5 scale)
data_1$Personality_1_Er <- 6 - data_1$Personality_1_Er


#keep only extraversion questions
data_1$Personality_2_A <- NULL
data_1$Personality_3_Cr <- NULL
data_1$Personality_4_N <- NULL
data_1$Personality_5_O <- NULL
data_1$Personality_7_Ar <- NULL
data_1$Personality_8_Cr<- NULL
data_1$Personality_9_N <- NULL
data_1$Personality_10_Or <- NULL
data_1$Personality_12_A <- NULL
data_1$Personality_13_C <- NULL
data_1$Personality_14_Nr <- NULL
data_1$Personality_15_O <- NULL


#make the rest variables numeric
```

```
data_1[c( "SMM_2", "SMM_4", "SMM_6", "SMM_8", "Personality_6_E",
     "Personality_11_E", "SMM_2_FUW", "SMM_4_FUW", "SMM_6_FUW",
     "SMM_8_FUW", "SMM_2_FUNO", "SMM_4_FUNO", "SMM_6_FUNO",
     "SMM_8_FUNO")] <-

 lapply(data_1[c( "SMM_2", "SMM_4", "SMM_6", "SMM_8", "Personality_6_E",
     "Personality_11_E", "SMM_2_FUW", "SMM_4_FUW", "SMM_6_FUW",
     "SMM_8_FUW", "SMM_2_FUNO", "SMM_4_FUNO", "SMM_6_FUNO",
     "SMM_8_FUNO")], function(x) as.numeric(unclass(x)))


#calculate total appraisal per condition


data_1$Total_Baseline <- rowSums(data_1[c("SMM_1", "SMM_2", "SMM_3", "SMM_4",
     "SMM_5", "SMM_6", "SMM_7", "SMM_8")])

data_1$Total_Wear     <- rowSums(data_1[c("SMM_1_FUW", "SMM_2_FUW",
     "SMM_3_FUW", "SMM_4_FUW", "SMM_5_FUW", "SMM_6_FUW",
     "SMM_7_FUW", "SMM_8_FUW")])

data_1$Total_NoWear   <- rowSums(data_1[c("SMM_1_FUNO", "SMM_2_FUNO",
     "SMM_3_FUNO", "SMM_4_FUNO", "SMM_5_FUNO", "SMM_6_FUNO",
     "SMM_7_FUNO", "SMM_8_FUNO")])


#calculate total extraversion

data_1$Extraversion_Total <- rowSums(data_1[c("Personality_1_Er", "Personality_6_E",
     "Personality_11_E")])


#convert to long format for analysis
```

```
library(tidyr)

long_data_1 <- pivot_longer(data_1,

                  cols = c(Total_Baseline, Total_Wear, Total_NoWear),

                  names_to = "Condition",

                  values_to = "Appraisal_Score")


# Clean condition labels

long_data_1$Condition <- factor(long_data_1$Condition,

                    levels = c("Total_Baseline", "Total_NoWear", "Total_Wear"),

                    labels = c("Baseline", "NoWear", "Wear"))


#median split for extraversion


median_extrav <- median(data_1$Extraversion_Total, na.rm = TRUE)

data_1$Extrav_Group <- ifelse(data_1$Extraversion_Total > median_extrav, "High", "Low")


#merge to long data set


long_data_1$Extrav_Group <- rep(data_1$Extrav_Group, each = 3)
```

```
#create appraisal type

long_data_1 <- long_data_1 %>%
  mutate(Appraisal_Type = ifelse(Appraisal_Score >= 16, "Challenge", "Threat"))
library(ggplot2)
#correct appraisal score to create appraisal types

long_data_1$Appraisal_Score <- long_data_1$Appraisal_Score / 8

long_data_rq2$Appraisal_Score <- long_data_rq2$Appraisal_Score / 8

library(dplyr)

summary_table <- long_data_1 %>%
  group_by(Condition) %>%
  summarise(
    min_appraisal = min(Appraisal_Score, na.rm = TRUE),
```

```
    max_appraisal = max(Appraisal_Score, na.rm = TRUE),
    mean_appraisal = mean(Appraisal_Score, na.rm = TRUE),
    sd_appraisal = sd(Appraisal_Score, na.rm = TRUE),
    var_appraisal = var(Appraisal_Score, na.rm = TRUE),


    min_extraversion = min(Extraversion_Total, na.rm = TRUE),
    max_extraversion = max(Extraversion_Total, na.rm = TRUE),
    mean_extraversion = mean(Extraversion_Total, na.rm = TRUE),
    sd_extraversion = sd(Extraversion_Total, na.rm = TRUE),
    var_extraversion = var(Extraversion_Total, na.rm = TRUE),
    .groups = "drop"
  )

#the correct assumptions testing

#normality

library(ggplot2)
ggplot(long_data_1, aes(x = Appraisal_Score)) +
  geom_histogram(bins = 20) +
```

```
  facet_wrap(~Condition) +
  theme_minimal()


# Shapiro-Wilk normality test for each condition
by(long_data_1$Appraisal_Score, long_data_1$Condition, shapiro.test)


#correct visual


ggplot(long_data_1, aes(sample = Appraisal_Score)) +
  stat_qq() +
  stat_qq_line() +
  facet_wrap(~Condition) +
  theme_minimal()


#homo...(Equal variances)


library(car)
leveneTest(Appraisal_Score ~ Condition, data = long_data_1)
```

```
#linearity between app and extra

ggplot(long_data_1, aes(x = Extraversion_Total, y = Appraisal_Score, color = Condition)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  theme_minimal()

#outliers

long_data_1$z <- scale(long_data_1$Appraisal_Score)
which(abs(long_data_1$z) > 3)

long_data_1[c(139, 147), ]

model_full <- lmer(Appraisal_Score ~ Condition + (1 | ID), data = long_data_1)
model_trim <- lmer(Appraisal_Score ~ Condition + (1 | ID), data = long_data_1[-c(139,147),
  ])
summary(model_full)
summary(model_trim)

#change according to feedback
```

```
# Make sure Condition is a factor

long_data_1$Condition <- factor(long_data_1$Condition,

                               levels = c("Baseline", "NoWear", "Wear"))


# Set wear as the reference level

long_data_1$Condition <- relevel(long_data_1$Condition, ref = "Wear")


# filtered dataset for rq2

long_data_rq2 <- long_data_1 %>%

  filter(Condition %in% c("Wear", "NoWear")) %>%

  droplevels()


long_data_rq2$Condition <- relevel(long_data_rq2$Condition, ref = "Wear")


#internal consistency


other_data <- data_1[, c("SMM_1", "SMM_2", "SMM_3", "SMM_4", "SMM_5", "SMM_6", "SMM_7", "SMM_8",

                         "SMM_1_FUW", "SMM_2_FUW", "SMM_3_FUW", "SMM_4_FUW",
     "SMM_5_FUW", "SMM_6_FUW", "SMM_7_FUW", "SMM_8_FUW",
```

```
                    "SMM_1_FUNO", "SMM_2_FUNO", "SMM_3_FUNO",
        "SMM_4_FUNO", "SMM_5_FUNO", "SMM_6_FUNO", "SMM_7_FUNO",
        "SMM_8_FUNO")]

# Calculate Cronbach's Alpha for all items combined across the three time points

cronbach_all <- alpha(other_data)

library(nlme)

# Add Time variable

long_data_1$Time <- rep(1:3, times = length(unique(long_data_1$ID)))

# Fit model 1 with random slope and AR(1)

model_ar1 <- lme(

  Appraisal_Score ~ Condition,

  random = ~1 + Condition | ID,

  correlation = corAR1(form = ~ Time | ID),

  data = long_data_1

)

summary(model_ar1)

#final model 2

# Fit the linear mixed-effects model with random slopes and AR(1) structure

long_data_rq2$Time <- rep(1:2, times = length(unique(long_data_rq2$ID)))

model_two <- lme(

  Appraisal_Score ~ Condition * Extrav_Group,
```

```
  random = ~1 + Condition | ID,
  correlation = corAR1(form = ~Time | ID),
  data = long_data_rq2
)
summary(model_two)
#plot 1
ggplot(long_data_1, aes(x = Condition, y = Appraisal_Score, fill = Condition)) +
  geom_boxplot(alpha = 0.5, outlier.shape = NA, color = "black") +
  geom_jitter(aes(color = Condition), width = 0.2, alpha = 0.6) +
  scale_fill_manual(values = c("Wear" = "#F8766D", "NoWear" = "#00BFC4")) +
  scale_color_manual(values = c("Wear" = "#F8766D", "NoWear" = "#00BFC4")) +
  labs(title = "Stress Appraisal Scores by Condition",
       x = "Condition",
       y = "Stress Appraisal Score") +
  theme_minimal(base_size = 14) +
  theme(legend.position = "none")
#second plot 1
ggplot(prop_data, aes(x = Condition, y = prop, fill = Appraisal_Type)) +
  geom_col(position = "fill", width = 0.6) +
  labs(
```

```
    title = " Appraisals Across Conditions",
    y = "Proportion of Appraisals",
    x = "Condition",
    fill = "Appraisal Type"
  ) +
  scale_y_continuous(labels = scales::percent_format()) +
  scale_fill_manual(
    values = c("Threat" = "#9467bd", "Challenge" = "#ff7f0e"),
    breaks = c("Threat", "Challenge")
  ) +
  theme_minimal(base_size = 12) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))


#plot 2222
ggplot(long_data_rq2, aes(x = Condition, y = Appraisal_Score, fill = Condition)) +
  geom_boxplot(alpha = 0.5, outlier.shape = NA, color = "black") +
  geom_jitter(aes(color = Condition), width = 0.2, alpha = 0.6) +
  scale_fill_manual(values = c("Wear" = "#F8766D", "NoWear" = "#00BFC4")) +
  scale_color_manual(values = c("Wear" = "#F8766D", "NoWear" = "#00BFC4")) +
  facet_grid(. ~ Extrav_Group) +
```

```
labs(title = "Stress Appraisal Scores by Condition and Extraversion",
     x = "Condition",
     y = "Stress Appraisal Score") +
theme_minimal(base_size = 14) +
theme(strip.text = element_text(size = 14),
      legend.position = "none")
```