A State-of-the-Art Review of Computational Models for Analyzing Longitudinal Wearable Sensor Data in Healthcare

Paula Lago

paula.lago@concordia.ca

Department of Electrical and Computer Engineering, PERFORM Center
Concordia University, Montreal, QC, Canada

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Abstract

Wearable devices are increasingly used as tools for biomedical research, as the continuous stream of behavioral and physiological data they collect can provide insights about our health in everyday contexts. Long-term tracking, defined in the timescale of months of year, can provide insights of patterns and changes as indicators of health changes. These insights can make medicine and healthcare more predictive, preventive, personalized, and participative (The 4P's). However, the challenges in modeling, understanding and processing longitudinal data are a significant barrier to their adoption in research studies and clinical settings. In this paper, we review and discuss three models used to make sense of longitudinal data: routines, rhythms and stability metrics. We present the challenges associated with the processing and analysis of longitudinal wearable sensor data, with a special focus on how to handle the different temporal dynamics at various granularities. We then discuss current limitations and identify directions for future work. This review is essential to the advancement of computational modeling and analysis of longitudinal sensor data for pervasive healthcare.

1 Introduction

Modern phones and wearable sensors have emerged as indispensable tools for capturing continuous, longitudinal, real-world behavioral and physiological data for health and health research [66, 80, 55]. The unprecedented depth of information, combined with advances in machine learning, opens the door to further our understanding of the relationship between health and behavior, to automatically assess and predict health status, and to create personalized interventions to improve health outcomes.

One practical challenge to realize the potential of research using such sensors is how to make sense of the large amounts of data collected over long periods. As stated by Xu. et.al. [87], the information captured by these sensors, "while information-rich, is also information-vague", requiring thoughtful analysis to

obtain valuable insights. A large body of research has focused on finding features in the data that correlate with a specific health condition, for example, COVID-19 [54], epilepsy [30], depression [17], schizophrenia [38], anxiety [73], or mild cognitive disease [50] among others. While the results are encouraging, few standards exist for the analysis. More often than not, the features are heavily dependent on the device used and hard to generalize [1, 18], which makes it difficult to translate research findings into policy or recommendations.

Longitudinal data can support applications such as early warning systems by identifying changes in behavior [52]. One critical aspect for these applications is finding typical patterns in the data. These typical patterns can be used to summarize the data, find anomalies, and measure the strength of the "typicality" or "variability" in day-to-day life. Research has shown associations of behavior regularity with physical health [49, 56], and disruptions of daily routine were found to be associated with mental health disorders [46], thus providing a foundation for the need to find objective measures of regularity and disruption using sensor data. For instance, activity patterns measured with passive sensors were found to be associated with Mild cognitive disease [21]. However, the lack of standards to analyze sensor data has made results obtained so far non-generalizable and difficult to replicate [69]. Consequently, there exists a pressing need to develop theories, tools, and techniques that not only model a baseline of typical patterns but also adeptly measure, interpret, and comprehend variations or changes to such baseline.

This work provides a comprehensive review of existing methods to model behavior and predict health using continuous, longitudinal sensor data. Two complementary views have emerged in the literature to address this problem: **routines and rhythms**. Both views underscore temporal aspects of behavioral and physiological regularity: routines focus on the frequency of events; rhythms emphasize temporal regularity and periodicity. Recently, **stability metrics** have also been proposed based on routine or rhythms views. We highlight their strengths and differences as well as the common open research challenges ahead.

Other reviews exist on the use of smartphones and wearable sensors in healthcare. A part of these reviews focuses on the application areas and evidence around the use of passive sensing for early diagnosis, management, or prediction of disease [47]. Other focus on the technologies accelerating the rise of passive sensing in healthcare. Fewer reviews focus on the modeling approaches for longitudinal patterns. Mohr et.al.[55] focuses on mental health applications, providing an overarching model of personal sensing, and reviewing the literature on using sensors to detect mental health conditions and related behavioral markers. The review by Witt et.al.[80] describes algorithmic approaches used to generate fitness- and health-related indicators from wearables data, all of which focus on providing a *current* picture of the user instead of focusing on their long-term patterns. They briefly review behavior change detection techniques which focus on the analysis of longitudinal data.

Meyer et.al. [52] have reviewed the implications of long-term tracking, clearly differentiating it from short-term tracking. Their review focuses on implications for the user collecting the self-track data. They define long-term "in timescales of years". Here, we review existing models that may support the modeling of such data for healthcare applications.

In this review, we focus on the modeling long-term patterns, their analysis, quantification, and the main issues in making sense of the large amounts of

data collected. We first provide a description of the rhythm (Section 2) and routine (3) models and their evolution over time, and then provide an overview of common metrics used to quantify the regularity of patterns (Section 4). We finalize the review with a discussion of open issues in both models (Section 5). In an effort to unify the clinical and computational perspectives, this review synthesizes the rhythmic and routine-based approaches to long-term pattern modeling, as well as the growing focus on metrics. This review contributes to the biomedical research by providing a comprehensive summary of the current methods to model, analyse and process longitudinal wearable sensor data.

2 Rhythms

A rhythm is a cyclic pattern, repeated at regular temporal intervals. Human behavior and physiology follow biological rhythms, the most common ones are linked to the day/night cycle. These rhythms are governed by an internal pacemaker called the suprachiasmatic nucleus (SCN), an internal structure located in the brain, and are affected by external factors like light, temperature, and social factors, among others [59]. Research has found strong links between the strength and alignment of this central clock with environmental and behavioral cycles and our physical and mental well-being. For this reason, the characterization of the various behavioral and physiological rhythms from sensor data is deemed as an important next step in understanding these rhythms in everyday life conditions to design personalized diagnostics and interventions.

Longitudinal measures of activity and physiology obtained with passive sensing have been used to either model the SCN rhythm or rhythms of processes such as activity, heart rate, or body temperature. While the latter may not strongly correlate with the SCN rhythm, as they are affected by various other factors, their characterization can still provide information about health status. Moreover, the study of multiple rhythms can shed light on how these rhythms and their alignments affect our health. We now explain four rhythm models.

2.1 Template curves

One simple way of modeling typical rhythms of the data is to model a "template" curve for the day. A template curve is created by averaging (or calculating the median value) across all days for each time slot in the day (e.g., every minute, hour). Activity curves [26] were proposed to model the probability of each activity happening at each time slot when the measurements are not continuous signals but rather, events.

These curves can be used for anomaly detection if values deviate more than a certain amount from the template. The main issue is defining the time over which to calculate the template. They have also been used to obtain deviation from the template as a feature for classification purposes.

While calculating template curves is simple, one of the major drawbacks of curves is the lack of context. A single template curve cannot account for differences due to day-to-day variations or monthly variations. Of course, template curves could be created for each day of the week or every day of the year, as is done with weather data, but it could lose representational power.

2.2 Cosine models

Rhythms are most commonly modeled as sinusoidal functions, characterized by multiple parameters. The first parameter is its period. As such, circadian rhythms are those with a 24-hour period (the average circadian period in humans is 24.2h), while an ultradian (infradian) rhythm is one with a period of less (more) than 24h [74]. While 24 hours is usually assumed for the period, due to its relevance for the internal master clock, frequency analysis methods like the Fourier Transform, wavelets, spectral analysis, and periodograms can be used to extract personalized periods from the longitudinal sensor data. This period analysis can help uncover individual variations, as well as various rhythms.

By modeling rhythms as a sinusoid, its amplitude, MESOR, and Phase describe the rhythm of behavioral or physiological signals. Phase measurements are of particular relevance as they enable the description of the relative timing of physiological rhythms with environmental and behavioral cycles. These metrics are obtained by fitting the sensor data to a cosine wave of a predefined period using the least square method — this is called the COSINOR method [23]. Equation 1 shows a single component COSINOR, other models include additional components to consider, for instance, the effect of light in the rhythm. Interested readers are referred to [36] for a complete discussion of circadian rhythm models.

$$Y(t) = M + A cos(\frac{2\pi}{\tau} + \phi) + e(t) \qquad (1)$$

While characterizing the rhythms of physiological and behavioral processes is important, the importance of understanding the relation between multiple rhythms should not be disregarded. Afsaneh et.al.[88] proposed a framework that combines period finding with COSINOR to independently describe rhythms of various signals and then uses these descriptors to predict depression risk. Runze et.al. [83] also models a cosine rhythm for each signal and finds that rhyhtmic models are correlated with productivity. While these are preliminary results in a specific population, they shows the potential of combining multiple rhythms in the development of digital health services.

2.3 Models to predict SCN rhythm

As previously mentioned, one common goal of modeling rhythms through sensor data is to model the SCN rhythm: predict its period, phase, and amplitude. The gold standard to measure the SCN rhythm is by taking multiple samples of melatonin, cortisol, or core body temperature under highly controlled conditions like dim light or a constant routine protocol [29]. These procedures are costly and invasive, so passive sensing provides a cost-effective and ecological way to predict it.

The COSINOR method has been used with actigraphy (accelerometer-based) and physiological data to model the SCN rhythm with relative accuracy in ambulatory settings. To account for influences on the measurement other than the circadian rhythm, various mathematical models of the clock have been proposed [36].

In most cases, though, passive sensor data is used to predict the onset of melatonin (time of peak), which is a gold standard metric of the SCN phase [29].

Deep learning and traditional machine learning techniques involving sensor measurements of activity, skin temperature, heart rate, and other physiological processes have been proposed for this purpose [76, 12]. While these methods are promising, other studies have shown that the error could be higher in populations who may benefit the most from precise metrics such as shift workers, jet-lagged people, and people with sleep disorders [82]. Novel methods still need to be evaluated with more diverse and specific populations.

Characterizing the SCN rhythm is pivotal to further our understanding of its role in health outcomes, however, researchers also acknowledge that different processes may exhibit different rhythms which need not have the same characteristics as other markers such as the melatonin onset (DLMO). Their characterization is useful for understanding underlying processes and might further increase our understanding of the role of the alignment of various rhythms with health. The methods to analyze such rhythms are similar to those described above, but models may consider the effects of confounder factors. For instance, to analyze the circadian rhythm of heart rate, Bowman et.al.[10] first removes the effects of activity, to uncover the underlying rhythm.

2.4 Rhythm Models excluding Cosine Regression

Since sensor data may not always follow a cosine waveform, non-parametric metrics have also been used to describe the rhythmic properties of sensor data, particularly activity data. These metrics are explained in Section 4. Non-negative matrix factorization (NMF) has also been proposed to discover typical daily rhythms [2] and multiday [13] rhythms without the need for a regression. A dataset of the daily or multi-day sensor signals is created where each column represents an individual's data, which can be daily, weekly, or monthly data. NMF factorizes this dataset (a matrix) to find a small number of common patterns, such that each individual's data can be represented as a linear combination of the patterns. This method is also used for routine modeling (Section 3) by creating a matrix of events.

3   Routines

One approach to modeling long-term patterns is through routines. A routine is generally thought of as a sequence or set of actions performed regularly. While there is no agreed formal definition of a routine, the term is usually used to describe recurring patterns of discrete *events* such as daily living activities, work tasks, or visited locations. As such, two main dimensions encompass a routine: co-occurring or sequences of events and their temporal recurrence. In contrast to rhythms that focus on the periodicity of sensor measurements, routines focus on the frequent repetition of events.

Interest in computationally modeling routines is longstanding. Their computational study first emerged as a way to support everyday tasks: routines enable the prediction of the next event, which helps a system provide effective recommendations, assistance, or information for that event. Understanding routines from sensor data has been studied to analyze daily life routines [34], family routines [25, 9], work-place routines [11, 70, 71], and travel routines [45, 37]. In the

context of healthcare applications, routines help understand behavioral patterns that can be associated with health outcomes either positively or negatively [4].

3.1 Models of routine

Routines are usually modeled as repetitive sequences of events. As such, to discover routines from sensor data, it is first required to define and identify events. What makes a sequence "repetitive" is considered from multiple points of view: the frequency of occurrence (frequentist approach), the likelihood of occurrence (bayesian approach), and the periodicity of occurrence.

3.1.1 Defining events

In the context of identifying routines from sensor data, an event can be defined as a significant occurrence or activity that can be detected or inferred from the data collected by sensors. It represents a specific action, behavior, or state of the individual being monitored. An important characteristic of events is their duration, that is, they are not instantaneous points in time, but rather an entity with a start and end time. In general, an event characterizes what is being done, by whom, when, and where.

Events can vary widely depending on the context and the type of sensor data being analyzed. For example, in the context of daily activities, events could include actions like cooking, walking, driving, sleeping, or working out [20] while in the context of travel routines, events correspond to locations visited [37]. Commonly, an event is described by a set of sensor readings obtained during a time window which may include changes in sensor readings, such as motion, location, temperature, or other relevant parameters, which correspond to the occurrence of the event and can be used to classify them [9].

Defining and identifying events can be a difficult task. Event definition depends on the sensor technology used and the probable duration of events. In some cases, events are defined directly by the sensor readings obtained during a window of time. In such cases, the number of events can be explosive, and unsupervised learning techniques are used to group them into a more manageable set (see next subsection). Events can also be identified by a `label`, requiring supervised learning to identify them. The activity recognition literature deals with this problem and has been extensively reviewed elsewhere [43, 15, 77, 14, 28].

3.1.2 Routines as highly probable events

Initial concepts of routine were based on daily routine, that is, how the day unfolds. The behavior of a particular day can be expressed as a vector b, describing the event that occurred at each particular time. This vector can be categorical, that is, each item bt identifies the event that occurred at time t as a category; or binary, that is, the item b_{jt} has the value of 1 if the event j occurred at time t. A matrix of multiple days $\mathcal{B} = D \times b$ describes the behavior over some time.

From this matrix, routines can be extracted. The concept of eigen-behaviors, representing the eigenvectors of this matrix, was used by Eagle et.al.[31] to find common behaviors in a day. An eigen-behavior represents an intrinsic behavior pattern, eigenbehaviors, then, can be used to describe the overall routine

of an individual as any particular day can be described as a linear combination of eigenbehaviors. While a predefined 24-hour period was assumed in this work, different behavior vectors were found for different situations showing that "eigenbehaviors" describe both typical patterns and variations of them.

Similar to this approach, topic models, a technique of natural language processing to automatically discover topics in a document collection, were used to find "topics" of behaviors [41, 62]. In these models, an event is considered a word, each day is a document and a set of days is a document collection. A topic describes a group of behaviors that typically occur together in a day, and each day can be described as a combination of topics.

One drawback of the previous methods is that they are based on individual data, suffering potentially from a cold-start problem. Only when there is sufficient data from a person, can we learn their routines and make inferences from their behavior patterns. To overcome this drawback, a collaborative-filtering-based approach was proposed by Xu. et al[84], which combines population data with personal data to find relevant behavioral features to infer depression.

The idea behind these techniques is that there is a set of behaviors occurring at a particular time *within predefined duration bins* that occur repeatedly. While a particular day exhibits a different combination of these typical patterns, the emerging patterns describe the routines of a person and can be used to represent any particular day.

The problem with this view is the lack of sequence representation. Each day is described as a "bag-of-events" with positional information. While this representation captures some of the sequential context, it cannot capture partial orders, such as events happening next to each other regardless of the time. For instance, "eigenbehaviors" can find patterns such as a late wake-up leading to a no-work day, it is harder to find sequences of activities that can happen together at no particular time. For example, a routine might consist of gym and then eating, but it can occur at different times of the day. Or if there is a sequence of office, gym, and then going home, always starting at 5 pm but having different durations for each depending on traffic, day, and others, it might be hard to discover due to the dependence on time and the predefined time bins.

3.1.3 Routines as highly probable sequences

Sequential models analyze data in the order of arrival, thus, capturing dependencies among the events. Both probabilistic and frequentist approaches have been used to model routines as sequences. From a frequentist perspective, routines are events that empirically occur frequently within a given timeframe based on repeated observations, while from a Bayesian perspective, routines involve incorporating prior beliefs or knowledge about the likelihood of events occurring and updating these beliefs with new evidence.

Frequent-sequential pattern mining and association rule mining [7, 34, 85] algorithms work under the frequentist assumption to identify events occurring repeatedly together in an event log. The extracted routine is then expressed as rules [85], action maps [7], or as a grammar [44]. Frequent sequences can represent typical sequences of events in the routine of a person but it is harder to model the uncertainty of multiple possible sequences. Another approach was proposed to consider context-based sequences [42], to model frequent sequences

that depend on the context such as day of the week or the weather, independently of the frequency of that context.

From a probabilistic perspective, Bayesian Networks, which include hidden Markov models, have been used to learn and model the sequential dependencies of events [45, 33, 16]. These networks model the transition probabilities between events, as well as the correlation between events and sensor readings. A common problem is defining the structure of the network to learn the parameters. Banovic et.al. [9] proposed a model based on reinforcement learning to learn the structure. The learned network of events describes the behavior of the person. By considering the context, such as location or time, in the description of the event, variations in behavior are modeled as well. However, the combinatorial explosion of the number of events and the need to manually describe them make it a computationally expensive model.

Both models have been used extensively in research, their main strength being the possibility of inspecting the routine and knowing exactly what is the next event, making them appropriate for intervention design. Their other strength is the possibility of modeling contextual changes. This is done either by adding it to the event definition or as part of the mining processing. In sequential patterns, modeling includes deciding the maximum length of the sequence and whether gaps or different orderings can be included. These decisions may affect the final learned routine.

Deep learning models have also been used to model longitudinal sensor data. For this, the events are defined by slices of data which can be a day of sensor events. Due to their black-box nature, Deep learning models have mostly been used in tasks to associate behavior with health outcomes. Recently, Xu et.al. [86] proposed a 1d Convolutional network to detect depression, which also learns the continuity of behavior. This can help learn the behavioral patterns but with the drawback of not being interpretable. While deep neural networks such as LSTM and GRU have been used to model other sequential data, their use to model routine from sensor data has been limited.

As mentioned before, models of routines are based on the definition and identification of events. This includes multiple assumptions about the duration of events, often left as predefined bins or windows, which may not accurately represent the duration of all activities leading to errors, and about the accuracy of identification. The propagation of errors from the identification of events to the modeling of routines can affect the usefulness of the model. While the events have also been defined as sensor event counts or statistics over predefined windows of time, this can lead to a combinatorial explosion in the number of possible states or require manual definition of thresholds to limit the possibilities. This is still a major drawback for routine analysis.

4 Quantifying behavioral stability with longitudinal sensor data

Both routines and rhythms model long-term sensor data, focusing on different characteristics of the patterns (periodicity, frequency, sequential dependencies). Other approaches focus on quantifying the *strength* of repetitiveness without modeling the specific patterns. A person with high strength (or stability) can

be thought of as having a more regular or strict routine while a person with lower strength will exhibit more variability in their day-to-day life. While these metrics can't describe the patterns, they characterize the repetitiveness of behavior. The simplicity of a single metric makes metrics attractive to perform statistical analysis, as a tool for early screening, and because they can be more easily interpretable than other models. For instance, less table and more fragmented rhythms have been associated with depression, higher BMI and smoking [48]. Research focuses on finding the relation between metrics and physical, mental, or cognitive health. These metrics can be classified as being uni-modal if they consider a single sensor modality, or multi-modal if they consider multiple sensor modalities at the same time. A summary of metrics is presented in Table 1, and they are discussed below.

4.1   Rhythm-based metrics

Rhythm-based metrics use a single sensor modality to obtain a measure of the strength of the rhythmicity of behavior, that is, how similar the measurements taken at the same over multiple days are. The interday stability, intraday variability, and relative amplitude (RA) metrics come from circadian rhythm research, as non-parametric measures of the strength of the circadian rhythm and are most commonly calculated using activity counts from actigraphy devices. They measure the strength, fragmentation, and amplitude of the rhythm, respectively.

The regularity and stability indexes have been proposed to measure the regularity from a variety of sensor modalities, but still consider only one modality at a time. They focus on measuring the similarity of events happening at the same time over multiple days. The regularity index measures how similar measurements taken at the same hour over two different days are, while the stability index compares the normalized cumulative distribution value at each hour over two days and then offers a value for a period by comparing all days to each other.

These metrics rely on having an aggregated measure, usually hourly, to compare the value across multiple days. While the aggregation could be in smaller segments, it is not clear how the aggregation might affect the result.

4.2   Event based metrics

Instead of relying on the measurements directly, event-based metrics rely on the detection of an event —i.e., an activity, a location— and then calculating the regularity of occurrences of this event over some time. For instance, the standard deviation in start/end time or duration of the event is a measure of how variable that event behavior is. The sleep regularity index focuses exclusively on the regularity of sleep schedule by measuring if the individual is asleep at the same times over the period being examined. Entropy measures the extent of repetition of events, regardless of their order, considering X as a random variable representing the activities in a day. For a person with a more stable routine, this random variable will have lower entropy, as the events are generated by a more regular process. Entropy measure is chosen for event-based analysis as the events are a categorical variable. The flexible regularity index [79] measures the edit distance between two days. By representing each event with a letter

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and considering the daily sequence of events as a character sequence, the edit distance calculates

Metric	Description	Formula
Sensor value-based metrics		
Intraday Stability [35]	A measure of how stable a person's rhythm is over multiple days, calculated from n samples of activity levels x, aggregated hourly q hour-bins. $\bar{x_h}$ represents the average activity during hour h. IS scores range from 0, indicative of a total lack of rhythm, to 1, indicative of perfectly stable rhythm	$IS = \frac{n\sum_{h=1}^{q}(\bar{x_h}-\bar{x})^2}{q\sum_{i=1}^{n}(x_i-\bar{x})})^2$
Interday Variability [35]	A measure of the fragmentation of activity or how activity level shifts between two consecutive time slots calculated from n samples of activity levels x, aggregated hourly q hour-bins. IV scores range of 0 to 2 with higher values indicating higher fragmentation	$IV = \frac{n\sum_{i=2}^{n}(x_i-x_{i-1})^2}{(n-1)\sum_{i=1}^{n}(x_i-\bar{x})^2}$
Rest-activity Amplitude [81]	Measures the difference between a person's daily activity (measured as the mean activity level over the most active 10 consecutive hours (M10)) and nocturnal activity (measured as the mean activity during the least active 5 consecutive hours (L5))	$RA = \frac{M10-L5}{M10+L5}$
Regularity Index [20, 79, 22]	Compares the uniformity of a person's schedule, comparing hourly (t) data from two days (a,b). Sensor measurements (x_a^t) are normalized to (-0.5, 0.5)	$RI_{a,b} = \sum_{t=1}^{T}\frac{x_t^a x_t^b}{T}$
Stability Index [38]	Measures the inverse of the median across a period of multiple days P of the distances between the normalized cumulative activity distributions $(C_b^{d_1})$ on two different days. It characterizes the degree to which behavioral patterns varied across the period. A higher index means higher stability.	$SI_b(P) = 1 - median(D_b(i,j)\|i,j \in P, i \neq j$ where $D_b(d_1,d_2) = \frac{1}{M}\sum_{i=1}^{M}\|C_b^{d_1} - C_b^{d_2}\|$

Metric	Description	Formula
Circadian Rhythm [79]	Measures the strength with which a user follows a 24-hour rhythm in behaviors by calculating the ratio of the energy that fall into the 24 ± 0.5 h period over the total spectrum energy in the 24 ± 12 h period. Here, psd(x) denotes the power spectral density at frequency bin x.	$CR = \frac{\int_{2\pi/23.5}^{2\pi/24.5} psd(x)dx}{\int_{2\pi/12}^{2\pi/36} psd(x)dx}$
	Event-based metrics	
Standard deviation [78, 79]	Measures the within-individual variability in a derived parameter (x) of an event. For example, the start time or duration of the event. A higher value indicates more irregular behavior.	$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}$
Sleep regularity index [58]	The probability of an individual being in the same state ($s_{i,j} = $ asleep or awake) at any two time points 24 hours apart, averaged over the number of days being studied (M). SRI values of 0 represent a random sleep schedule and a score of 100 represents a periodic sleep schedule. N is the number of time points in a day.	$SRI = -100 + \frac{200}{M(N-1)}* $ $\sum_{j=1}^{M}\sum_{i=1}^{N}\delta(s_{i,j},s_{i+1,j})$
Flexible Regularity Index [79]	Edit-based distance to measure the difference between two days by counting the number of operations (insert, delete, substitute) to convert one day's events into the other day's events. Higher values indicate more dissimilar days.	
Entropy [37, 65]	Measures the repetition of isolated events (i.e. travel events, activities), where E is the set of all possible events. A value of zero indicates no uncertainty (more stability) and a value of 1 indicates all events are equally possible	$H(X) = -\sum_{xinE} p(x)log_2 p(x)$
	Multimodal metrics	

Metric	Description	Formula
Entropy Rate of a Sequence [37]	Measures the extent to which ordered subsequences of events repeat over time. p_n denotes the joint probability distribution of a subsequence of length n	$$H(X) = \lim_{x \to \infty} - \sum_{x_1^n \in E^n} p_n(x_1^n) log_2 \frac{p_n(x_1^n)}{p_n(x_1^{n-1})}$$
Multiscale Fuzzy Entropy [60]	Measures the complexity of a time series	See reference.

Table 1: Behavior stability/variability metrics

4.3 Multimodal metrics

Previous metrics measure the stability of behavior considering one measured variable, but they can't measure relations across various behavioral and physiological measures such as sleep, steps, and heart rate. Amon et.al. [4] proposed an approach based on Multidimensional Recurrence Quantification Analysis (MdRQA) to provide a metric of the stability of behavior from multiple sensor signals. This method quantifies the interactions between multiple signals, thus offering a more holistic view of the repetition of patterns, which can also be understood as contextualizing the signals and their regularity. Similarly, the entropy rate [37] looks at the regularity of multiple events instead of an isolated event by considering the sequence of events.

4.4 Metrics summary

Metrics are valuable because they provide a quantifiable marker whose correlation with a health outcome can be more easily measured than the whole description of longitudinal data. Metrics can also provide personalized insights as they quantify the individual's behavior over some time. Commonly, researchers use metrics to evaluate their correlation with health conditions such as depression, schizophrenia, or cognitive decline. The strength of that correlation measures the usefulness of the metric.

As was discussed, most metrics rely on a single signal modality and a given time frame, thereby restricting the analysis. It is common to calculate metrics for all signal modalities separately and to calculate them using different groups of days. For instance, it is not uncommon to calculate the standard deviation across all days, across weekdays and across weekends. A combination of these metrics are usually used as input to a machine learning models to improve the predictive power. Multimodal metrics can provide a more holistic or contextualized view of the stability or variability of the behavior. However, it is possible that a single metric can hide some effects. For example, He-Yueya et.al. [38] found differences in the meaning of stability. For some signals, greater stability was desired for better outcomes but, for others, more variability was associated with better outcomes. An improved quantification of the relation between the variability/stability of different signals could help improve our understanding of the influence of behavior in health.

5 Discussion

Having examined three approaches to analyzing longitudinal sensor data, we now move on to discussing some open research challenges.

5.1 Choosing a model

The first key open question is how to choose a model for long-term sensor data analysis. A key consideration is the goal of the patterns. Common uses include (1) to find associations with health outcomes, to which metrics have an appeal due to their simplicity; (2) to provide assistance and predictions of the next events to which routines may be more suited; and (3) to find change and deviations, to which possibly all three models may help.

A combination of models is not uncommon, especially in conjunction with machine learning and deep learning for all three tasks. For this, the following open issues need to be solved as well.

5.2 Windows and window length

During the analysis of longitudinal sensor data, an important consideration is the amount of time (window length) to analyze. It is important to recognize two different types of windows, neither more important than the other: one window to aggregate sensor data as features or events and another to analyze the patterns in sensor data.

The first type of window, the event window, defines the length of time that is used to recognize an event or a feature (such as the number of steps taken or the average heart rate) that will later be used to obtain patterns in the form of routines, rhythm, or (ir)regularity metrics. This window is often defined in the range of seconds, a few minutes, or one hour. Extensive reviews have looked at the impact of the size of this window, for example, in activity recognition [8, 39]. Automatic segmentation has also been studied for this problem, where the window size is automatically determined by changes in the data distribution [27].

The second type of window, the pattern window, considers how historical data is used to analyze the patterns, for instance, 7 days or 1 month. Routines, rhythm features, and metrics might change depending on this length. Very little work has been done in the analysis of the impact of this length or how to define it. Most commonly, multiple window lengths are evaluated to find the one with the most predictive value for the problem at hand [60, 38]. In general, shorter window lengths will have a narrow but current view of the person's patterns, while longer windows will have a wider view but it could be influenced by outdated patterns— the weight of history is heavy.

A lack of standards in the size of windows hinders the comparability of results and efforts for data sharing. It is not uncommon to find datasets that aggregate data in a too coarse way, making it harder for others to evaluate or compare results that were obtained with smaller windows.

5.3 Baseline establishment and change analysis

Related to the problem of determining the pattern window length is the issue of change analysis. Ideally, when analyzing longitudinal data, one is interested not

only in the patterns found in data but also in identifying if any pattern changes have occurred. It is, after all, changes that may be more correlated with health changes or health outcomes after an intervention [53, 19]. However, most of the research so far focuses on analyzing the current behavioral patterns and the predictive power of these patterns for the health outcome being studied, and there is less research on how to analyze changes in behavior *across* windows.

Routine analysis has been used to identify changes in routine and anomalies by comparing current behavior with the learned models [42, 32]. To analyze changes in phase or amplitude of circadian rhythms over time, Bayesian spectral analysis and detrended fluctuation analysis have been used [6]. Changes are also detected statistically [51]. Some approaches based on *distribution changes* evaluate whether behavior changed in two different windows of time by comparing the distribution of sensor data of one window to that of the other window [67, 22]. The work by Cook et. al [22] determines behavior change over two time windows as a probability distance. By defining the average probability that an activity occurs during a time interval (i.e. an hour of the day) over the time window, it defines behavior as a probability distribution for each time interval. It then calculates the distance between two time windows using the KL divergence of the two distributions.

To quantify the change, [78] uses the slope of the data to quantify how values are changing inside a given window, but it does not quantify if the stability/rhythmicity is changing over various windows. Cook et.al. [22] use a permutation-based test to determine the statistical significance of detected changes.

The problem of detecting and quantifying behavior or rhythm change can also be framed as a change point detection problem. While there are multiple time series change point detection methods [3], these methods usually focus on the raw sensor values, which can be less meaningful for wearable sensor data, as the changes might be too granular or too fast. For instance, a changing heart rate due to exercise. For longitudinal data, the relevant changes span weeks or months of baseline pattern.

Other works frame the problem as an anomaly detection problem [24, 89, 5, 61]. Anomaly detection algorithms analyze deviations from current patterns to detect abnormal activities, heart rate, or other abnormal values, but they do not focus on identifying if the baseline patterns are changing. In other words, while they detect a momentary deviation, they assume the overall pattern remains constant.

Overall longitudinal pattern change analysis remains elusive, due to the difficulties in obtaining enough data for the analysis, the difficulties in defining time windows for the analysis, and the difficulties related to the evaluation of any such approaches.

5.4 Model Evaluation

Evaluating how accurately the routine, rhythm, or behavioral stability of a person is, is undoubtedly a difficult task. Unlike other tasks, such as supervised classification of activities, there is no ground truth data that can be used to compare the model. Routines have been evaluated by letting the user review the output and agree/disagree on it. However, this is still a subjective evaluation. For rhythms, comparison with rhythm parameters of the melatonin or cortisol

provides an error measure, but as was discussed, this can be misleading, as different processes may have different rhythms.

Recently, the evaluation focus has shifted to predictive power, that is, how well the patterns or metrics can detect or predict a health outcome (hospitalization, schizophrenia, depression, etc). These evaluations are important, as they focus on the clinical importance instead of computational metrics, but they are also elusive as they depend on the population in the sample, and have proven difficult to generalize. Moreover, they are difficult to translate to other uses of longitudinal pattern analysis, such as providing assistance with a task or identifying abnormal patterns.

5.5 Data Heterogeneity and Data Quality

Related to the evaluation and generalization of results is the **data heterogeneity** issue. Different platforms, vendors, form factors, users, and software libraries result in significant differences in data [68]. These differences can result in very different pattern estimations, whether in routines or rhythms. While metrics are developed and hand-crafted to find associations with health outcomes, their values can differ significantly due to the high heterogeneity, making it hard to generalize across different domains (sensing platforms, population groups, time) [75, 90].

For this reason, deep learning methods have been proposed as a way to find more stable features in the sensor data to classify and predict health outcomes that could have behavioral symptoms mainly with multi-task learning to learn patterns in the different domains [40, 57, 64, 63]. However, the generalization issue persists.

A second issue for data quality is the inevitability of missing data [72]. When data is being collected in natural settings, missing data may come due to battery issues, non-wearing events, or due to platform restrictions [79].

Proposals to deal with missing data include interpolation techniques and discarding data that contains missing data over a threshold percentage [88]. There are no standards set for this and the correct management of missing data is still an open research issue.

5.6 Context

Another issue in the current analysis methods is the lack of context in most of them. Several contextual factors can affect routine, rhythms, and the different metrics, including weekends, holidays, weather, or family visits. Not considering this can result in biased metrics, misunderstanding of the patterns, or a lack of insights into what causes changes in stability. Some models of routine consider contextual variations as a way to explain routine deviations and differentiate them from changes in behavioral patterns [42]. Some metrics, such as the regularity index, consider the day-to-day similarity, which may consider differences due to day-of-week changes, but not for other contextual factors. As was mentioned, this is also considered in the calculation of other metrics, such as the standard deviation, by filtering the set of days used as input. However, efficient computation techniques to deal with multiple contextual variables, as well as their possibly combinatorial explosion, are less often considered.

Understanding the association with context might be critical for designing interventions for health, and for providing more holistic insights, therefore, including context in the modeling and analysis of behavioral and physiological signals is critical.

5.7   Limitations of this study

This study does not adhere to the methodology of a systematic literature review, and consequently, may be subject to a degree of bias in the selection of papers. The myriad of terms and techniques employed in the field posed a significant challenge to conducting a systematic review. Instead, the primary focus was directed towards identifying and establishing commonalities and distinctions among the various models, as well as their respective applications. The study aims to encompass a wide array of literature to furnish a comprehensive overview of the models pertaining to long-term patterns.

6   Conclusion

In this state-of-the-art review, we explored computational models for making sense of longitudinal wearable sensor data for healthcare applications. Our examination of rhythms and routines revealed their distinct roles in capturing temporal patterns. Additionally, we provide an overview of critical challenges related to data heterogeneity, quality, and temporal granularity for the analysis.

Both routines and rhythms are used to model typical recurring patterns. While routines focus on the definition of an event, rhythms focus more on periodic patterns on the signal, overcoming the need for specific event recognition. Both models describe the data and can be used for predictions (of the next event in the case of routines or the next peak in the case of rhythms). Nevertheless, the evaluation of their accuracy and the results remains challenging as models are often highly dependent on the sensors used. As a way to mitigate this, researchers have focused on developing metrics focusing on the strength of the routine or how typical any particular day can be.

Several open research challenges exist including choosing the right model for data analysis, determining window lengths for analysis, and dealing with data heterogeneity and quality. There is a need for context in analysis as a significant gap in current research pertains to the exploration of the interrelation between behavioral changes and physiological alterations. Future research should explore the integration of wearable data with other health-related sources to create a holistic view of individual well-being.

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