Flexibility Versus Routineness in Multimodal Health Indicators: A Sensor-based Longitudinal in Situ Study of Information Workers

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Although some research highlights the benefits of behavioral routines for individual functioning, other research indicates that routines can reflect an individual's inflexibility and lower well-being. Given conflicting accounts on the benefits of routine, research is needed to examine how routineness versus flexibility in health-related behaviors correspond to personality traits, health, and occupational outcomes. We adopt a nonlinear dynamical systems approach to understanding routine using automatically sensed health-related behaviors collected from 483 information workers over a roughly two-month period. We utilized multidimensional recurrence quantification analysis to derive a measure of health regularity (routineness) from measures of daily step count, sleep duration, and heart rate variability (which relates to stress). Participants also completed measures of personality, health, and job performance at the start of the study and for two months via Ecological Momentary Assessments. Greater regularity was associated with higher neuroticism, lower agreeableness, and greater interpersonal and organizational deviance. Importantly, these results were independent of overall levels of each health indicator in addition to demographics. It is often believed that routine is desirable, but the results suggest that associations with routineness are more nuanced, and wearable sensors can provide insights into beneficial health behaviors.

CCS Concepts: • **Human-centered computing → Empirical studies in ubiquitous and mobile computing**; • **Computing methodologies → Model development and analysis**;

Additional Key Words and Phrases: Multimodal, nonlinear dynamics, multidimensional recurrence quantification analysis, routine, sensor technology, workplace effectiveness

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1 INTRODUCTION

The virtues of routine, or recurrent patterns of action, have been a long-standing topic of debate and point of interest for the general population. Research often focuses on the benefits of behavioral routines for individual functioning, for example, by increasing efficiency, reducing stress, improving mental health, and helping people feel that life is meaningful [3, 19, 38, 56, 102]. One cannot dispute the health benefits of regular sleep, meals, getting a daily constitutional and so on. However, despite the benefits of routine under certain conditions, routine behaviors can become maladaptive when they are negative (e.g., smoking a cigarette after meals), when they persist regardless of contextual changes, and when they have negative consequences (e.g., when ignoring e-mails in the afternoon affects work performance) [49].

People differ in the extent to which they are prone to developing routines. Whereas some people value spontaneity and adapt easily to new environments and situations, others prefer predictability and structure [49]. A few studies identify factors associated with the propensity for repetitive behaviors, including chronic stress [40, 104] and time pressure [13, 14]. However, given that much has been made of the benefits of routine, relatively little is known about the types of people who practice greater routineness (e.g., personality characteristics) and how behavioral routineness corresponds to individual differences in personality and outcomes such as workplace effectiveness.

Though individuals may vary in their propensity for routineness, people can be educated and conditioned to alter their repetitive behaviors, making it a viable approach for improving individual functioning [33, 34, 64, 70, 72, 86, 113, 115, 116]. For example, the Anxiety and Depression Association of America endorses healthy habits, such as regular sleep patterns and exercise, to improve mental health [19]. Beyond clinical intervention, research suggests that the benefits of healthy habits and routines extend to the general population. For example, Avni-Babad [3] demonstrated that performing simple repetitive behaviors like sitting in a regular chair during a class promoted feelings of safety, confidence, and well-being.

Although incorporating healthy behaviors into one's routine is important, that does not mean that habit and routine are inherently beneficial. This is apparent when considering how routines are formed. Routine behaviors are initially driven by a particular goal, but, over time, become decoupled from the original motivation, becoming more automatic and less cognitively demanding [69]. In the process, routines become insensitive to reinforcement signals and can impede one's ability to respond to daily challenges [131]. For example, an over-reliance on habitual or routine behaviors may lead to ineffective decision-making, where intentions are overwhelmed by "behavioral inertia" and default responses [3, 61]. In the workplace, inflexible routines are challenged by shifting task demands due to changes in projects, workflow, policies, or social dynamics, a pattern that is more likely to be the norm in the workplace of the future [48]. Routine behavior can reflect an individual's inflexibility and need for predictability, and uncertainty can lead to increased stress and anxiety [37, 49].

Moreover, routine and habits are not always healthy behaviors, for example, in the case of substance abuse, gambling, or obsessions or compulsions [2]. In some circumstances, repetitious behaviors may represent a "vulnerability marker" for disorders where behavioral routines are taken to an extreme, manifesting in overly repetitive or maladaptive behaviors [49]. Thus, while it may be desirable to make healthy behaviors routine to some extent, the benefits of routine may be more nuanced, and individuals who engage in more routine are not necessarily healthier or better adapted to the environment.

Research on routine focuses on activities that contribute to a healthy lifestyle such as regular exercise, sleep patterns, and stress reduction [60, 75]. These health-oriented routines appear in the workforce through corporate wellness programs that attempt to improve the health and work-life balance of employees. Although these programs promote specific healthy behaviors, an individual's weekly activities likely include many different types of routines, both negative and positive. Thus, whereas previous literature focuses primarily on unimodal health routineness, more research is needed on routineness across a number of measures (multimodal routineness). In addition, research is needed to examine how routineness in health-related behaviors corresponds to well-being and work effectiveness. More generally, it is an open question as to how routineness can be effectively tracked and quantified across a variety of health-related behaviors.

We address these questions with a nonlinear dynamical systems approach (refer to Section 3) to understanding flexibility versus routine in health-related behaviors. First, we describe the calculation of a multidimensional indicator of routine regularity. Then, we use this calculation to explore the relationship between routineness, personality, affect, and work effectiveness. We focus on collective patterns in **heart rate variability (HRV)**, sleep duration, and step count collected over the course of several weeks. Specifically, we utilize HRV to identify individual patterns of stress, with greater HRV corresponding to enhanced regulatory and homeostatic autonomic nervous system functions that allow the body to cope with stressors [63]. In addition, we use step count to identify levels of physical activity [128] and sleep duration as an integral part of a healthy lifestyle [126]. Although previous research has demonstrated the importance of these behaviors separately in relation to health outcomes (see Section 2), we are the first to examine the significance of their collective temporal regularity over time.

This work expands the literature on routine in the following ways: First, we focus on global patterns of routine over the course of weeks and months for a large number (N = 483) of information workers from five distinct cohorts across the U.S. Contrasting prior work that typically relies on self-report data, our data was collected using wearable sensor technologies. Compared to self-report data (e.g., Ecological Momentary assessments), automatically sensed data are objective and require little to no participant input other than ensuring that devices are charged. Additionally, while self-report can be used for certain data, it cannot be used for others (e.g., HRV). Thus, sensors can offer new insights into routineness not available from self-report. Second, we utilize a multimodal, nonlinear calculation of routine to examine the collective temporal regularity of three key health variables: Step count, sleep duration, and HRV. This contrasts research that relies on unimodal calculations of routine and studies that utilize aggregate scores of individual measures, for example, demonstrating that disrupted circadian rhythmicity in rest levels is associated with vulnerability to mood disorders [73]. Third, we test the relationship between our health regularity measurement and personality, affect, and workplace effectiveness in order to connect multimodal health behavior routineness from wearable sensor data to real-world outcomes. In doing so, we also compare the predictive validity of multimodal routineness to unimodal measures of overall HRV, sleep duration, and step count levels, as well as a composite health score that indicates the overall level of the collective health behaviors. Fourth, whereas much of the literature on routine focuses on clinical populations [34, 70, 86], our study focuses on a non-clinical sample of information workers. Fifth, our results—that are highly novel in the context of health routineness—are consistent with concepts from complex systems theory. Thus, we provide a strong theoretical approach to understanding health routineness that, to our knowledge, is new to the literature. The findings identify linkages between the collective regularity of health-related behaviors and individual characteristics that have not been explored previously.

In what follows, we demonstrate the use of **multidimensional recurrence quantification analysis (MdRQA)** for studying routineness from a large sample (N = 483) of automatically sensed multimodal health data. We use our measure of multimodal routineness to explore the relationships between health routineness, personality, affect, and work effectiveness using regression analyses. See Figure 1 for an overview of the study design and analyses.

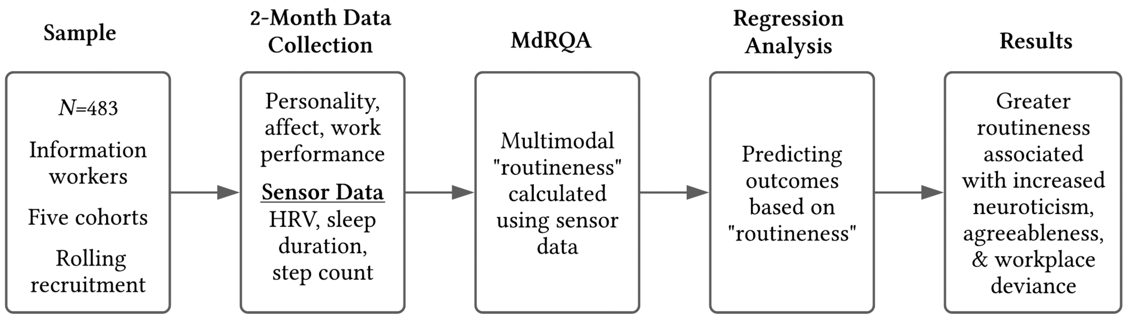

Fig. 1. Overview of study design, analyses, and results.

2 BACKGROUND AND RELATED WORK

Previous research has focused on linkages between the individual health behaviors considered here and individual functioning. We briefly review the literature on sleep, step count, and HRV to highlight their importance in the context of healthy routines, as well as provide an overview of several existing methods for calculating routine that have been used in the literature to predict health outcomes.

2.1 Sleep Routine

The American Academy of Sleep Medicine, the Sleep Research Society, and the National Sleep Foundation recommend at least seven or more hours of sleep per night for adults [58, 126]. Lack of sleep, too much sleep, or sleep disorders such as insomnia are associated with increases in co-morbidity and with mental health (e.g., anxiety) [16]. Sleep deprivation has been linked to decreased mood [43], increased depression [114], and problems with physical health including cardiovascular issues and death from all causes [52, 67].

Though the sleep literature has traditionally examined average sleep behaviors, Bei and colleagues [11] emphasize the importance of looking beyond the mean to measures of sleep variability. Sleep routines support healthy sleep duration. Indeed, cognitive behavioral therapy, a popular and effective treatment for insomnia [18], instructs participants to maintain a regular wake time in order to improve sleep quality [46]. Kang and Chen [62] report that increased bedtime irregularity was associated with decreased sleep time and increased sleep disturbance [21]. Sleep irregularity is associated with shorter sleep duration, as well as poor academic performance [81, 87]. Thus, unimodal measures of sleep duration consistently point to the importance of routine.

2.2 Step Count

Moderate and regular physical activity is another key component of healthy living that has been linked to better health outcomes [60], including cardiovascular health [65, 76] and mental health [23, 39, 55]. Lack of physical activity or increased sedentary behaviors such as sitting have been linked with adverse health outcomes, such as increased risk of mortality, risk of type 2 diabetes [45], and obesity [41, 118]. Given the benefits of regular moderate exercise and the detriments of sedentary behavior, a commonly recommended general health goal includes 30 minutes of brisk walking, resulting in approximately 10,000 steps per day [128], though a more recent study suggests lower mortality rates can be realized in as little as 4,400 steps in some populations [71]. A study of older adults [130] found that habitual walking, but not leisure time activities or sports, was related to better oxygen consumption and cardiovascular fitness.

2.3 Heart Rate Variability

Heart Rate Variability (HRV) has been utilized as a biomarker for mental and physical stress [30, 117]. HRV is derived from heart rate and is defined by variability in duration between heartbeats [99]. Heart rate and HRV reflect a balance point between the parasympathetic nervous system, which is dominant in 'at rest' situations, and the sympathetic nervous system, dominant in stressful situations [30, 117, 120]. For healthy individuals with infrequent stress, higher resting HRV has been associated with greater health and wellness, including lower mortality, lower depression, better sleep, and greater cognitive flexibility [28, 30, 53, 85, 93, 117].

2.4 Routine

Ecological Momentary Assessment (EMA) is one of the most common techniques used by researchers and healthcare professionals to track patient progress [105]. EMAs typically require participants to complete longitudinal, periodic surveys as events unfold over time. In the area of sleep, EMAs have been used to analyze sleep routine via the **Sleep Regularity Index (SRI)**, or the probability of an individual being in the same state (asleep or awake) at time points 24 hours apart, averaged across the period of measurement [87]. In their initial development of the SRI, Phillips et al. [87] reported significant positive associations between sleep regularity in students and academic performance. In addition to calculating routineness from EMAs, patterns of behavior derived from EMAs have been modeled using techniques like **vector autoregression (VAR)** [66, 97, 110] to explore the interdependencies between multiple timeseries. VAR has been used to model the relationship between depressive symptoms and physical activity measured over time through self-report, uncovering directional effects of mood on regular activity and vice versa [97]. While research on routineness using EMAs has contributed significantly to the literature, the downside of these approaches is that data collection is reliant on self-reports with known biases [44]. Self-reports can also be burdensome and contribute to participant attrition and dropout [83]. Health data collected passively, such as the data collected by wearable devices, provides a less intrusive alternative to EMA for tracking routine. Smart watches, for instance, continuously track step count, heart rate, sleep activity, and location.

There is some work on estimating routineness from automatically sensed data. The routine index, proposed by Canzian and Musolesi [25], utilizes location information to calculate the regularity of movements during specific periods of the day across several days and has been used successfully to predict the severity of depressive symptoms. Alternative approaches, such as the Stability index [57] and the Flexible regularity index [124], can account for different types of data and are more flexible across timescales. Wang et al. [124], for instance, utilized the Flexible regularity index to estimate regularity in aspects of sensed behaviors captured via smartphone activity and, using this index, found a positive association between ambient sound regularity and openness as measured by the Big Five Inventory. While these measures may be effective at estimating the routineness of a specific sensor measurement, they are typically limited to providing this estimation for only a single measure at a time, such as a participant's movement patterns [25, 27, 77, 79, 101, 132], whereas the present focus is on multimodal routineness. Multimodal measures may provide a more holistic view of what a healthy routine entails by describing the joint dynamics of multiple health-related behaviors and taking into consideration their interaction in determining personal outcomes such as stress, anxiety, and work performance. For example, unimodal measures of sleep routine ignore any potential interaction between sleep and physical activity.

3 QUANTIFYING MULTIMODAL HEALTH REGULARITY VIA IN-SITU SENSING AND MULTIDIMENSIONAL RECURRENCE QUANTIFICATION ANALYSIS

We leverage concepts derived from **nonlinear dynamical systems theory (NDST)** in order to adopt a systems approach to understanding routine. The current section provides the necessary background for understanding **Multidimensional Recurrence Quantification (MdRQA**; Section 3.1) and a description of the MdRQA procedure, which results in a measure of recurrence rate as an index of routineness (Section 3.2).

3.1 Overview of Multidimensional Recurrence Quantification Analysis

The current study outlines a novel application of NDST used to calculate a multimodal index of routineness applicable to a wide range of data types. NDST describes how multiplicative interactions of components of a

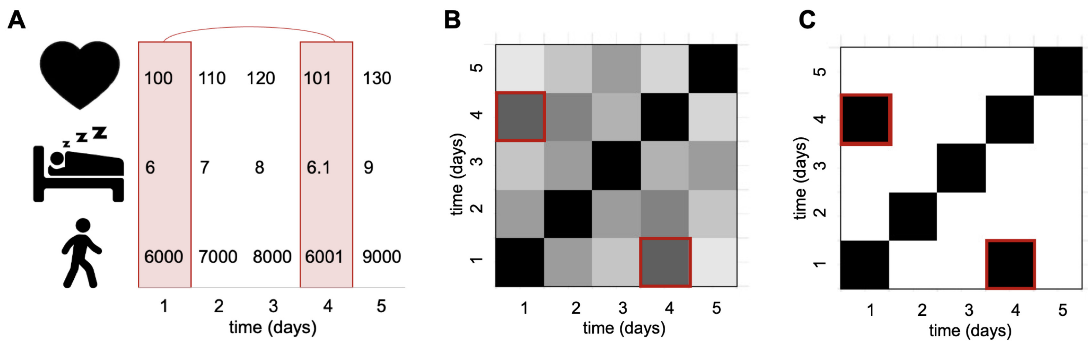

Fig. 2. Example identification of a single recurrent pattern with toy data. Panel A represents a single recurrent point, highlighted in red, where the multimodal configuration during day 1 and day 4 is similar. Panel B represents the distances between multimodal time points, with darker points indicating greater similarity in the collective configuration between two time points. The diagonal line in black represents the LOI, where points are identical with themselves at lag 0. Mirroring Panel A, time points 1 and 4 are relatively similar to one another and, thus, their distance is highlighted as smaller (darker) than all other points outside of lag 0. Panel C represents the recurrence matrix, where a radius is applied to transform the distance matrix into a binarized recurrence matrix. Each point in the matrix represents the relative similarity of data across days represented on x- and y-axes. Each point in black is a recurrent multimodal configuration (i.e., the multimodal time series returned to a sufficiently similar state). Notably, black points in the Panel C recurrence matrix can represent different repetitive patterns. White points represent non-recurrent states that unfold over time. For example, the multimodal configuration during time point 1 on the x-axis does not match with the configuration during time point 5 on the y-axis. In short, black points represent more routine patterns of multimodal health behaviors, whereas white points represent more novel multimodal health behaviors.

system give rise to global patterns of behavior, where feedback loops yield sudden, nonlinear shifts over time [96]. NDST can offer new opportunities for understanding the benefits and drawbacks of routine by describing multimodal, system-level patterns of behavior as they unfold over time. NDST provides a wide variety of tools appropriate for characterizing complex systems by capturing the temporal evolution of behavior. These methods have the advantage of bypassing assumptions of linear statistics, such as normality, linearity, and stationarity, and can therefore be applied to a wide range of data [107]. **Recurrence quantification analysis (RQA)** is one NDST method that captures the degree to which one or more signals revisit similar, or "recurrent," states over time [127].

Traditionally, RQA measures the degree of repetitiveness within one time series (auto-RQA) or the degree to which two time series have the same values (cross-RQA). A relatively new extension of RQA, **multidimensional-RQA (MdRQA)**, accommodates multiple time series that can reflect different modalities [122]. In this way, MdRQA quantifies the degree to which the collective organization of multiple signals exhibit regular or irregular patterns of behavior, where regularity corresponds to periods when the multidimensional system visits repeat states (e.g., one routine pattern for daily health-related variables might involve approximately eight hours of sleep, 8,000 steps, and a heart rate variability of 60 over a 24-hour period). Importantly we focus on routineness and not overall levels of each signal. That is, one routine-oriented person may consistently have five hours of sleep while another person consistently gets eight hours of sleep—both could have equal degrees of routineness but different health outcomes. Figure 2(a) demonstrates how RQA can be leveraged to identify routineness across very different channels, with one recurrent pattern of behavior highlighted in red, where the three channels of interest revisit a sufficiently similar configuration (as defined by the radius). Figure 2(a) illustrates how MdRQA can be leveraged to examine daily routineness across different modalities, in this case, HRV, sleep duration, and step count. In Figure 2(a), day 1 and day 4 represent one recurrent, multimodal pattern. Notably, MdRQA can identify numerous different patterns as recurrent. Figure 2(c) is an example recurrence matrix derived from MdRQA and depicts recurrent points across a time series and at various time lags. Points in black correspond to points where two time points across the time series are sufficiently similar to one another and, in turn, constitute a recurrent pattern of behavior. The diagonal represents the **line of identity (LOI)** where time series points at a lag 0 are self-similar and, thus, recurrent. Lines perpendicular to the LOI represent distances between points at various time lags, with lines closer to the LOI representing shorter time lags. Although a number of measures can be extracted using MdRQA, here we measure system-level regularity as the percent of combinations that are recurrent, excluding the LOI. In this context, behavioral routine is the degree to which individuals demonstrate repetitive patterns of behavior over time. We discuss RQA and MdRQA in more detail below.

We define routine in terms of recurrent patterns of action, where "patterns" are those behaviors that repeat. We can see individual participants' patterns in recurrence matrices, for example, in the right-most panels of Figure 2. Each recurrence matrix illustrates the repeat states or patterns that span a given participant's time series. Because the matrices represent the temporal structure of participant time series, MdRQA provides a means for quantifying multimodal patterns of routine.

As previously noted, numerous recurrent patterns can exist within the MdRQA matrix, which offers considerable advantages relevant to the quantification of routine. Previous research interested in behavioral routine has often relied on self-report [9, 19, 22, 49, 70, 80] and variability measures such as standard deviation [20, 42], which is limited in assuming central tendency (i.e., the mean) with greater deviation from the mean representing less routineness. Not only is a standard deviation approach highly sensitive to outliers and limited due to the assumption of normal data (which is often violated), it fails to account for intricacies in routine behavior. For example, it is possible for a person with a rigidly held routine to consistently sleep six hours on weekdays and ten hours on weekends. With a standard deviation approach, such a person could be equated to someone who is less routine because it cannot capture the bimodality in the distribution. With an RQA approach, the six hours and ten hours of sleep would both be counted as repetitious, thus distinguishing the rigidly scheduled person from someone who is less routine.

MdRQA also allows the examination of numerous interacting processes, or multimodal signals, as well as indexing nonlinear and possibly nonstationary patterns of behavior as they unfold. This contrasts recent unimodal approaches to measuring routineness. For example, Cao and colleagues [26] used the revisitation curve to examine frequency of returns to the same websites over time. This measure is similar to MdRQA in examining recurrent points over time but differs most notably in its ability to examine repetition within only one time series at a time. Our approach offers the unique opportunity to examine multimodal or multichannel routineness. Our use of MdRQA follows a trend of emerging approaches for the analysis of multimodal signals [133]. For example, another similar approach is cyclic hidden Markov models [88], which allows for analysis of multidimensional measurements but focuses explicitly on cycles, such as menstrual cycle symptoms, as opposed to routines that can vary moment-to-moment. Thus, while similar measures have been successfully applied to understand the temporal aspects of behavior, we propose MdRQA as a measure highly relevant to gaining a comprehensive account of individual routineness.

3.2 Multidimensional Recurrence Quantification Analysis Procedure

We used MdRQA in the current study to examine collective patterns of regularity across our three health indicators—daily indices of HRV, sleep duration, and step count. MdRQA computes a distance matrix for each participant's timeseries data representing the pairwise Euclidean distances between elements of the multidimensional time series, where each point in the matrix reflects the distance between another point at a particular time lag (Figure 3 middle panel). Formally, with time series forming a three-dimensional space (vectors x, y, and z for the three channels), a point in the distance matrix would capture the change in value (i.e., distance) at time point i and time point j:

$$D_{ij} = \sqrt{\left(x_{t_i} - x_{t_j}\right)^2 + \left(y_{t_i} - y_{t_j}\right)^2 + \left(z_{t_i} - z_{t_j}\right)^2} \tag{1}$$

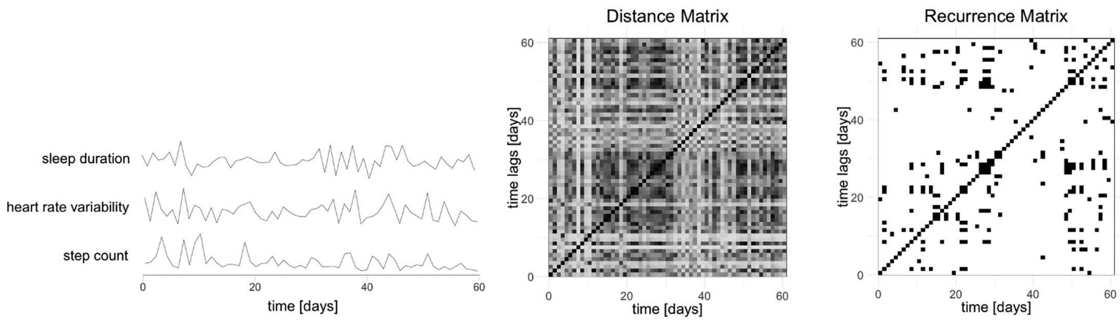

Fig. 3. Application of MdRQA to an example participant's time series. MdRQA transforms multidimensional signals (left) representing daily HRV, sleep duration, and step count into a distance matrix (middle) that represents the Euclidean distances between time series elements at various time lags (see Equation (1)). In the distance matrix, darker values represent more similar time series elements and lighter values represent relatively dissimilar time series elements. A radius is applied to the distance matrix to create a binary recurrence matrix (right), where distances below the radius value are considered a repeat value (or "recurrent") and distances above the radius are considered non-recurrent. That is, the (darker) more similar time series elements from the distance matrix are recoded as a 1 (recurrent point), and (lighter) less similar time series elements from the distance matrix are recoded as a 0 (non-recurrent point) in the recurrence matrix. Recurrence rate is the percent of recurrent points within the recurrence matrix and represents the degree to which the multidimensional time series repeat the same pattern.

The main diagonal of the matrix is the LOI where signals are self-similar at lag 0 ($t_i = t_j$), thereby providing no useful information. Lines parallel to the LOI represent distances between points at different time lags (e.g., $(t_1,\ t_3)$ for lag 2), with diagonals further from the LOI corresponding to greater lags. Next, a radius is applied to transform the distance matrix into a binarized **recurrence matrix (RP)**, where distances below the set radius are considered sufficiently similar to one another and are counted as recurrent (value of 1), and distances above the radius are non-recurrent (value of 0; Figure 3 right panel). A recurrent point is one in which the collective signals return to the same state as they were in previously (within the radius). Specifically, a point in the recurrence matrix is considered recurrent if the Euclidean distance value (D_{ij}) in the distance matrix is smaller than the radius R. This can be written as follows:

$$RP_{ij} = \begin{cases} 1 & if\ D_{ij} < R \\ 0 & elsewhere \end{cases} \tag{2}$$

Recurrence rate (RR) is one of the more straightforward measures derived from MdRQA, representing the percentage of recurrent points in the matrix outside of the LOI. RR can therefore be used as an aggregate measure of a participant's multimodal health regularity. For time series of length t, the recurrence rate is given as:

$$RR = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} RP_{ij}}{t^2} \tag{3}$$

Thus, RR can be considered as an indicator of the overall routineness, or repetitiveness, of the multimodal time series. Refer to Wallot and colleagues' [122] article for additional details.

Visualizing the underlying distance matrices and recurrence matrices can provide further insight into how the behaviors of a single participant unfold over time. Whereas a miniature matrix is shown in Figure 2, a participant's real data is illustrated in Figure 3, providing an additional visualization of the MdRQA process. For instance, the right-most recurrence matrix shows that this participant's behavior involved markedly less regularity in collective daily steps, HRV, and sleep duration between time periods 30 and 50. During this period, the participant is demonstrating more variable and novel health behaviors, where there is not sufficient consistency across the three channels to constitute a repeat pattern. Note that missing data is not included in the MdRQA analyses or matrices.

4 METHOD

4.1 Data Source

This work is part of a larger project investigating job performance, and we use a subset of the measures here. Study procedures were approved by an **Institutional Review Board (IRB)** located in the midwestern United States, which served as the IRB on record with a signed authorization agreement from a collaborating IRB located in the western United States, and all participants provided informed consent.

4.2 Participants

Participants were 757 salaried, full-time information workers (e.g., engineers, consultants, business/finance) from across the United States who were recruited on a rolling basis. They were recruited via partnerships with their employers, as well as through messaging boards and advertisement platforms. We had five participant cohorts: a large western United States tech firm (cohort 1), a small Midwest United States tech firm (cohort 2), a medium-sized Midwest university (cohort 3), an unassigned cohort (e.g., friends of recruited participants, respondents to newspaper articles, etc.; cohort 4), and a nationally distributed consulting firm (cohort 5). Payment structure was related to the requirements set by participating institutions. Participants were compensated up to $750 for their participation (cohort 1-4) or via lottery-based monetary incentives (cohort 5). Participants were compensated based on an average of 80% compliance for wearable, phone app, and daily surveys (see below). Assuming full compliance, they received $50 at week 1, $150 at month 3, $200 at month 6, and $350 at the conclusion of the study. For lottery-based compensation, compliance of 80% or better in each sensing stream (wearable, phone app, surveys) generated a lottery probability each day. A $250 prize was awarded each week per group of 25 participants (e.g., 25 enrolled participants = 1 x $250 prize; 100 enrolled participants = 4 × $250 prizes). Winners' tickets were then set to zero, but they were eligible for future weekly drawings. In addition, participants were eligible for one of five $1,000, drawn quarterly.

As required by the funding agency, a subset of participants ($n = 151$) were randomly assigned to a blinded group and the researchers did not receive survey data for these participants. Of the remaining 606 participants, 483 were included in the final analysis (see Section 5.3 for Exclusion Criterion). The average age of these participants was 34.60 (SD = 9.61) years, 59% were males, 12% were non-native English speakers, and 43% indicated that they were in a supervisory role. Most participants had a Bachelor's degree (46%) or higher (28% had some education beyond a Bachelor's degree; 18% had a Master's degree), and 8% had only a high school education.

4.3 Measures

Data on personality, affect, and work effectiveness was collected during an initial battery and over two months of follow-up EMAs. These data were then aggregated into a single score per variable of interest; see Table 1 for a summary of the measures included. In the initial battery, we also collected demographic information from participants including age, sex, language, and supervisory position. Personality, consisting of the dimensions of conscientiousness, neuroticism, openness, agreeableness, and extraversion, was assessed by the **Big Five Inventory-2 (BFI-2)** [108]. Fluid and crystallized intelligence was measured by Shipley's Abstraction and Shipley's Vocabulary, respectively [106]. Fluid intelligence refers to basic cognitive processes, such as reasoning and memory, and crystallized intelligence refers to acquired knowledge such as vocabulary and factual knowledge [59]. The inclusion of crystallized intelligence and fluid intelligence in our models was motivated by previous research demonstrating a strong relationship between intelligence measures and job performance [103]. Positive and negative emotion was measured by the **Positive and Negative Affect Schedule-Expanded Form (PANAS-X)** [125], and anxiety was measured with the **State-Trait Anxiety Inventory (STAI)** [111].

Table 1. Summary of Primary Measures

Domain	Construct/s
Health indicators	Daily heart rate variability (HRV), sleep duration, step count
Demographics	Age, gender, language, supervisory role
Personality	Conscientiousness, neuroticism, openness, agreeableness, and extraversion
Affect, stress, and anxiety	Positive and negative affect Stress and anxiety
Job Performance	Task performance Organizational citizenship behavior Interpersonal and organizational deviance

Job performance was measured along the widely-used dimensions [98] of: task performance, organizational and citizenship behavior, and counterproductive work behaviors. Task performance was assessed through two measures: **in-role behavior (IRB)** [129] and **individual task proficiency (ITP)** [54]. **Organizational and citizenship behavior (OCB)** consists of actions that employees take to improve the organization overall even if the behavior is not formally rewarded, e.g., organizing an after-work social event [84]. Employees can also engage in behaviors that harm the organization, called **counterproductive work behaviors (CWB)** [100]. Harm can be directed at individuals (e.g., spreading negative rumors about a colleague) or at the organization (e.g., inflating hours on a time sheet). We assessed OCB with the OCB checklist [51], and CWB via the interpersonal and organizational deviance survey [12]. While objective measures of workplace performance may be attainable, they vary from workplace-to-workplace and job role-to-job role. That is, a software engineer in one company may be assessed using different performance metrics than the same job in another company. Additionally, a software engineer may also be assessed on a different metric than a salesperson within the same company. Further, self-reports might be more accurate to measure CWB as others might not be aware of all the participant's behaviors. Self-reports of OCB also align with informant-reports [29]. Thus, despite known limitations, the use of self-reports is an acceptable method to measure job performance in the industrial and organizational psychology literature. After the initial battery, participants received EMAs via text message which contained a link to a Qualtrics survey at either 8 am, noon, or 4 pm.

Surveys varied day-to-day in content and time of administration, but all participants were administered the same survey with the same content for that day. Specifically, each daily EMA consisted of a base survey that included the PANAS Short Form to measure daily affect [74], single item questions that asked participants to rate current levels of stress and anxiety with a response scale from 1 to 5. For example, the stress question asked, "Overall, how would you rate your current level of stress?" with responses ranging from "No stress at all" to "A great deal of stress." In addition to the base survey, participants received an additional set of questions on different schedules, with one of three other sets: health, job performance, or personality. The health survey assessed exercise, sleep, and other health constructs, and was administered 3–4 times a week in the 8 am or noon timeslot. Earlier times were chosen to decrease the amount of time since sleep (which occurred the day before and into the current day's morning). The job performance survey included questions about CWB and OCB and was only administered at 4 pm toward the end of a workday, three times a week, as it asks about job performance of that day. Finally, a personality assessment was administered at any time slot (8 am, noon, 4 pm), once every other week with items from the short BFI-10 [108]. The base survey was always administered first, followed by one supplemental survey. Within the base survey, the context assessment was first, but the order of the other subsections was randomized. Within the other three surveys (health, job performance, and personality), the order of subsections was randomized.

Surveys were administered approximately 56 days following initial enrollment (which occurred on a rolling basis) and were designed to take less than five minutes to complete. The EMA administration time and content were scheduled such that participants received roughly the same proportions of each kind of survey, equally split across the day, regardless of the date of enrollment. For instance, across 56 days, a participant could expect a stress question 56 times, occurring roughly 19 times at 8 am, 19 times at noon, and 19 times at 4 pm. Participants could finish the survey up to 4 hours post-administration.

Surveys from the initial battery and the corresponding EMA surveys were combined into a single, aggregate measure as they were correlated and combining them can increase reliability by the principle of aggregation [105]. For the initial surveys (administered only once), we generated scores from surveys following survey instructions. For instance, the PANAS-X instructs separating and then summing negative and positive items to generate a positive affect score and a negative affect score. Each EMA was scored in similar fashion. For example, the PANAS-Short consists of five negative and five positive items which are summed to generate a negative and positive score for the day. These individual EMA scores were averaged to generate an overall participant-level EMA score aggregated across the participant's time in the study. A z-score was then calculated for the initial survey and the participant-level average EMA, and these z-scores were averaged together. This was performed for each domain measured with a few exceptions to this basic approach. Stress and anxiety EMAs were highly correlated ($r = .83$), so we averaged them before combining with the STAI. Similarly, we averaged in-role behavior and individual task proficiency scores due to high correlation ($r = .77$) before combining with task performance scores. Further, in order to maximize available data, we proceeded with one measure (i.e., initial or EMA) for the few cases where the complementary measure was missing. Thus, each participant was assigned a single, aggregate score for the survey measures of interest.

4.4 Wearable Sensors

Participants wore a Garmin Vivosmart 3 wrist-based sensor which has an accelerometer and heart rate monitor capable of streaming **Beat-to-Beat Interval (BBI)** to collect time series. This device was chosen because it was waterproof, had a battery life of 4–5 days, and a robust API that allowed for easy data retrieval and worked with both iOS and Android smartphones. We obtained daily summaries of sleep data and activity from the Garmin API. In addition, participants installed a researcher-created smartphone app [123], which allowed us to collect BBI from the Garmin Vivosmart 3, used to calculate heart rate variability (HRV) in the manner described by Stein and colleagues [112]. Participants were asked to wear the device 24/7 on their wrist, and it was recommended that participants charge the device during showering. Details on extracting our focal measures from the sensor are provided below.

4.5 Procedure

Participants were enrolled either in-person at their workplaces or remotely via the web conference software Zoom. After granting consent, participants completed a Qualtrics survey consisting of an initial ground truth battery of various measures described above (Section 4.3). The initial survey took approximately one hour, and the session was monitored by either an in-person proctor or a proctor via web conference. Following the survey, in-person participants received and set up a Garmin Vivosmart 3, Bluetooth beacons (not analyzed here), a phone app, device batteries, and a payment card (for cohorts which allowed direct payment), and granted researchers access to their social media streams (not analyzed here). Remotely enrolled participants differed in that the devices were mailed to them, and remote participants were provided an instruction sheet and the ability to schedule a remote follow-up with researchers to ensure proper device function. Participants then received the daily EMA surveys as discussed above. Participants completed an average of 78% (Mdn = 87.3%; SD = 23.1%) of the surveys.

5 ANALYTIC PROCEDURE

5.1 Extracting Routineness with MdRQA

We applied MdRQA RR to capture system-level patterns of regularity spanning the three select health-oriented behaviors: step count, sleep duration, and HRV. For each participant, we removed days from analysis that were missing data from any of the channels of interest, because inclusion of missing data can artificially increase regularity (see Section 5.3 for details). After *z*-scoring each time series separately, we submitted participants' measures of daily step count, sleep duration, and heart rate variability to MdRQA using MATLAB code adapted from Wallot and colleagues [122]. It is considered ideal to keep the average RR relatively low [35] in order to avoid ceiling effects, where a large radius might result in some participants having almost all recurrent points, while a lower radius will better differentiate between participants' routineness. As is typical in the RQA literature, radius is held constant across participants. Thus, consistent with previous literature, a radius was set to maintain an average RR of less than five percent across all participants (*radius* = .307 for our data) [35]. Phase space reconstruction is sometimes recommended in order to recover underlying dimensions of a signal [127]; in this case, we opted not to use this procedure given that multidimensional signals were already being used (thus we set the embedding dimension and delay parameters to 1). The average RR for participants in our sample was 3.89 (*SD* = 1.74).

5.2 Computing Health Behaviors

Data was retrieved from the Garmin API via **Open Authentication (OAuth)** permissions granted by study participants. Syncing data from the wearable to the cloud via the Garmin Connect app generated a callback to our servers with the data, and these callbacks could also be initiated by researchers if data was missing. In addition, HR data was collected directly from the Garmin via Bluetooth and used to calculate HRV (see below). In terms of sleep duration, a 24-hour calendar day was measured from noon-to-noon. Step count and HRV were measured on a 24-hour calendar day from midnight-to-midnight. We aligned HRV and step count with sleep duration from the previous night's sleep.

5.2.1 Sleep Duration. Bed time and wake time were collected directly from the Garmin health API. However, wearables rely on motion to detect sleep and can be inaccurate [7], and missing data can be a problem in wearable studies of sleep [8]. First, to reduce the likelihood of naps included in the sleep calculation, we restricted bed times to between 5 pm and 7 am the next day, and wakeup times to between 10 pm and noon the next day. This contrasts with Garmin's methodology which looks for bed times and wake times from noon to noon. If multiple sleep periods were detected and fell within this restriction, the sum of durations between bed and wake times were calculated. For instance, a person who goes to bed at 10 pm, wakes up at 2 am, returns to sleep at 3 am, and wakes up for the last time at 7 am would be considered to have 8 (4 + 4) instead of 9 hours of sleep.

If we detected phone usage (e.g., unlocking a screen) within 90 minutes after bed time(s) or 90 minutes before wake time(s), we adjusted the bed and or wake times accordingly. If Garmin bed or wake times were unavailable or outside the restricted time period, we imputed the sleep duration from the phone agent alone, using the last unlock of the night and the first unlock of the morning for estimation. If neither wearable nor phone agent data were available, duration was set to be missing. Our combined measure of daily sleep duration, which takes into account wearable sensing and phone usage, brings our sensing and self-report measurements into agreement within an average of eight minutes difference.

5.2.2 Heart Rate Variability. Data was collected via the phone agent based on methodology from Wang and colleagues [123] and allowed for real-time HR data collection. This allowed us to collect the time between detected beats in milliseconds, or beat-to-beat interval (BBI), which was more fine-grained than what is sent to Garmin's backend servers. Using the collected BBI, we calculated **Standard Deviation of Average Normal-to-Normal (SDANN)** as our measure of HRV; this is an international standard for capturing long-term components of HRV [24]. We first calculated the average BBI across sliding five-minute windows incremented at 1 minute (e.g., 8:00 am to 8:05 am; 8:01 am to 8:06 am). These values were only calculated if four of five minutes (80%) are present. Then, a standard deviation was calculated from these average 5-min BBI windows within a 24-hour calendar day, resulting in a daily SDANN measure. The Garmin Vivosmart 3 recorded an average 70% of daily HR across all participants, and our app to stream BBI, which requires the phone be in Bluetooth proximity, charged, etc., collected less, though this is in line with at least one other study that reports an average of 33% of **photoplethysmography (PPG)** missing data [4]. Given the stringent measurement standard of 4 out of

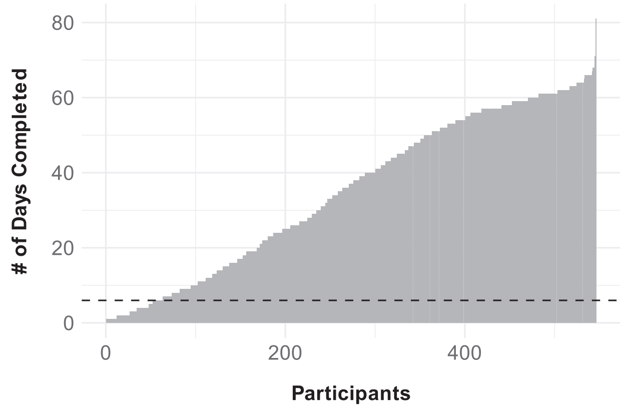

Fig. 4. Plot illustrating total days of data collection completed by each participant, where participants were recruited on a rolling basis. On the *x*-axis, each individual participant is plotted (i.e., one bar per participant) and sorted in ascending order by total number of days with completed sensor data. The dashed line indicates the threshold of completed days required for participants to be included in the analyses. Participants with less than seven days of complete sensor data (i.e., HRV, sleep duration, and step count) were excluded.

5 minutes present to calculate a bin, and the importance of continuous data (e.g., 2 minutes of missing BBI excludes 10, 5-minute bins), 24-hour SDANN values are based on approximately 38% of minutes per day.

5.2.3 Step Count. Step count was collected directly from the Garmin health API and consisted of a daily count summary.

5.2.4 Outlier Treatment. Given that HRV and sleep duration variables exhibited long right-tail distributions, we removed values with a mean absolute deviation greater than |2.5|, excluding .061 and .058 proportion of values due to outlier removal, respectively. Step count exhibited a relatively normal distribution, such that outlier removal was not necessary.

5.3 Exclusion Criteria

For each participant, a given day of data was excluded from analysis if any of the three variables (sleep, step count, or HRV) were unavailable or unreliably recorded because imputing missing values with a constant (e.g., 0) can artificially inflate RR. Across all participants, 534 days of data were removed because of missing sleep recordings (2.71% of days) and an additional six days were removed for missing heart rate data (.03% of days). Participants were excluded if they had less than a total of seven days of data with complete step count, sleep duration, and HRV data, yielding a final sample of 483 participants. A cut-off of seven days was selected to retain as many participants as possible while allowing for sufficient variability in behavior for the analyses. Because participants were recruited on a rolling basis, participants had an average of 39 days of data available across all three health behaviors at the time of analysis (*SD* = 18.65; see Figure 4). As evident in Figure 4, most of the sample more than adequately satisfied the threshold. Nevertheless, the Pearson's correlation between RR and days available for analysis indicated a small to medium effect, $r = .265$, $p < .001$, so we included the number of days of available data as a covariate (control variable) in all subsequent analyses.

6 RESULTS

6.1 Preliminaries

We used linear regression models to examine the relationship between health regularity and personality, affect, stress and anxiety, and job performance. **Variance inflation factors (VIF)** were less than the recommended

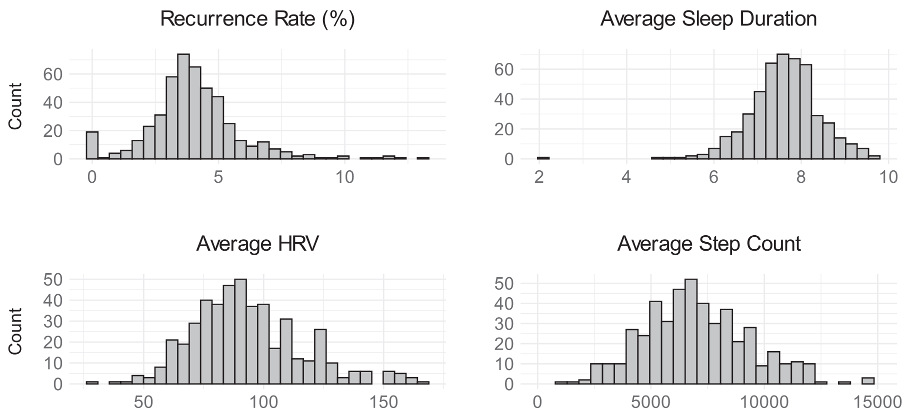

Fig. 5. Average RR, HRV, sleep duration, and step count per participant.

Table 2. Standardized Estimates (β) for Linear Regression Models Examining Relationships between Multimodal Health Regularity and Participant Demographics

	Recurrence rate		
Predictors	β	*CI*	*p*
Intercept			**<.001**
Cohort 1	.008	−.108 −.123	.895
Cohort 2	−.051	−.145 −.042	.284
Cohort 3	.007	−.088 −.102	.879
Cohort 4	.054	−.049 −.156	.307
Age	.038	−.052 −.128	.405
Gender	.025	−.069 −.118	.605
Language (native English)	.009	−.080 −.098	.842
Supervise (yes)	−.087	−.187 −.013	.089
Covariate: Number of days analyzed	.239	.149 −.329	**<.001**
Observations	473		
R^2/adjusted R^2	.083/.065		

cutoff of 4 [1], indicating the models were not compromised by multicollinearity. Health regularity was defined in the current study as MdRQA RR, and participants' RR ranged from 0 to 13.12 (M = 3.89, SD = 1.74). Across participants, the average HRV was 122.17 (SD = 35.09), average sleep duration was 7.60 hours per night (SD = .80), and there was an average of 6,907.47 steps per day (SD = 2,310.96; see Figure 5 for distributions). The Pearson correlations between RR and participant-level individual health behaviors were $r < .18$ ($r_{HRV} = .17$, $p < .001$; $r_{Sleep\ duration} = .01$, $p > .05$; $r_{Step\ count} = .15$, $p < .001$).

6.2 Relationship Between Regularity and Demographics

We investigated the relationship between regularity and individual demographic variables by regressing MdRQA RR on participants' age, cohort, gender, language (English as native language or not), and supervisory role (supervisor or not). In addition, we included number of days available for analysis in this and all subsequent models to account for differences in regularity arising from amount of available data per participant (see above). Regularity was relatively equivalent across ages, cohorts, genders, language, and supervisory role (see Table 2). Thus, health regularity seems to be largely independent of demographic information.

6.3 Regularity as a Predictor of Personality

We used a series of linear regression models to investigate the relationship between participants' regularity and self-reported dimensions of personality (agreeableness, conscientiousness, extraversion, neuroticism, and openness; see Table 3). Similar to the model presented above, participants' age, cohort, gender, language (English as native language or not), role (supervisor or not), and number of days available for analysis were entered as covariates to control for these variables. In this way, we examined the predictive value of regularity over-and-above a number of other potential predictors of personality. For example, supervisory role was selected *a priori* as a covariate, in part, on the number of participants who were supervisors (43%). Relevant to our measures of stress and step count, research documents that supervisors may experience especially high levels of stress, which may be moderated by exercise [17]. In addition, average HRV, sleep duration, and step count were included as covariates, as we were interested in the incremental predictive validity of MdRQA RR over-and-above more traditional measures of health.

Controlling for a number of covariates, we found that greater MdRQA RR was associated with lower agreeableness ($\beta = -.149$, $p = .002$), greater neuroticism ($\beta = .109$, $p = .022$), and (marginally) lower extraversion ($\beta = -.090$, $p = .064$), but not of openness or conscientiousness, ps > .1. These results are consistent with previous research suggesting that propensity for routine may correspond to greater neuroticism [49], which we extend to lower levels of agreeableness. Notably, the individual health indicators did not predict personality, ps > .1.

6.4 Regularity as a Predictor of Affect, Stress, and Anxiety

We next examined the extent to which MdRQA RR predicted participants' positive affect, negative affect, as well as stress/anxiety using linear regression, controlling for the same individual difference variables reported in the previous models (see Table 4). Though the relationship was relatively weak, we found that regularity was marginally associated with higher stress and anxiety ($\beta = .082$, $p = .088$), but not positive or negative affect, ps > .1. Similar to the previous models, the individual health indicators were not significant predictors of positive affect, negative affect, or stress and anxiety, ps > .1, with the exception of a marginally positive relationship between step count and positive affect ($\beta = .089$, $p = .087$)

6.5 Regularity as a Predictor of Workplace Performance

We investigated the degree to which MdRQA RR predicted workplace performance (see Table 5). In addition to the same covariates as above, we also included Shipley Abstraction and Shipley Vocabulary scores to control for the influence of intelligence on work performance due to robust relationships among the two [103]. We found that regularity was negatively associated with work effectiveness, such that participants with greater regularity demonstrated more interpersonal and organizational deviance ($\beta = .101$, $p = .033$). The relationships between regularity and task performance ($\beta = -.060$, $p = .212$) and regularity and organizational and citizenship behavior ($\beta = -.069$, $p = .133$), were negative but statistically non-significant. In contrast to the previous models where individual health indicators were not significant predictors, average HRV had a negative relationship with interpersonal and organizational deviance ($\beta = -.128$, $p = .014$) and a marginal positive relationship with task performance ($\beta = .095$, $p = .071$). In addition, sleep duration had a negative relationship with organizational and citizenship behavior ($\beta = -.106$, $p = .016$).

6.6 Moderation Effects by Composite Health Indicators

Given that higher levels of the three health behaviors—higher HRV and more sleep and exercise—are often associated with positive outcomes, there is the question of whether RR would be moderated by overall levels of health behaviors. For example, regularity might be a positive predictor of work deviance if accompanied by unhealthy routines (consistently sleeping less, low step count, and low HRV) but an alternate pattern might emerge for more healthy routines (getting sufficient sleep each night, exercising daily, and having high HRV).

Table 3. Standardized Estimates (β) Examining Relationships between Multimodal Health Regularity and Personality Traits

	Agreeableness			Conscientiousness			Extraversion			Neuroticism			Openness		
Predictors	β	*CI*	*p*	β	*CI*	*p*	β	*CI*	*p*	β	*CI*	*p*	β	*CI*	*p*
Intercept			.279			.051			.071			.360			.196
MdRQA RR	−.149	−.243 −.056	**.002**	−.028	−.122 −.067	.567	−.090	−.185 −.005	.064	.109	.016 −.201	**.022**	.012	−.085 −.108	.815
M HRV	.076	−.041 −.193	.206	−.046	−.164 −.073	.451	−.005	−.124 −.114	.941	.038	−.063 −.140	.460	−.034	−.140 −.072	.527
M sleep duration	.042	−.053 −.136	.385	−.028	−.124 −.067	.564	.041	−.055 −.137	.404	.011	−.079 −.100	.817	−.058	−.151 −.035	.222
M step count	.036	−.060 −.132	.466	.064	−.033 −.161	.198	.029	−.068 −.127	.557	.014	−.085 −.112	.785	−.038	−.141 −.065	.471
Cohort 1	.042	−.062 −.145	.433	−.051	−.156 −.054	.345	−.019	−.124 −.087	.727	−.135	−.251 −.018	**.024**	.049	−.072 −.171	.425
Cohort 2	.176	.084 −.267	**<.001**	.142	.049 −.235	**.003**	−.040	−.133 −.053	.397	.003	−.091 −.096	.957	.054	−.043 −.152	.276
Cohort 3	−.051	−.149 −.046	.303	−.079	−.178 −.019	.116	−.092	−.191 −.006	.067	−.083	−.178 −.013	.091	−.011	−.111 −.088	.824
Cohort 4	−.083	−.172 −.007	.072	−.023	−.114 −.068	.621	−.099	−.190 −.008	.033	−.015	−.118 −.088	.772	.103	−.005 −.210	.062
Age	−.045	−.146 −.057	.388	.003	−.099 −.106	.950	.083	−.020 −.186	.113	−.103	−.194 −.011	**.028**	−.030	−.125 −.065	.538
Gender (male)	−.016	−.106 −.074	.732	.016	−.075 −.107	.737	−.028	−.120 −.063	.543	−.219	−.316 −.123	**<.001**	.001	−.099 −.102	.979
Language (English)	−.054	−.156 −.049	.307	.057	−.047 −.161	.282	−.036	−.140 −.068	.495	−.039	−.128 −.050	.389	.054	−.039 −.146	.258
Supervise (yes)	−.094	−.193 −.006	.065	.121	.021 −.222	**.018**	.077	−.024 −.178	.134	−.028	−.129 −.072	.582	−.026	−.131 −.079	.625
Covariate: Number of days analyzed	.010	−.084 −.104	.831	.009	−.086 −.105	.850	−.077	−.173 −.018	.114	−.068	−.162 −.025	.153	−.004	−.101 −.093	.936
Observations	473			473			473			473			473		
R^2/adjusted R^2	.087/.062			.065/.039			.060/.033			.101/.076			.025/−.003		

Table 4. Standardized Estimates (β) for Linear Regression Models Examining Relationships between Multimodal Health Regularity and Affect, Stress, and Anxiety

	Positive affect			Negative affect			Stress and anxiety		
Predictors	β	*CI*	*p*	β	*CI*	*p*	β	*CI*	*p*
Intercept			**<.001**			**<.001**			.440
MdRQA RR	−.001	−.097 −.095	.979	.046	−.048 −.140	.340	.082	−.012 −.176	.088
M HRV	.018	−.088 −.123	.739	.021	−.083 −.125	.692	.063	−.040 −.166	.234
M sleep duration	.019	−.073 −.112	.680	.005	−.086 −.096	.919	−.002	−.093 −.088	.959
M step count	.089	−.013 −.192	.087	−.014	−.114 −.087	.788	−.062	−.162 −.038	.224
Cohort 1	.018	−.103 −.138	.772	−.148	−.267 −.030	**.014**	−.131	−.248 −.013	**.030**
Cohort 2	.025	−.073 −.122	.618	−.043	−.139 −.052	.374	−.041	−.136 −.054	.399
Cohort 3	.056	−.042 −.155	.264	−.119	−.216 −.022	**.017**	−.097	−.193 −.000	.051
Cohort 4	−.011	−.118 −.095	.836	−.027	−.132 −.078	.610	−.058	−.163 −.046	.273
Age	.013	−.081 −.107	.783	−.144	−.237 −.052	**.002**	−.119	−.212 −.027	**.011**
Gender (male)	.015	−.085 −.114	.776	.029	−.069 −.128	.561	−.162	−.260 −.064	**.001**
Language (native English)	−.136	−.228 −.044	**.004**	−.071	−.162 −.020	.127	.079	−.011 −.169	.087
Supervise (yes)	.087	−.018 −.191	.104	.034	−.068 −.137	.512	.028	−.074 −.130	.591
Covariate: Number of days analyzed	−.023	−.120 −.073	.639	−.093	−.188 −.002	.056	−.048	−.142 −.047	.325
Observations	471			471			473		
R^2/adjusted R^2	.040/.012			.069/.043			.078/.052		

Table 5. Standardized Estimates (β) for Linear Regression Models Examining Relationship between Multimodal Health Regularity and Work Effectiveness

	Task performance			Organizational and citizenship behavior			Interpersonal and organizational deviance		
Predictors	β	*CI*	*p*	β	*CI*	*p*	β	*CI*	*p*
Intercept			.605			**<.001**			.940
MdRQA RR	−.060	−.154 −.034	.212	−.069	−.158 −.021	.133	.101	.008 −.193	**.033**
M HRV	.095	−.008 −.199	.071	−.031	−.129 −.067	.537	−.128	−.229 −.026	**.014**
M sleep duration	−.032	−.123 −.058	.483	−.106	−.192 −.020	**.016**	.036	−.053 −.125	.427
M step count	−.057	−.158 −.043	.262	−.038	−.133 −.058	.438	.064	−.034 −.163	.201
Cohort 1	.025	−.094 −.143	.681	.037	−.076 −.150	.520	−.054	−.170 −.063	.365
Cohort 2	−.003	−.098 −.092	.951	−.032	−.122 −.059	.494	.060	−.034 −.153	.213
Cohort 3	.082	−.016 −.179	.101	.069	−.024 −.161	.146	−.046	−.142 −.049	.340
Cohort 4	.064	−.040 −.169	.230	.068	−.032 −.167	.183	−.016	−.119 −.087	.760
Age	.191	.095 −.287	**<.001**	−.021	−.112 −.071	.659	−.291	−.385 −.196	**<.001**
Gender (male)	−.168	−.266 −.069	**.001**	−.080	−.173 −.014	.095	−.038	−.134 −.059	.447
Language (native English)	−.029	−.125 −.067	.551	.059	−.032 −.150	.203	.114	.020 −.209	**.018**
Supervise (yes)	−.008	−.110 −.094	.872	.296	.199 −.393	**<.001**	.072	−.028 −.172	.161
Fluid intelligence	.021	−.078 −.119	.678	−.146	−.240 −.053	**.002**	−.027	−.124 −.070	.581
Crystallized intelligence	−.086	−.187 −.015	.096	−.038	−.134 −.058	.439	.070	−.029 −.170	.165
Covariate: Number of days analyzed	.009	−.086 −.104	.856	−.090	−.181 −.000	**.050**	.019	−.074 −.112	.690
Observations	473			473			473		
R^2/adjusted R^2	.080/.050			.170/.143			.112/.083		

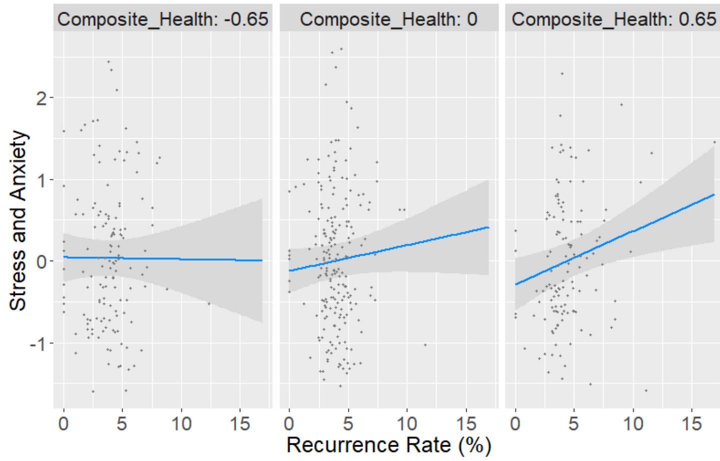

Fig. 6. Simple slopes analysis demonstrating the relationship between RR and stress/anxiety at composite health at mean (center) and one *SD* below (left) and above (right) the mean. The relationship between RR and stress/anxiety was only significant when the health score was one SD above the mean (right).

To test this hypothesis, we first constructed a composite measure of overall behavior levels (i.e., the average of participant-level z-scored HRV, sleep duration, and step count). This measure was only weakly correlated with recurrence rate ($r = .173$, $p < .01$). We then repeated the above models by replacing the individual health behaviors with this composite score as an interaction term to examine the degree to which the predictive power of RR was moderated by the collective level of the three health behaviors.

The findings revealed that RR—our measure of multimodal routineness—remained a significant predictor of agreeableness ($\beta = -.15$, $p = .002$), neuroticism ($\beta = .10$, $p = .038$), and counterproductive work behavior ($\beta = .10$, $p = .037$) even with the composite health score entered into the models, which was not a significant predictor of those outcome variables (ps $> .1$). In fact, the composite health score was only a significant predictor of stress/anxiety ($\beta = -.19$, $p = .036$). We also found that the interaction between RR and composite health score was significant in this model ($p = .016$), which supersedes the main effect of health score. We probed this interaction with simple slopes analysis, which examines the association between the predictor variable (RR) and the dependent variable (stress/anxiety) at varying levels of the moderator variable (composite health score), typically at the mean and one standard deviation (*SD*) above and below the mean [36]. These analyses (see Figure 6) indicated that RR was a positive predictor (unstandardized coefficient $B = .067$, $p = .005$) of stress/anxiety when the health score was one *SD* above the mean, but not when it was at the mean ($B = .032$, $p = .15$) or one *SD* below the mean ($B = -.002$, $p = .93$).

The results demonstrate that global patterns of routineness more strongly predict the dependent variables than a composite health indicator, and, with the exception of stress/anxiety, the overall levels of health behaviors did not moderate the relationship between RR and the dependent variables.

7 DISCUSSION

The present study extends previous research on the relationships between routine, personality, affect, and workplace effectiveness. Using longitudinal wearable-sensor data from a large number of diverse participants, we introduce multimodal health regularity as a composite measure of the joint dynamics of three key health indicators (HRV, step count, and sleep duration). In the remainder of this section, we discuss our main findings regarding health regularity, followed by limitations and future directions.

7.1 Main Findings

The present study demonstrates health regularity as a viable construct that predicts facets of personality and work effectiveness. With respect to personality, previous research has pointed to potential linkages between health regularity and neuroticism, suggesting that certain types of routineness are a vulnerability marker for addiction and disorders involving compulsions [49]. Our findings help confirm that regularity is associated with greater neuroticism, but also extends to an association with lower agreeableness. Moreover, there was a marginal, but non-significant, association between health regularity and elevated levels of stress and anxiety. Taken together, these findings emphasize the relationship between health regularity and neuroticism and suggest a potential link to increased stress. People prone to greater regularity may be driven by a need for structure and predictability, such that new challenges elicit elevated stress levels. Although more research is needed to examine the effect in different work contexts, it is possible that a mismatch between worker-workplace routineness results in particularly high levels of stress.

Given that health regularity was associated with reduced agreeableness and emotional stability (i.e., neuroticism), it follows that it should also be associated with reduced work effectiveness. Indeed, individual health regularity significantly corresponds to greater interpersonal and organizational deviance even after accounting for numerous related variables (e.g., demographic information, overall levels and daily variation in individual health indicators). Those exhibiting greater health regularity were therefore at a disadvantage in their interpersonal interactions with colleagues and during work tasks.

Notably, health regularity was only weakly correlated ($r < .18$) with and exhibited greater predictive power than both individual and composite health measures. Moreover, health regularity, individual health indicators, and composite health score tended not to predict the same outcome variables. Average levels of individual health indicators did not significantly predict personality, affect, stress, or anxiety, whereas health regularity was associated with aspects of personality and, to a lesser extent, stress and anxiety. The only outcome variable predicted by both health regularity and an individual health indicator was interpersonal and organizational deviance. In addition, health regularity remained a significant predictor in these models even when adding a composite health score into the models, and the latter was generally not a significant predictor of the outcome variables. The only exception was in the case of stress and anxiety, where there was an interaction between health regularity and composite health score: Health regularity was a positive predictor of stress and anxiety, but only when the composite health score was approximately one *SD* above the mean. The findings indicate that overall levels of health behaviors do not explain the predictive power of health regularity, and our measure of global routineness is a stronger predictor of our outcome variables than a composite measure that only examines overall levels of health behaviors. It is worth noting that *R*-squared values in range of those reported here are common in the social sciences and represent small to medium effect sizes [50]. Our dependent variables consisted of personality traits, affect, and self-reported work effectiveness, and these variables are likely influenced by a large number of external factors. Our statistical findings regarding the predictive value of routineness—taken together—are consistent in indicating that too much health behavior routineness can lead to less desirable outcomes.

At first blush, the findings that greater health regularity correspond to greater neuroticism and reduced work effectiveness may seem counterintuitive given that literature often emphasizes the importance of healthy routines. It might be the case that getting the same amount of exercise each day contributes to physical well-being but does not translate into better performance at work. It is also possible that our examination of a large non-clinical sample differentiates our findings from those focusing on clinical populations. For example, our findings showing that health regularity predicted stress and anxiety, but only when the composite health score was high, suggests that some people may engage in health behaviors to an excessive degree of routineness. Further, it is important to interpret findings in light of the fact that our measure of health regularity focused on patterns of behavior irrespective of the specific levels of the component variables. Thus, our approach to quantifying multi-channel health regularity offers a truly unique lens through which to view the benefits of routine.

The present findings are consistent with nonlinear dynamical systems theory (and, relatedly, complex systems theory), which emphasizes system flexibility as an important indicator of healthy functioning. That is, in order to function properly, an organism must be both stable and adaptable—not too rigid or too chaotic—where these opposing forces are balanced. Systems that exhibit a functional balance between order and disorder are called "far from equilibrium," which is considered a universal feature of complex systems [15]. This principle has been demonstrated extensively in brain, cardiovascular, motor, and psychological systems, where oftentimes excess rigidity is a sign of dysfunction [10, 31, 32, 47, 78, 91]. For example, healthy cardiovascular systems tend to show less regular and more complex dynamics [91]. This is hypothesized to correspond to increased communication and coupling between subsystems that allows for faster and more effective adaptation [68, 89, 90]. The importance of flexibility versus rigidity has also been explored in relation to emotions, where people who experience greater emotional diversity are more flexible [82, 95] and exhibit better mental and physical health [94]. Considered in this context, greater health regularity may be dysfunctional by reflecting a person's inability to effectively adapt to shifting environmental demands, including those in the workplace.

Health-oriented routines are an important intervention method for both clinical and non-clinical populations. However, our findings suggest that some individuals may develop overly rigid routines and also suffer from greater neuroticism and decreased work performance. It is possible that these individuals can benefit from being encouraged to break routine and learn healthy methods for coping with new situations (e.g., a new exercise class, socializing with new people, taking on a new project at work). This is similar to interventions used to treat anxiety disorders such as obsessive-compulsive disorder, where individuals gradually endure and adapt to more-and-more challenging situations as they learn effective coping skills and develop healthier responses to aversive stimuli [121]. Interventions promoting flexibility and relevant coping skills could be beneficial to a wide range of people, including sub-clinical populations or people experiencing specific problems in their relationships. Relatedly, Banovic and colleagues [5, 6] designed an approach for identifying maladaptive features of driving routines to encourage safer, less aggressive behaviors on the road, demonstrating how information gathered from analysis of routine can be directly applied to behavioral interventions. Furthermore, it is also possible that wearable sensors can be used to identify populations prone to stress and anxiety who would benefit from such interventions. Certainly, more research is needed to identify how to promote health and wellness with wearable sensors, and the present research identifies new directions for doing so.

Though not a central focus in the present work, the findings also corroborate those from a number of previous studies. For example, older participants were less neurotic and similar in terms of extraversion and openness as compared to their younger peers [109] and—consistent with prior literature—engaged in less interpersonal and organizational deviance [92]. One counter-intuitive finding that emerged in the models is the negative relationship between average sleep duration and organizational and citizenship behavior. Given that organizational and citizenship behavior entails taking action to improve the organization even if the behavior is not formally rewarded, it is possible that participants engaged in these activities are self-sacrificing, including in terms of sleep. It is also possible that there is a mediating variable not accounted for in the present models that drives this relationship. Future research is needed to adjudicate amongst these possibilities.

Finally, the current study included measures of fluid and crystallized intelligence in order to control for previously observed relationships between intelligence and workplace performance [103]. However, the present findings reveal that fluid intelligence was negatively associated with organizational and citizenship activities, implying that individuals with higher fluid intelligence took fewer actions to improve their organization. Considering that previous research has reported a positive relationship between emotional intelligence and citizenship behaviors [119], it seems likely that there is a more nuanced relationship between the different dimensions of intelligence and components of workplace effectiveness than what is accounted for by the current study. In addition, the present study focused on information workers, specifically, and it is possible that the relationship between fluid intelligence and workplace performance is moderated by an additional variable such as organizational culture.

7.2 Limitations and Future Directions

The present study focused on the daily behaviors of a large number of information workers across the United States. It is possible that people in this field are required to engage in less routine work than the general population, such that more routine-oriented workers are at a disadvantage in these professions. More research is needed to test the extent to which the present findings generalize to different populations.

It is also possible that the relationship between routine regularity, PANAS scores, and workplace effectiveness may differ based on the variables considered. In the present study, we selected HRV, sleep duration, and step count in order to represent three important and distinct aspects of health. However, it is possible to change both the type and number of variables considered. For our purposes, we were interested in the relationship between collective routineness across three distinct channels. However, we anticipate that including three sleep measures (e.g., sleep duration, onset, and offset) might yield different results that indicate sleep routine has positive effects on professional outcomes. More research is needed to test the extent to which the present findings generalize to routineness in different health-related behaviors.

Lastly, a common limitation of longitudinal and sensor-based studies is the prevalence of missing data. For that reason, we compensated participants based on an average of 80% compliance for wearable, phone app, and daily survey data. In addition, participants had to meet certain eligibility criteria to be included in the final sample and we controlled number of days available as a covariate in each model. However, missing data remains a common issue with this type of research and is a limitation of the present research.

7.3 Conclusions

The benefits and drawbacks of routineness have implications for the health and well-being of the general population. To date, the majority of research on routineness is unimodal in focusing on the relative consistency of single measures, is typically based on self-report measures like EMA, and often focuses on clinical populations. In contrast, we introduce a novel application of MdRQA used to quantify the multimodal dynamics of routineness, analyzing wearable sensor data from a large number of information workers. Moreover, prior research on routineness offers conflicting perspectives: Although some researchers emphasize the benefits of incorporating health-oriented behaviors, a smaller body of literature outlines significant drawbacks of excessive routineness. The present findings indicate that a more nuanced perspective is needed to understand the relationship between health regularity, individual differences, and adaptive functioning. Our results suggest that greater health regularity is predicted by underlying differences in personality that correspond to higher neuroticism, lower agreeableness, and higher workplace deviance. Thus, although it is often desirable to incorporate healthy behaviors into one's routine, greater regularity is not inherently beneficial. Although these findings are novel in the context of health routineness, they are consistent with a great deal of prior work in complexity science and associated concepts of "far from equilibrium" systems. Thus, the present study highlights a novel approach to quantifying multimodal routineness from sensor-based data and a new perspective on routineness with a strong theoretical backing.

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