Modelling Employee Resilience Using Wearables and Apps: A Conceptual Framework and Research Design

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Abstract **– Occupational stress can cause health problems, productivity loss or absenteeism. Resilience interventions that help employees positively adapt to adversity can help prevent the negative consequences of occupational stress. Due to advances in sensor technology and smartphone applications, relatively unobtrusive self-monitoring of resilience-related outcomes is possible. With models that can recognize intra-individual changes in these outcomes and relate them to causal factors within the employee's context, an automated resilience intervention that gives personalized, just-in-time feedback can be developed. This paper presents the conceptual framework and methods behind the WearMe project, which aims to develop such models. A cyclical conceptual framework based on existing theories of stress and resilience is presented as the basis for the WearMe project. The operationalization of the concepts and the daily measurement cycle are described, including the use of wearable sensor technology (e.g., sleep tracking and heart rate variability measurements) and Ecological Momentary Assessment (mobile app). Analyses target the development of within-subject (n=1) and between-subjects models and include repeated measures correlation, multilevel modelling, time series analysis and Bayesian network statistics. Future work will focus on further developing these models and eventually explore the effectiveness of the envisioned personalized resilience system.**

Keywords – Occupational Stress; Personalized eHealth; Sensors; Wearables; Virtual Coaching.

I. INTRODUCTION

The *Wearables and app-based resilience Modelling in employees (WearMe)* project focuses on the mental resilience of employees with a stressful occupation [1]. Occupational stress can cause health problems, such as musculoskeletal disease, cardiovascular disease, depression and burnout [2]. Consequently, it can also lead to financial burdens due to treatment costs, productivity loss and absenteeism [3]. The cumulative wear and tear on bodily systems caused by stress is particularly detrimental for health and well-being [4]; this so-called 'allostatic load' increases the brain's sensitivity to appraise stimuli as threats and reduces resources to cope, which can result in a loss spiral [5].

Resilience can be defined as the process of positively adapting to adverse events [6]. It entails the use of individual (e.g., personality) and contextual (e.g., social support) resources to cope with adversity [7]. By utilizing these resources, resilient individuals are able to recover from the negative impact of stress relatively quickly and thus decrease their risk of negative long-term consequences.

Companies and institutions may offer resilience interventions to their employees to promote their health and employability and prevent stress-related problems. These interventions often target a broad population which unfortunately disregards the variability between employees. More personalized approaches might monitor for early signs of stress-related outcomes, link these to causal factors in the employee's own context, and provide personalized advice to sustain relevant resources that may prevent the aforementioned loss spiral. Due to advances in sensor technology and smartphone applications, relatively unobtrusive self-monitoring of changes in resilience related outcomes is increasingly possible [8]. While these advances open up the possibility of personalized monitoring in resilience interventions, models are needed to recognize intra-individual changes in these outcomes and relate these to causal factors and future consequences; this would allow for the opportunity to create automated resilience interventions that give personalized, just-in-time feedback, for employees to utilize in workplace applications.

In this paper, we present the conceptual framework and the study protocol of the ongoing WearMe project. After introducing the rationale behind the WearMe project in Section I, Section II describes a cyclical conceptual framework that is based on existing theories on stress and resilience. This framework represents the concepts and interrelations between concepts that we predict are necessary to model employee resilience. In Section III, we elaborate on how these concepts are operationalized in the WearMe Project, including the use of consumer-available wearables and an Ecological Momentary Assessment (EMA) app. Afterwards, we describe in Section IV the methods of the first WearMe study. Finally, Section V discusses possible directions for future work that can help develop predictive employee resilience models and personalized interventions.

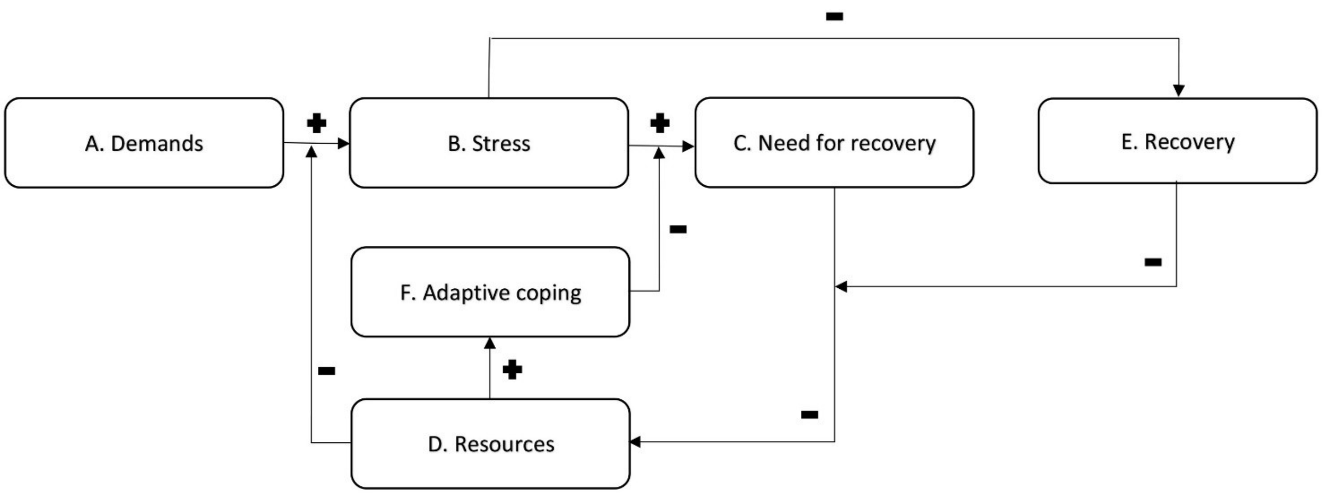

Figure 1. Conceptual framework for the WearMe study.

II. CONCEPTUAL FRAMEWORK

The conceptual framework of the WearMe project is presented in Figure 1. It illustrates our hypotheses on how the accumulation of the negative consequences of stress has a cyclical nature and how it can contribute to a loss spiral. This framework is based on the *Transactional Model of Stress and Coping* [9], the *Job Demands-Resources Model of Burnout* [10], the *Effort-Recovery Model* [11] and the *Conservation of Resources Theory* [5].

Stress accumulates when (job) *demands,* such as time pressure or physical workload, are appraised as threats due to inefficient available *resources* to *adaptively cope* with them [9]. Afterwards, an individual's *need for recovery*, characterized by feelings of exhaustion and reduced vigor to undertake new activities, depends on the individual's ability to utilize the available resources to adaptively cope with the demands [9][10]. A high need for recovery (i.e., little vigor to undertake activities), has a negative impact on an individual's resources to appraise and cope with new demands – unless there is sufficient *recovery* to alleviate this effect [11]. Aside from causing a perceived need for recovery, stress can also decrease sleep quality [12] and psychological detachment [13], which are aspects of *recovery* [14].

This framework's cyclical nature is supported by the Conservation of Resources theory [5], which states that initial loss of resources increases one's vulnerability to stress. Since additional resources are necessary to battle stress, this may lead to a depletion of resources or a loss spiral.

III. OPERATIONALIZATION

Based on the conceptual framework described above, we developed a measurement cycle to operationalize concepts using consumer-available wearables and an EMA smartphone application. All concepts are measured daily except adaptive coping—due to its highly context-specific nature which makes it difficult to quantify. In this section, we will first briefly present our daily measurement cycle. Following this, we will describe each concept and its operationalization.

The presented conceptual framework is not bounded by a specific timeframe. However, since the WearMe study particularly aims to investigate day-to-day and multi-day trends, we operationalized the concepts in a daily measurement cycle (Figure 2). For the daily measures, the WearMe study protocol utilizes: (1) a wrist-worn tracker for unobtrusive, continuous measurements throughout the day and night, (2) a Bluetooth chest strap and a smartphone application for a physiological measurement taken upon awakening and (3) a smartphone application for EMA questionnaires taken upon awakening and before bedtime.

A. Demands

Demands refer to the physical, social or organizational aspects that require sustained physical or mental effort and are therefore associated with certain physiological costs [15]. Participants' perceived daily demands are scored with the evening EMA questionnaire and is based on the self-composed diary question *"How demanding was your day?"*;

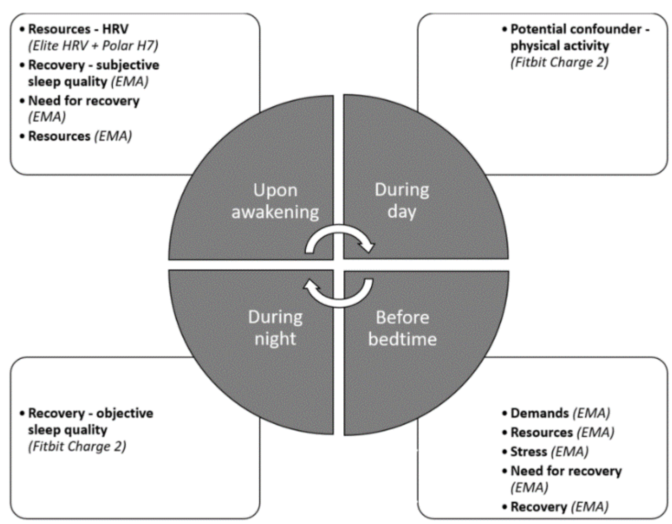

Figure 2. Measurement cycle of the WearMe study.

this is scored on an 11-point Numeric Rating Scale (NRS) that ranges from 0 (*"Not at all"*) to 10 (*"Extremely"*).

B. Stress

Participants' perceived total daily stress is scored in the evening EMA questionnaire with a validated single-item scale [16]: *"How much stress did you perceive today?"*. The question was rephrased to be applicable for daily use and the NRS that ranged from 1 (*"No stress"*) to 6 (*"Extreme stress"*) was adjusted to range from 0-10 for consistency.

C. Need for recovery

Need for recovery can be defined as a conscious emotional state and is connected with a temporal reluctance to continue with the present demands or to accept new demands; it is related to the depletion of resources following effort to meet certain demands [17]. The concept is characterized by a combination of perceiving high fatigue, as well as low vigor to undertake new activities. Participants' perceived fatigue is questioned in both the morning and evening EMA questionnaires to allow the calculation of within-day changes, while mental exhaustion is only measured during the evening. For fatigue, a validated single-item scale (*"How fatigued do you currently feel?"*) is used [18]. Item 3 of the Need For Recovery Scale is used to inquire mental exhaustion [19]: *"I felt mentally exhausted as a result of my activities"*. All items are scored on an 11-point NRS ranging from 0 (*"Not at all"* for fatigue and *"Strongly disagree"* for exhaustion) to 10 (*"Extremely"* for fatigue and *"Strongly agree"* for exhaustion).

D. Resources

According to the Job Demands-Resources model, job resources refer to physical, psychological, social or organizational aspects of a job that: (1) are functional in achieving work goals, (2) reduce job demands and the associated physiological and psychological costs and (3) stimulate personal growth, learning and development [10]. The resources in our conceptual framework can be seen as personal resources that enable an individual to better deal with stress. These resources include vigor, fitness, general self-efficacy (GSE), happiness, work engagement, and heart rate variability (HRV). Items for vigor, fitness, general self-efficacy (GSE) and happiness are included in both the morning and evening EMA questionnaires, and are all scored on an 11-point NRS ranging from 0 (*"Not at all"*) to 10 (*"Extremely"*). Below, the measured resources are described in more detail.

Vigor can be characterized by high levels of energy and mental resilience, the willingness to invest effort in one's work and persistence even in the face of difficulties [20]. Having high perceived vigor can therefore be seen as an individual resource during the appraisal of and coping with high demands. The item for vigor (measured in the morning and the evening) is based on an item of the vigor subscale of the Utrecht Work Engagement Scale (UWES) and rephrased for daily use in a neutral setting (*"Do you feel like undertaking activities?"*) [21]. Additionally, one item from the dedication subscale of the UWES is only included in the evening EMA questionnaire (*"Today, my activities were full of meaning and purpose."*) [21].

Fitness is also an individual resource for the appraisal of and coping with high demands; it is scored with a self-composed item that is similarly phrased to the fatigue item: *"How fit do you currently feel?"*. The item on fitness is included due to its more physical characteristics in comparison to the other items.

GSE is the belief in one's competence to tackle novel tasks and cope with adversity in a broad range of stressful or challenging encounters [22]. High GSE is associated with high optimism, self-regulation and self-esteem, and low depression and anxiety [22]; it can therefore be seen as an individual resource that is addressed during the appraisal of a stressor. The EMA item for GSE is based on the item with the highest factor loading (item 6) of the Generalized Self-Efficacy Scale and is rephrased for daily use: *"Do you feel capable of solving problems today?"*. During the evening, *"today"* is replaced with *"tomorrow"*.

Happiness is a state of well-being and contentment, characterized by frequent positive affect, high life satisfaction and infrequent negative affect [23]. Happiness has an inverse correlation with stress [24] and contributes to the psychological capital (resources) that may be key in better understanding the variation in perceived symptoms of stress [25]. Positive emotions like happiness can also predict increases in (trait) resilience and life satisfaction [26]. Participants' perceived happiness is scored using a validated single-item scale (*"Do you feel happy?"*) [27].

HRV refers to the variation in the inter-beat-intervals between heartbeats and is considered a proxy for autonomous nervous system functioning [28]. While HRV mostly serves as a parameter that illustrates physiological changes during acute stress, the resting HRV can remain decreased during and after acute stress [15][16]. In addition, having a lower resting HRV has been associated with increased sensitivity for stress [31], decreased emotion-regulation [32], decreased physical performance [33] and an increased risk of long-term physical or mental health problems [34]. In the WearMe study, resting HRV is therefore considered to be a potential indicator for the accumulation of stress, as well as an individual resource used in the appraisal of and coping with upcoming demands. Participants measure their resting HRV in the morning after waking up and before getting out of bed for 2 minutes in a supine position using the Elite HRV smartphone application [35] and a Polar H7 chest strap [36]. This aligns with existing standards that suggest a duration of 1-5 minutes under consistent circumstances with as little influence of circadian rhythms, meals, smoking, posture changes and significant mental or physical exertion [36][37]. We chose not to apply guided breathing, as respiratory rate influences HRV [38][39], and we intend to measure the natural resting state of the participant. The exported inter-beat-interval data are analysed using Kubios Premium software, version 3.1.0 [41]. Our analyses will focus on a time-domain outcome called Root Mean Square of the Successive Differences (RMSSD).

E. Recovery

Recovery refers to the recuperation from potential load effects after the exposure to certain demands [11]. The concept of recovery consists of two components that are known to limit the spillover of a perceived need for recovery from the previous day to the next day: (1) sleep and (2) being able to psychologically detach from work during leisure time [42]. Since stress is known to have a negative effect on sleep quality [12] and psychological detachment [13], deteriorated sleep and psychological detachment are also considered to be potential indicators for the accumulation of the negative consequences of stress. Sleep deprivation contributes to the accumulation of allostatic load [42][43], but also attenuates the relationship between negative affect experienced at work and negative affect in the next morning [45]. Sleep is therefore an important component in the recovery from (work-related) stress and helps limit the potential loss of resources.

Detachment is measured with an item from the psychological detachment subscale of the Recovery Experience Questionnaire that had the highest average correlation to the other three included subscale questions [14]: *"During my off-job time, I distanced myself from my work"*. Additionally, the perceived availability of time to recover throughout the day is measured based on an item used in a prior study [17]: *"Today I had enough time to relax and recover from work"*. Both items are included in the evening EMA questionnaire and scored on an 11-point NRS ranging from 0 (*"Strongly disagree"*) to 10 (*"Strongly agree"*).

The Fitbit Charge 2 wrist-worn tracker is used to objectively measure the total sleep time and sleep efficiency. Additionally, the subjective sleep quality is measured in the morning EMA questionnaire with a validated single-item [47]: *"How was the quality of your sleep?"* and is scored on an 11-point NRS ranging from 0 (*"Worst possible sleep"*) to 10 (*"Best possible sleep"*).

F. Other

In order to account for potentially confounding effects and explain relevant variance, two other variables are included in the daily measures: (1) alcohol intake and (2) physical activity. Alcohol intake is associated with a lower resting HRV [48], but is sometimes also used as a strategy to cope with increased stress [49]. Alcohol intake is therefore measured during the morning EMA questionnaire by asking for the number of alcoholic beverages that the participant consumed during the previous day. While the absolute amount of alcohol in different types of beverages may deviate, asking for the number of alcoholic beverages consumed is both convenient for daily inquiry and consistent with the widely used AUDIT-C questionnaire [50]. Finally, physical activity (steps, sedentary minutes, minutes of moderate-to-vigorous physical activity) is measured throughout the day using the Fitbit Charge 2 [51]. Physical activity levels are associated with decreased stress reactivity [52], a higher resting HRV [53] and improved sleep [54]; therefore, physical is a potential confounder.

IV. PRESENT STUDY

The first WearMe study aims to test the usability of the described measurement protocol, as well as to gather a first wave of data to be able to test the hypothesized relations in the conceptual model. Additionally, the development of both intra-individual and population models will be explored. The study protocol was approved by the ethical committee of the Hanze University of Applied Sciences Groningen (heac.2018.008).

A. Population

For the first WearMe study, students who are starting their first full-time internship for Social Work and Applied Psychology are invited to participate. We anticipate this population to be at risk of experiencing stress due to the potentially stressful nature of these disciplines and the fact that these are the first full-time internships in the participants' curriculum. The students need to own an Android or iOS smartphone in order to participate. For recruitment, a message is placed on the school's digital learning environment and the students who are scheduled for their first internships receive an e-mail. Participation in the study is voluntary. In order to facilitate recruitment and optimize adherence during participation, participants who collect at least 80% valid data points are rewarded with a €25 gift voucher. Additionally, participants who collect enough data to create intra-individual models receive individual feedback. Since this first WearMe study is exploring a new topic, it was impossible to perform an accurate power calculation based on the considered data-analysis methods (paragraph IV.C). Due to the availability of materials, a maximum of 15 participants can be simultaneously recruited. Therefore, the recruitment and data-collection processes are divided over two waves. The first recruitment wave started in September 2018, whereas the second waive started in September 2019.

B. Data collection

The total data collection period is 15 weeks, targeting a maximum of 105 full days of data per participant. The operationalization of the conceptual model and items included in the EMA questionnaires are described in Section III. The participants use a Polar H7 Bluetooth chest strap in combination with the Elite HRV smartphone application to measure their resting HRV upon awakening and used a Fitbit Charge 2 wrist-worn tracker to continuously measure their physical activity and sleep. In order to collect the subjective EMA questionnaire data, TNO's self-developed *"How am I?"* smartphone application is used. Participants are instructed to fill in their morning EMA questionnaire (7 items) after measuring their resting HRV and fill in their evening EMA questionnaire (12 items) before going to bed. The morning questionnaire is available between 06:00 and 15:00 and the evening questionnaire is available between 21:00 and 06:00 in order to offer participants a broad window to fill in the questionnaires (e.g., when potentially staying up late or sleeping in during weekends). Additionally, participants receive smartphone notifications as reminders at 06:00 for the morning questionnaires and at 21:00 for the evening questionnaires. Where available, validated Dutch versions of

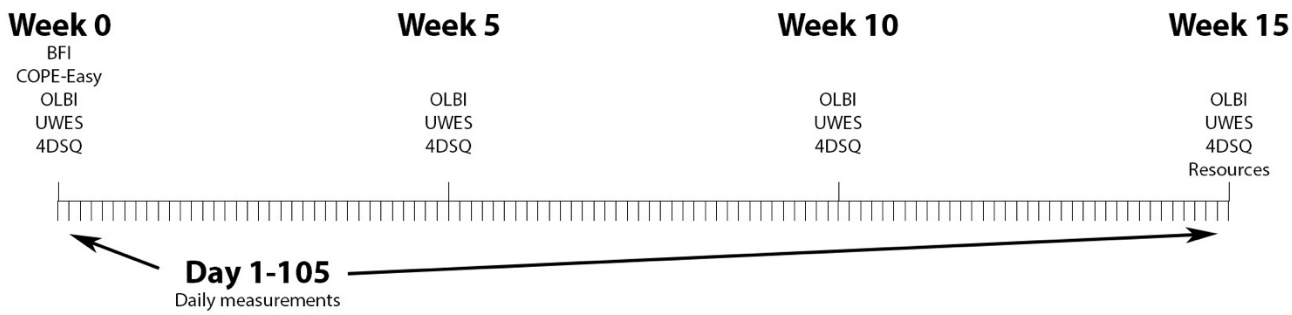

Figure 3. The WearMe study timeline.

the questionnaires described in Section III are used. Items based on questionnaires that were only available in English were translated into Dutch. For validation of these items, backwards translation by a native English speaker was performed. No differences that significantly changed the meaning of the items were found during this process.

The daily measurements described in Section II consisted of concepts that can vary on a day-to-day basis. However, some of the concepts of the conceptual framework included aspects that are more trait-like (e.g., personality traits as potential resources or preferred coping strategies) or could be expected to vary over a longer timeframe (e.g., burnout, depression). Therefore, several full questionnaires are administered to benefit the development of population models using between-subject analyses: a questionnaire on personality traits (the *Big Five Inventory*; BFI) [55], coping strategies (the *COPE-Easy*) [56], burnout (the *Oldenburg Burnout Inventory*; OLBI) [57], work engagement (the *Utrecht Work Engagement Scale*; UWES) [20] and symptoms of somatization, distress, depression and anxiety (the *Four-Dimensional Symptom Questionnaire*; 4DSQ) [58]. The questionnaires on burnout, work engagement and symptoms of somatization, distress, depression and anxiety are also administered after 5, 10 and 15 weeks. Finally, after 15 weeks, participants fill out a resources questionnaire to retrospectively assess the perceived personal and environmental resources throughout the internships, since participants are not able to accurately assess the environmental resources prior to or at the beginning of their internship. This resources questionnaire was inspired by resources questionnaires that were developed for other domain-specific work environments [58][59] and adjusted to better align with the participants' internship contexts. Additionally, the distributed questionnaires consisted of items that were derived from existing validated questionnaires such as the *Life Orientation Test* [61], the *Connor Davidson Resilience Scale* [62] and the *Dispositional Resilience Scale* [63]. Figure 3 illustrates the timeline for the measurements in the first WearMe study.

C. Data analysis

Several approaches to data-analysis will be explored. First, the hypotheses formulated in the conceptual framework that were introduced in Section II will be tested using within-day relations and, if possible, on multi-day trends. The repeated measures correlation technique as described by Bakdash and Marusich [64] will be used to analyze the correlation between two variables while taking into account that data points are repeated measures within participants. Random intercept, fixed slopes multilevel modelling will be applied when two or more variables within a specific concept or potential confounders are included to predict the variance within a single dependent variable. Both methods allow the scores between participants to differ (random intercepts), but explore a fixed effect between the two variables (fixed slopes). We anticipate that there will be insufficient data available to explore whether the effect between the included variables differ between participants (random slopes).

Second, we will explore the development of intra-individual (n=1) models for within-day and, if possible, multi-day trends using the data of the participants with the highest adherence. Aside from the aforementioned techniques, the use of time series analysis techniques and Bayesian statistics will be considered for the multi-day trend analyses.

Finally, the data of the full questionnaires will be used to explore (1) if trends in relevant daily outcomes like sleep, resting HRV and the presence of resources and need for recovery can be predicted based on personality traits or preferred coping strategies measured at baseline, (2) if these trends are also predictive for changes in burnout, work engagement and symptoms questionnaires and (3) if there is an association between the daily measured state-related variables (e.g., individual resources and perceived stress) and the trait-variables measured at baseline (the personality traits and preferred coping strategies).

V. CONCLUSION AND FUTURE WORK

This article presented the conceptual framework for the WearMe project and a detailed description of the operationalization of these concepts in the first (ongoing) WearMe study. Data collected with a wrist-worn wearable tracker, a Bluetooth chest-strap and a smartphone EMA questionnaire app on a daily will be used to explore if the hypotheses that are presented in the conceptual framework are indeed supported.

When the results affirm that tracking sleep and resting HRV with the use of consumer wearables is feasible and can be useful in resilience modelling, the current models will be expanded. Future studies will therefore focus on the development of predictive models that allow early detection of stress-related symptoms. In addition, expanding the current model by using additional consumer-available wearables or apps that can unobtrusively collect potentially relevant data (e.g., GPS location, calendar events) may be explored. When our conceptual framework is validated, a more inductive approach to data-analysis may also be explored (e.g., using machine learning) to increase the explained variance of the individual models. If successful, these models can be implemented in applications that create personalized feedback on how to cope with demands or limit the loss of relevant resources, which may help employees optimize their resilience.

Furthermore, it is likely that the development of within-subject models requires a long period of data collection. This means that in the envisioned automated resilience system, an individual will have to collect data for a relatively long period before receiving personalized feedback. The creation of a classification algorithm and the identification of subgroups with similar outcome trajectories using between-subject analyses of baseline and first-week data in a larger sample might allow for the development of a system that combines both methods [65]. In such a system, participants could receive semi-personalized feedback early on based on their subgroup classification and receive fully personalized feedback when enough within-subject data are available. Such a method would be a compromise between deductive methods that test assumptions based on existing knowledge and inductive methods that allow specific intra-individual predictors to be included in even more personalized feedback.

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