Individualized Quality-of-Life Monitorings an Alternative to Population-Norms in Preventive Medicine

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Abstract: ***This study proposes an individualized approach to quality-of-life monitoring that shifts from population-based reference norms to personalized physiological comfort zones. By modelling each participant's baseline across eight biometric, psychophysiological, and environmental parameters, the method detects deviations that traditional standardized thresholds may overlook. Artificial data were generated to simulate diverse human profiles, followed by anomaly detection using personal comfort zones defined as ± 2 standard deviations. Principal Component Analysis was applied to visualize multidimensional health trajectories and highlight temporal instability. The results demonstrate a reduction in false positive and false negative compared to population norms and support the use of individualized baselines as a more sensitive, personalized alternative for preventive health monitoring.***

Keywords: Quality-of-life monitoring, Personalized baseline, anomaly detection, comfort zones modelling, PCA analysis

1. Introduction

Modern medicine relies heavily on biological norms established from large population studies. These reference values (e.g., resting heart rate 60-100 bpm, fasting blood glucose < 1.0 g/L) constitute essential diagnostic tools but present fundamental limitations when applied to individual longitudinal monitoring [1,2]. First, these norms capture a heterogeneous population, which can mask considerable inter-individual variability. An endurance athlete with a resting heart rate of 45 bpm and a sedentary individual at 85 bpm may both be classified as normal, although they are at opposite ends of the spectrum. Second, the population-based approach ignores the notion of personal baseline: a 15-bpm increase in resting heart rate may be insignificant for one individual but represent an early warning signal for another, indicating, for example, overtraining, emerging infection, or chronic stress [3,4]. Third, population norms are by definition cross-sectional and static, whereas human biology and behaviour are dynamic and contextual. An individual may present natural seasonal variations (weight, physical activity, sleep) or environmental exposure variations (ambient CO_2 levels) that are acceptable for them but fall outside standardized norms [5].

The concept of an individual comfort zone relies on modelling intra-individual variability rather than population-based reference thresholds. Instead of evaluating measurements against a fixed external norm, anomalies are detected as deviations from each individual's own baseline. This approach aligns with precision medicine frameworks that account for inter-individual heterogeneity in physiological and behavioural signals [6]. By constructing a dynamic baseline from longitudinal biometric, psychophysiological, and environmental data, the proposed method improves the sensitivity and specificity of quality-of-life change detection.

In this study, we are interested in three complementary objectives: First, we generate realistic artificial data that simulate human diversity across eight biometric, psychophysiological, and environmental parameters representing the main systems related to quality of life. Then, we implement an anomaly detection system based on individualized comfort zones (mean ± 2σ), and demonstrate its superiority over population thresholds in terms of reducing false positives and negatives. Finally, we used three-dimensional principal component analysis (PCA) to visualize and characterize multidimensional temporal trajectories of individuals, enabling a holistic representation of overall well-being state.

2. Methods and Results

2.1. Artificial Data Generation

In this study, we generated a realistic artificial dataset designed to represent human diversity across physiological, psychophysiological, and environmental dimensions. The dataset included 436 individuals, each characterized by demographic variables (sex, age, height, and weight) and monitored monthly over a 12-month period for eight parameters. These parameters were selected to cover major quality-of-life systems and grouped into four complementary domains: Body composition (body fat percentage, BMI (Body Mass Index), and hydration), Cardiovascular autonomic function (HRV "Heart Rate Variability") and MAI "Metabolic Activity Index"), Psychophysiological balance (sleep duration and stress level), and Environmental exposure (ambient CO_2). Parameter ranges were defined to reflect those observed in healthy or typical populations, ensuring inter-individual heterogeneity while maintaining intra-individual consistency of quality-of-life indicators. Detailed specifications for each parameter are provided in **Table 1**.

Stress levels were simulated according to the BioWell system, which assesses psychophysiological stress through gas discharge visualization (GDV) technology. The BioWell scale ranges from 0 to 10, where values between 0–2 indicate a calm state, 2–4 a normal state, 4–6 an excited state, and values above 6 a stress level [7]. For the purposes of this simulated dataset, stress values were restricted to the range [0–5] to represent a generally healthy population under typical daily conditions, with values ≥4 considered indicative of elevated stress requiring attention.

Body mass index (BMI) was computed as weight (kg) divided by height squared (m^2), with simulated values between 15–40 kg/m^2 to encompass underweight, normal, overweight, and obese categories in a healthy-to-typical population [8].

Metabolic Activity Index (MAI) represents cellular vitality and metabolic status as measured by bioimpedance devices like the Z-Métrix (Bioparhom/COSMED). This index reflects active cell mass and metabolic function [9]. Our simulated MAI values ranged from 3 to 7 AU, with higher values indicating better metabolic activity and cellular health.

Table 1: Specifications of Generated Parameters

Parameter	Min	Max	Unit
Body fat (BodyFat)	10	32	%
BMI (Body Mass Index)	15	40	kg/m^2
HRV (heart rate variability)	20	150	ms
Metabolic activity index (MAI)	3	7	index
Sleep duration	5	10	hours
BioWell stress level	0	5	scale
Ambient CO_2	400	2000	ppm
Body hydration	40	70	%

For each simulated individual, demographic characteristics (sex, age, height, and weight) were randomly assigned to obtain a diverse virtual population. Monthly values for the eight monitored parameters were subsequently generated within the [Min, Max] ranges specified in Table 1, with inter-month variability introduced manually to emulate natural fluctuations due to daily living conditions, seasonal effects, and lifestyle changes. This procedure yields heterogeneous individual profiles while preserving realistic intra-individual uniformity in quality-of-life indicators over the 12-month observation window.

To illustrate the range of profiles captured in the artificial dataset, **Table 2** reports the 12-month mean values for two contrasting cases: a 28-year-old active male (ID 19) and a 43-year-old sedentary male (ID 112). These examples show how distinct lifestyle patterns translate into different signatures across physiological, psychophysiological, and environmental parameters.

Table 2. Example profiles from the artificial dataset showing 12-month mean values

Parameter	Active Male	Sedentary Male	Unit
Age	28	43	years
Height	1.72	1.78	m
Weight (mean)	82.05	86.90	kg
Body fat (mean)	18.94	30.67	%
BMI	27.7	27.4	kg/m^2
HRV (mean)	65.48	58.04	ms
MAI (mean)	7.03	4.53	index
Sleep duration (mean)	7.95	7.92	hours
Stress level (mean)	2.48	3.24	scale
Body hydration (mean)	56.03	59.98	%
Ambient CO_2 (mean)	443.8	1770.1	ppm

Despite similar BMI values (approximately 27 kg/m^2), these two individuals exhibit significantly different profiles. The active individual presents lower body fat (18.94% vs. 30.67%), higher HRV (65.48 vs. 58.04 ms), higher metabolic activity (MAI 7.03 vs. 4.53), and lower stress levels (2.48 vs. 3.24). In contrast, the sedentary individual experiences significantly higher ambient CO_2 exposure (1770 vs. 443.8 ppm), which may reflect prolonged occupancy of poorly ventilated indoor environments. This example highlights the limitations of population-based reference ranges for personalized health monitoring: although both individuals fall within broad "normal" ranges for most parameters, their individual baselines differ substantially. Monitoring deviations from these personalized baselines is therefore more informative than comparing individuals to population averages alone.

Figure 1 : Visualization of comfort zones for each parameter and outliers for an artificial individual

2.2. The Concept of Individual Comfort Zone

An individual's comfort zone is statistically defined as the expected range of variation of their biometric, psychophysiological, and environmental parameters under stable conditions. Formally, for an individual *i* and a parameter *p*:

$$CZ(i,p) = [\bar{x}\,(i,p)\; - \; k \cdot s(i,p)\,;\, \bar{x}(i,p) \; + \; k \cdot s(i,p)] \quad (1)$$

where $\bar{x}\,(i,p)$ represents the sample mean of the 12 monthly measurements and $s(i,p)$ the corresponding sample standard deviation.

The 12-month period was assumed to represent a relatively stable physiological state. We acknowledge that if an individual is chronically dysregulated during this reference period, the sample mean may not reflect a true equilibrium state, which constitutes a limitation of baseline-based approaches. First, assuming approximate normality of monthly variations within a stable health state, ±2s captures 95.4% of expected values, consistent with the 95% confidence level standard in medical research [10]. Other else, in preventive medicine, ±2s offers a pragmatic balance: sensitive enough to detect meaningful deviations while conservative enough to prevent overdiagnosis [11].
For each individual, the 12 months and 8 parameters were analysed, identifying values falling outside the comfort zone. A month was marked as critical if at least one parameter exceeded its personal limits.

Figure 1 illustrates this approach for an artificial individual, showing the dynamics of each parameter over time. The green zone represents the normal variation range for this specific individual. The red points signal a significant deviation from the individual's personal baseline.

2.3. Comparison with Societal Norms

The failure of societal norms: When applying population norms to individual profiles, we observe two types of critical errors: false positives and false negatives. These errors are conceptually illustrated in Figure 2.

2.3.1. False Positives: Unnecessary Alerts

A false positive occurs when a healthy individual is flagged as abnormal because their baseline lies outside the population mean, even though they are in optimal well-being and their values are stable relative to their own baseline. **Figure 2(a)** illustrates an example of an individual whose average body fat remains chronically below 10%, which systematically falls outside commonly accepted reference ranges for healthy adults (14-24% for men, 21-31% for women) [12]. Although this level is physiologically stable and normal for this person (e.g., trained endurance athlete), it is nonetheless flagged as

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'abnormal' when interpreted individually against population-based norms shown by the red dotted lines.

Similarly, **Figure 2(b)** shows an individual with naturally high heart rate variability (HRV) around 100 ms constantly triggering alerts based on population norms for healthy adults. Studies on healthy individuals aged 20-70 years report typical HRV values ranging from approximately 25-70 ms depending on age, with values decreasing progressively with aging [13]. Although significantly elevated compared to reference ranges, this individual's HRV reflects excellent physiological condition and represents a stable personal baseline.

2.3.2. False Negatives: Missed Deviations

A false negative occurs when a dangerous or clinically significant change is missed because the parameter value remains within the normal societal range, even though it has significantly deviated from the individual baseline.

Example in **Figure 2(d)**: an individual's HRV drops to 35 ms, while their baseline is 44 ms. This decrease is an alarm signal that may indicate overtraining, emerging infection, or stress [14]. However, this value of 35 ms remains within the population norm and triggers no alert, thus masking a potential deterioration of their well-being.

Similarly, **Figure 2(c)** illustrates another false negative scenario with body fat percentage. An individual with a personal baseline around 18% body fat experiences an increase to 20%. While both values fall well within population-based healthy ranges (typically 14-24% for men [12]), this represents an 11% increase from their personal norm. For this specific individual, such an increase might signal meaningful changes in activity level, dietary patterns, or metabolic health. Yet because 20% remains comfortably within societal norms, a population-based monitoring system would fail to flag this deviation, potentially missing an early indicator of declining health or lifestyle changes requiring attention.

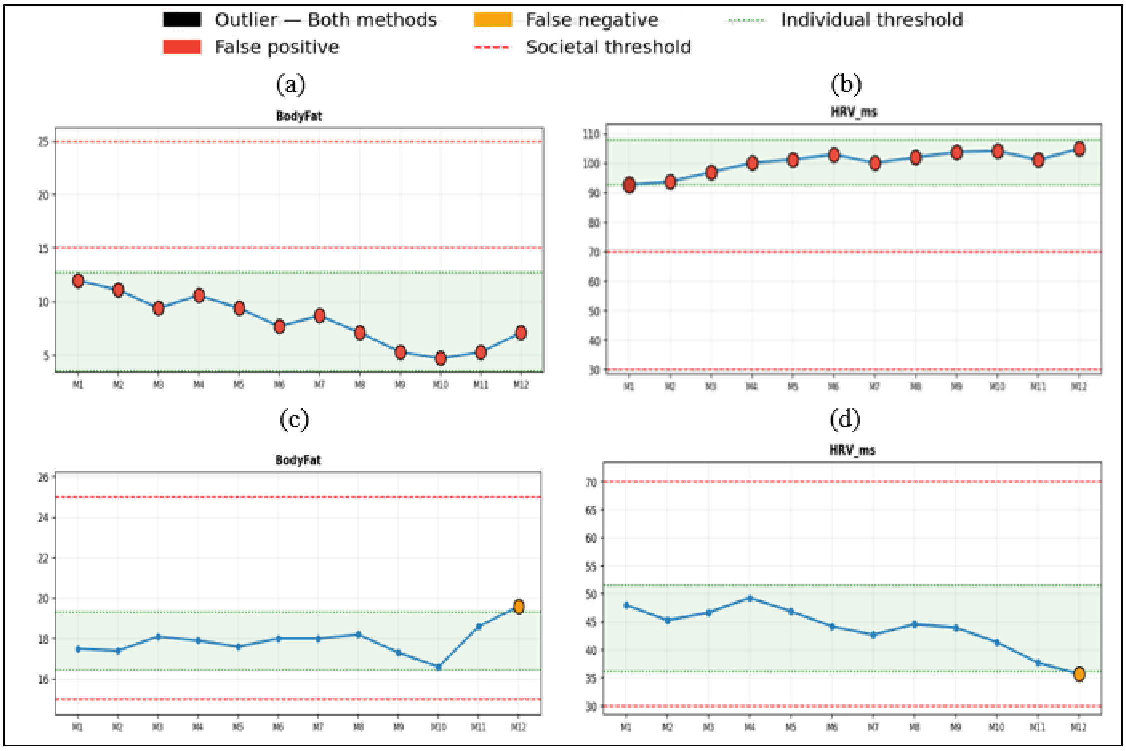

Figure 2: Comparison of individual and societal detection thresholds, with examples of false positives (a) (b) and false negatives (c)(d)

2.4. Analysis of Multidimensional Trajectories by PCA

While univariate analysis of comfort zones (Section 2.1) is effective for identifying deviations specific to each parameter, simultaneous interpretation of eight distinct parameters over a long period rapidly becomes complex and demanding. Moreover, this approach does not capture the interrelationships and overall dynamics between different physiological, psychophysiological, and environmental systems. An individual constitutes a complex system where parameters interact non-linearly, and a global view is necessary to apprehend overall well-being status and quality of life trajectories [15]. Principal Component Analysis (PCA) is a dimensionality reduction method that transforms a set of potentially correlated variables into a smaller number of uncorrelated variables called principal components, while retaining most of the original information [16]. Instead of analysing eight parameters independently, PCA projects the data into a lower-dimensional space, thereby revealing underlying patterns and overall well-being trajectories.

For each individual, we construct a 12 × 8 matrix (12 months, 8 parameters), which we standardize (centering and scaling using z-score normalization) to prevent a parameter with large numerical scale from artificially dominating the analysis. We then apply PCA and we retain the first three principal components, as they capture a majority proportion of total variance, while enabling an intuitive and visually interpretable three-dimensional representation. The individual PCA analyses the monthly variations of a single individual across the 8 parameters. When a month is marked as an outlier (red point), it means that at least one parameter deviates significantly from that individual's personal mean. By projecting the 12 months of data into a three-dimensional space, each point represents a month, and points are connected chronologically to form a temporal trajectory (**Figure 3**).

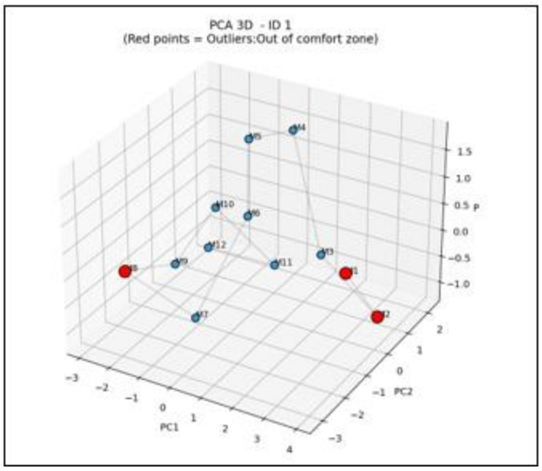

Figure 3: 3D PCA of an individual with outlier points in red

The morphology of the trajectory in the full PCA space becomes an indicator of quality-of-life dynamics. The full PCA transformation provides an embedding of the subject trajectory through time by encoding the physiological and environmental measurements into a compact latent space maximized for capturing the most significant variations or patterns in the physiological and environmental measurements.

On the other hand, a progressive drift of the trajectory or points brusquely moving away from the centroid (often the months identified as outliers) signal instability or a break in quality-of-life balance. These changes may indicate a transition to a new state, potentially less stable or problematic. PCA thus offers us an overall and integrative view that parameter-by-parameter analysis alone cannot provide.

3. Discussion

This study introduces an innovative approach to Quality-of-life monitoring, centered on individualization of comfort zones. The main originality lies in moving from inter-individual comparative logic (where is this individual relative to the population) to intra-individual temporal logic (where is this individual relative to themselves). This philosophy aligns with the principles of personalized and precision medicine, recognizing that inter-individual variability is often more important than differences between optimal states at the population level [17].

The individual comfort zone approach enables earlier detection of deviations, before they become large enough to fall outside population norms. In preventive medicine, this allows identification of at-risk profiles and prioritization of interventions in a more targeted and efficient manner. In sports medicine, it helps detect overtraining before the occurrence of injuries or chronic fatigue syndrome. In occupational medicine, it could identify employees at risk of burnout or professional exhaustion before clinical decompensation.

In addition, this approach reduces anxiety and unnecessary consultations. An individual genetically predisposed to 28% body fat but stable over time does not receive constant alerts, unlike a population-based approach that would systematically classify them as at risk of overweight or obesity

The integration of PCA as a visualization tool for multidimensional trajectories brings substantial added value. It allows surpassing the fragmented parameter-by-parameter view to access an overall representation of well-being state.
Several development axes open for this research. The integration of model-based statistical learning could enable predictive monitoring, anticipating future deviations from current trends. Enrichment with contextual variables (weather conditions, professional workload, life events) would explain more variance and contextual variations from problematic deviations.

Finally, prospective clinical validation studies are necessary to demonstrate the effectiveness of this approach in real populations, with clinically relevant outcome criteria (reduction in morbidity, improvement in quality of life, optimization of healthcare utilization).

4. Conclusion

This study demonstrates that individualized comfort zones, supported by PCA-based multidimensional analysis, offer a more precise and responsive alternative to population-based norms in quality-of-life monitoring. By emphasizing personal baselines and temporal trajectories, the method enables earlier detection of meaningful deviations and aligns with the principles of preventive and personalized medicine [15]. Future work should integrate predictive statistical models and validate this approach in real populations to assess long-term clinical benefits.

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