HolisticOS Data Requirements and Metrics Framework

Executive Summary

This document establishes a comprehensive data requirements and metrics framework for the HolisticOS agentic AI system, specifically designed to optimize integration with Sahha API for health biomarkers and Firebase Analytics for engagement metrics. The framework defines the precise data points, collection strategies, processing pipelines, and quality assurance mechanisms needed to enable sophisticated behavioral analysis and adaptive planning that outperforms existing health optimization tools.

The framework is structured around three primary data streams: health biomarkers from Sahha API, engagement analytics from Firebase, and behavioral data from the HolisticOS application itself. Each data stream is designed to provide specific insights that contribute to the overall understanding of user behavior, health status, and optimization potential. The integration of these data streams enables the agentic system to create a comprehensive picture of each user that supports truly personalized and adaptive health optimization.

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1. Data Architecture Overview

1.1 Integrated Data Ecosystem

The HolisticOS data architecture is designed as an integrated ecosystem that combines physiological health data, behavioral engagement data, and application interaction data to create a comprehensive understanding of each user's health optimization journey. This multi-dimensional approach enables the agentic system to understand not just what users do, but why they do it, how they respond to different interventions, and what patterns predict success or challenges.

The architecture operates on the principle of data convergence, where multiple data streams are combined to create insights that are greater than the sum of their parts. Health biomarkers from Sahha provide objective physiological indicators, Firebase analytics reveal engagement patterns and user journey behaviors, and application behavioral data captures specific interactions with health optimization routines. When combined through sophisticated analysis algorithms, these data streams enable unprecedented personalization and adaptation capabilities.

The system is designed to handle both real-time data streams for immediate adaptation and historical data analysis for pattern recognition and long-term optimization. Real-time data enables the system to respond immediately to user actions and physiological changes, while historical data provides the context and patterns needed for sophisticated behavioral analysis and predictive modeling.

1.2 Data Flow Architecture

Data flows through the system in a carefully orchestrated manner that ensures quality, consistency, and optimal processing efficiency. The architecture employs a multi-stage processing pipeline that includes data ingestion, validation, normalization, feature engineering, and analysis stages. Each stage is designed to add value while maintaining data integrity and enabling sophisticated downstream analysis.

The ingestion stage handles data collection from all sources, implementing robust error handling and retry mechanisms to ensure reliable data collection even under challenging network conditions. The validation stage ensures data quality and consistency, flagging anomalies and implementing quality scores that inform

downstream analysis confidence levels. The normalization stage standardizes data formats and time zones, enabling consistent analysis across different data sources and user locations.

Feature engineering transforms raw data into meaningful features that support behavioral analysis and pattern recognition. This includes calculating derived metrics, identifying trends, and creating composite indicators that capture complex behavioral patterns. The analysis stage applies sophisticated algorithms to identify patterns, generate insights, and support decision-making across all system agents.

1.3 Privacy and Security Framework

The data architecture implements comprehensive privacy and security measures that protect user data while enabling sophisticated analysis. All data is encrypted in transit and at rest, with access controls that ensure only authorized system components can access specific data types. The system implements data minimization principles, collecting only data that directly supports health optimization goals.

User consent and control mechanisms are built into the architecture, enabling users to understand what data is collected, how it's used, and providing granular control over data sharing and retention. The system supports data portability and deletion requests, ensuring compliance with privacy regulations while maintaining analytical capabilities.

Anonymization and aggregation techniques are employed where possible to protect individual privacy while enabling population-level insights that improve system performance. The architecture includes audit trails and monitoring systems that track data access and usage, ensuring accountability and enabling detection of any unauthorized access or misuse.

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2. Sahha API Integration Requirements

2.1 Health Biomarker Data Specifications

The Sahha API integration focuses on collecting comprehensive health biomarkers that provide objective indicators of user physiological state and health optimization progress. The integration is designed to capture both real-time indicators for

immediate adaptation and historical trends for pattern analysis and long-term optimization planning.

Heart Rate Variability (HRV) Data: HRV serves as a critical indicator of autonomic nervous system function and recovery status. The system collects HRV measurements with timestamps, measurement context (resting, active, sleep), and quality indicators. HRV data is processed to identify trends, optimal measurement windows, and correlations with user activities and stress levels. The system tracks both short-term HRV patterns for daily adaptation and long-term trends for overall health trajectory assessment.

Sleep Quality and Architecture Data: Sleep data provides fundamental insights into recovery, cognitive function, and overall health status. The integration collects sleep duration, sleep efficiency, sleep stages (deep, REM, light), sleep onset time, wake frequency, and sleep quality scores. This data is processed to identify sleep patterns, optimal sleep timing, and correlations with daily activities and routine adherence. The system uses sleep data to optimize routine timing, intensity, and recovery recommendations.

Activity and Movement Metrics: Physical activity data provides insights into user energy expenditure, movement patterns, and exercise capacity. The integration collects step counts, active minutes, exercise sessions, movement intensity, and sedentary time. This data is analyzed to understand user activity preferences, optimal exercise timing, and capacity for physical challenges. The system uses activity data to calibrate routine intensity and recommend appropriate movement interventions.

Stress and Recovery Indicators: Stress-related biomarkers provide critical insights into user psychological and physiological state. The integration collects stress scores, recovery metrics, resting heart rate trends, and physiological stress indicators. This data is processed to identify stress patterns, recovery capacity, and optimal intervention timing. The system uses stress data to adapt routine complexity and recommend stress management interventions.

2.2 Data Collection Protocols

Real-Time Data Streaming: The system implements real-time data streaming from Sahha API to enable immediate adaptation to physiological changes. Real-time data is processed within minutes of collection to identify significant changes that may require

routine adaptation. The streaming protocol includes error handling, retry mechanisms, and quality validation to ensure reliable data collection.

Batch Data Processing: Historical data is collected through batch processing to enable trend analysis and pattern recognition. Batch processing occurs daily for comprehensive analysis and weekly for deep pattern analysis. The batch processing protocol includes data validation, gap detection, and quality assessment to ensure comprehensive historical analysis.

Data Quality Assurance: All Sahha data is subject to comprehensive quality assurance protocols that validate data ranges, identify anomalies, and assess measurement reliability. Quality scores are assigned to all data points, enabling the system to weight data appropriately in analysis and decision-making processes. The quality assurance system includes automated anomaly detection and manual review processes for significant outliers.

2.3 Pydantic Models for Sahha Integration

```python
from pydantic import BaseModel, Field, validator
from typing import Optional, List, Dict, Union
from datetime import datetime
from enum import Enum

class SahhaDataQuality(str, Enum):
    HIGH = "high"
    MEDIUM = "medium"
    LOW = "low"
    INVALID = "invalid"

class SahhaHRVData(BaseModel):
    user_id: str
    measurement_timestamp: datetime
    hrv_rmssd: Optional[float] = Field(ge=0, le=200, description="HRV RMSSD in milliseconds")
    hrv_pnn50: Optional[float] = Field(ge=0, le=100, description="HRV pNN50 percentage")
    measurement_context: str = Field(description="resting, active, or sleep")
    measurement_duration: int = Field(ge=30, le=300, description="Measurement duration in seconds")
    data_quality: SahhaDataQuality
    confidence_score: float = Field(ge=0.0, le=1.0)

    @validator('hrv_rmssd')
    def validate_hrv_rmssd(cls, v):
        if v is not None and (v < 5 or v > 150):
            raise ValueError('HRV RMSSD outside normal physiological range')
        return v

class SahhaSleepData(BaseModel):
    user_id: str
    sleep_date: datetime
    sleep_onset: Optional[datetime] = None
    sleep_offset: Optional[datetime] = None
    total_sleep_time: Optional[int] = Field(ge=0, le=720, description="Total sleep time in minutes")
    sleep_efficiency: Optional[float] = Field(ge=0, le=100, description="Sleep efficiency percentage")
    deep_sleep_minutes: Optional[int] = Field(ge=0, description="Deep sleep duration in minutes")
    rem_sleep_minutes: Optional[int] = Field(ge=0, description="REM sleep duration in minutes")
    light_sleep_minutes: Optional[int] = Field(ge=0, description="Light sleep duration in minutes")
    wake_episodes: Optional[int] = Field(ge=0, description="Number of wake episodes")
    sleep_quality_score: Optional[float] = Field(ge=0, le=10, description="Sleep quality score 0-10")
    data_quality: SahhaDataQuality

class SahhaActivityData(BaseModel):
    user_id: str
    activity_date: datetime
    step_count: Optional[int] = Field(ge=0, le=100000, description="Daily step count")
    active_minutes: Optional[int] = Field(ge=0, le=1440, description="Active minutes per day")
```

```
    sedentary_minutes: Optional[int] = Field(ge=0, le=1440,
description="Sedentary minutes per day")
    calories_burned: Optional[int] = Field(ge=0, description="Calories burned")
    exercise_sessions: Optional[List[Dict[str, Union[str, int, float]]]] = None
    movement_consistency: Optional[float] = Field(ge=0, le=1,
description="Movement consistency score")
    data_quality: SahhaDataQuality

class SahhaStressData(BaseModel):
    user_id: str
    measurement_timestamp: datetime
    stress_score: Optional[float] = Field(ge=0, le=10, description="Stress
score 0-10")
    recovery_score: Optional[float] = Field(ge=0, le=100, description="Recovery
score percentage")
    resting_heart_rate: Optional[int] = Field(ge=30, le=200,
description="Resting heart rate")
    heart_rate_trend: Optional[str] = Field(description="increasing, stable, or
decreasing")
    physiological_stress_indicators: Optional[List[str]] = None
    data_quality: SahhaDataQuality

class SahhaDataSummary(BaseModel):
    user_id: str
    summary_date: datetime
    hrv_data: Optional[SahhaHRVData] = None
    sleep_data: Optional[SahhaSleepData] = None
    activity_data: Optional[SahhaActivityData] = None
    stress_data: Optional[SahhaStressData] = None
    overall_data_quality: SahhaDataQuality
    data_completeness: float = Field(ge=0.0, le=1.0, description="Percentage of
expected data collected")
    anomaly_flags: List[str] = Field(description="List of detected anomalies")
```

2.4 Integration Performance Requirements

Data Latency Requirements: Real-time data must be available within 5 minutes of measurement for immediate adaptation decisions. Batch data must be processed within 2 hours of collection for daily analysis. Historical data analysis must be completed within 24 hours for comprehensive pattern recognition.

Reliability and Uptime: The Sahha integration must maintain 99.5% uptime with automatic failover and retry mechanisms. Data collection failures must be detected within 15 minutes with automatic recovery procedures. Missing data must be identified and flagged for quality assessment.

Scalability Requirements: The integration must support concurrent data collection for up to 1 million users with linear scaling capabilities. Data processing must maintain sub-second response times for real-time queries and complete batch processing within specified time windows regardless of user volume.

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3. Firebase Analytics Integration Requirements

3.1 Engagement Analytics Specifications

The Firebase Analytics integration focuses on capturing detailed user engagement patterns that reveal behavioral preferences, usage patterns, and engagement quality indicators. This data provides critical insights into user psychology and behavior that complement physiological data from Sahha and enable sophisticated behavioral analysis.

Session and Usage Analytics: The system tracks user session patterns including session frequency, duration, timing, and feature usage within sessions. This data reveals user engagement patterns, optimal interaction timing, and feature preferences that inform routine design and adaptation strategies. Session analytics include both quantitative metrics (duration, frequency) and qualitative indicators (feature engagement depth, interaction quality).

User Journey Analytics: The integration captures detailed user journey data including navigation patterns, feature discovery paths, and engagement progression over time. This data reveals how users interact with the health optimization system, which features drive engagement, and where users encounter challenges or drop-off points. Journey analytics enable optimization of user experience and identification of engagement enhancement opportunities.

Feature Engagement Metrics: Detailed feature usage analytics provide insights into which health optimization tools and features users find most valuable and engaging. This includes tracking usage frequency, engagement depth, feature completion rates, and user-initiated feature exploration. Feature analytics inform routine design and help identify which interventions are most effective for different user types.

Behavioral Event Tracking: The system tracks specific behavioral events that correlate with health optimization success, including goal setting behaviors, routine customization actions, progress review frequency, and social engagement patterns. These behavioral events provide insights into user motivation, self-regulation patterns, and engagement sustainability.

3.2 Custom Event Framework

Health Optimization Events: Custom events are defined to track specific health optimization behaviors including routine completion, goal achievement, challenge acceptance, and adaptation responses. These events provide direct insights into user engagement with health optimization activities and success patterns.

Engagement Quality Events: Events are tracked to assess engagement quality including time spent on educational content, depth of progress review, frequency of goal adjustment, and proactive behavior initiation. These events help distinguish between passive and active engagement patterns.

User Initiative Events: The system tracks user-initiated actions including routine customization, goal modification, feature exploration, and community engagement. These events provide insights into user autonomy, motivation levels, and system ownership patterns.

Adaptation Response Events: Events are tracked to monitor user responses to system adaptations including acceptance rates, modification behaviors, and engagement changes following adaptations. These events enable optimization of adaptation strategies and timing.

3.3 Pydantic Models for Firebase Integration

```python
class FirebaseSessionData(BaseModel):
    user_id: str
    session_id: str
    session_start: datetime
    session_end: datetime
    session_duration: int = Field(ge=0, description="Session duration in seconds")
    screen_views: List[Dict[str, Union[str, int]]]
    feature_interactions: Dict[str, int]
    engagement_depth: float = Field(ge=0.0, le=1.0, description="Engagement depth score")
    session_quality: str = Field(description="high, medium, or low")

class FirebaseUserJourney(BaseModel):
    user_id: str
    journey_date: datetime
    entry_point: str
    navigation_path: List[str]
    feature_discovery: List[str]
    completion_points: List[str]
    drop_off_points: List[str]
    journey_duration: int = Field(ge=0, description="Total journey duration in seconds")
    journey_success: bool = Field(description="Whether journey achieved user goal")

class FirebaseFeatureEngagement(BaseModel):
    user_id: str
    feature_name: str
    engagement_date: datetime
    usage_frequency: int = Field(ge=0, description="Usage count in time period")
    engagement_duration: int = Field(ge=0, description="Total engagement time in seconds")
    completion_rate: float = Field(ge=0.0, le=1.0, description="Feature completion rate")
    user_rating: Optional[float] = Field(ge=1.0, le=5.0, description="User rating if provided")
    feature_effectiveness: float = Field(ge=0.0, le=1.0, description="Measured effectiveness")

class FirebaseBehavioralEvent(BaseModel):
    user_id: str
    event_name: str
    event_timestamp: datetime
    event_parameters: Dict[str, Union[str, int, float, bool]]
    event_context: Dict[str, str]
    event_value: Optional[float] = None
    user_initiated: bool = Field(description="Whether event was user-initiated")

class FirebaseEngagementSummary(BaseModel):
    user_id: str
    summary_date: datetime
    total_sessions: int = Field(ge=0)
    total_session_time: int = Field(ge=0, description="Total session time in seconds")
    average_session_duration: float = Field(ge=0.0)
```

```
    feature_usage_distribution: Dict[str, float]
    engagement_trend: str = Field(description="increasing, stable, or
decreasing")
    engagement_quality_score: float = Field(ge=0.0, le=1.0)
    behavioral_events: List[FirebaseBehavioralEvent]
```

3.4 Real-Time Analytics Processing

Stream Processing Architecture: Firebase data is processed through real-time stream processing to enable immediate behavioral analysis and adaptation. The stream processing system identifies significant engagement changes, behavioral anomalies, and adaptation opportunities within minutes of user actions.

Event Correlation: The system correlates Firebase events with health biomarkers and routine performance to identify behavioral patterns that predict success or challenges. This correlation analysis enables proactive adaptation and personalized intervention timing.

Engagement Prediction: Real-time analytics include predictive models that forecast user engagement patterns, identify disengagement risks, and recommend proactive interventions. These predictions enable the system to maintain optimal user engagement through adaptive strategies.

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4. Application Behavioral Data Requirements

4.1 Plan Completion and Adherence Metrics

The application behavioral data represents the most direct indicators of user engagement with health optimization routines and provides critical insights into user behavior patterns, preferences, and capacity for change. This data stream captures detailed information about how users interact with their personalized plans and routines.

Task Completion Analytics: The system tracks detailed task completion data including completion rates by task type, timing precision, completion quality indicators, and completion context factors. This data reveals user preferences, optimal challenge levels, and patterns that predict successful routine adherence. Task

completion analytics include both quantitative metrics (completion rates, timing) and qualitative indicators (completion enthusiasm, modification patterns).

Routine Adherence Patterns: The system monitors adherence to routine timing, sequencing, and structure to understand user preferences and capacity for structured approaches. Adherence patterns reveal optimal routine complexity, timing preferences, and flexibility requirements that inform adaptive planning strategies.

Completion Quality Indicators: Beyond simple completion tracking, the system assesses completion quality through user feedback, engagement indicators, and outcome measures. Quality indicators help distinguish between enthusiastic engagement and reluctant compliance, enabling more sophisticated adaptation strategies.

Modification and Customization Behaviors: The system tracks user modifications to recommended routines including task substitutions, timing adjustments, and complexity modifications. These behaviors provide insights into user preferences, capacity limitations, and optimization opportunities.

4.2 User Initiative and Proactive Behavior Tracking

Self-Directed Activity Addition: The system tracks when users add activities beyond recommended routines, including the types of activities added, timing patterns, and success rates. This data reveals user motivation levels, interest areas, and capacity for self-directed optimization.

Goal Setting and Modification Behaviors: User interactions with goal setting and modification features provide insights into motivation patterns, ambition levels, and goal ownership. The system tracks goal selection patterns, modification frequency, and achievement rates to understand user psychology and optimal goal calibration.

Proactive Engagement Patterns: The system monitors proactive user behaviors including progress review frequency, educational content engagement, and feature exploration. These patterns indicate user engagement quality and predict long-term adherence and success.

Community and Social Engagement: When available, the system tracks user engagement with community features, social sharing, and peer interaction patterns. Social engagement data provides insights into motivation sources and optimal social integration strategies.

4.3 Pydantic Models for Application Behavioral Data

```python
class TaskCompletionData(BaseModel):
    user_id: str
    task_id: str
    plan_id: str
    completion_date: datetime
    scheduled_time: datetime
    actual_completion_time: datetime
    completion_status: str = Field(description="completed, partial, skipped, or modified")
    completion_quality: float = Field(ge=0.0, le=1.0, description="Quality assessment score")
    time_deviation: int = Field(description="Minutes early/late from scheduled time")
    user_feedback: Optional[str] = None
    completion_context: Dict[str, str] = Field(description="Context factors during completion")

class RoutineAdherenceData(BaseModel):
    user_id: str
    routine_date: datetime
    plan_id: str
    total_tasks: int = Field(ge=0)
    completed_tasks: int = Field(ge=0)
    adherence_rate: float = Field(ge=0.0, le=1.0)
    timing_adherence: float = Field(ge=0.0, le=1.0, description="Adherence to scheduled timing")
    sequence_adherence: float = Field(ge=0.0, le=1.0, description="Adherence to task sequence")
    modification_count: int = Field(ge=0)
    modification_types: List[str]
    overall_quality: float = Field(ge=0.0, le=1.0)

class UserInitiativeData(BaseModel):
    user_id: str
    initiative_date: datetime
    initiative_type: str = Field(description="activity_addition, goal_modification, or exploration")
    initiative_description: str
    initiative_context: Dict[str, str]
    success_outcome: Optional[bool] = None
    integration_success: float = Field(ge=0.0, le=1.0, description="How well initiative integrated with routine")
    motivation_indicator: float = Field(ge=0.0, le=1.0, description="Motivation level indicator")

class EngagementConsistencyData(BaseModel):
    user_id: str
    tracking_period: str = Field(description="daily, weekly, or monthly")
    period_start: datetime
    period_end: datetime
    engagement_frequency: int = Field(ge=0)
    engagement_consistency: float = Field(ge=0.0, le=1.0)
    engagement_depth: float = Field(ge=0.0, le=1.0)
    streak_length: int = Field(ge=0)
    break_frequency: int = Field(ge=0)
    recovery_time: Optional[int] = Field(ge=0, description="Time to recover from breaks in days")
```

```python
class BehavioralPatternData(BaseModel):
    user_id: str
    pattern_date: datetime
    pattern_type: str = Field(description="completion, timing, modification, or
initiative")
    pattern_strength: float = Field(ge=0.0, le=1.0)
    pattern_consistency: float = Field(ge=0.0, le=1.0)
    pattern_trend: str = Field(description="strengthening, stable, or
weakening")
    supporting_evidence: List[str]
    confidence_level: float = Field(ge=0.0, le=1.0)
```

4.4 Behavioral Data Processing Pipeline

Real-Time Behavioral Analysis: Application behavioral data is processed in real-time to enable immediate adaptation to user behavior changes. The processing pipeline identifies significant behavioral shifts, completion pattern changes, and engagement anomalies within minutes of occurrence.

Pattern Recognition Processing: The system employs sophisticated pattern recognition algorithms to identify behavioral patterns from application data. These patterns include completion timing preferences, modification patterns, initiative-taking behaviors, and engagement consistency patterns.

Predictive Behavioral Modeling: Application behavioral data feeds predictive models that forecast user behavior, identify optimal intervention timing, and predict routine success probability. These models enable proactive adaptation and personalized optimization strategies.

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5. Data Processing and Quality Framework

5.1 Data Quality Assurance Protocols

The data quality framework ensures that all data flowing through the HolisticOS system meets high standards for accuracy, completeness, and reliability. This framework is critical for maintaining the integrity of behavioral analysis and ensuring that adaptive decisions are based on high-quality information.

Multi-Source Data Validation: The system implements comprehensive validation protocols that check data consistency across multiple sources. When health biomarkers, engagement analytics, and behavioral data are available for the same

time periods, the system validates consistency and identifies potential data quality issues. Cross-source validation helps identify measurement errors, data collection issues, and user behavior anomalies.

Anomaly Detection and Handling: Sophisticated anomaly detection algorithms identify data points that fall outside expected ranges or patterns. The system distinguishes between meaningful anomalies that indicate significant user changes and data quality issues that require correction or exclusion. Anomaly handling protocols include automatic flagging, confidence score adjustment, and manual review processes for significant outliers.

Data Completeness Assessment: The system continuously monitors data completeness across all sources and time periods. Completeness assessments identify gaps in data collection, evaluate the impact of missing data on analysis quality, and implement appropriate handling strategies. The system maintains completeness scores that inform analysis confidence levels and adaptation decision-making.

Quality Score Assignment: All data points receive quality scores based on measurement reliability, consistency with other data sources, and adherence to expected patterns. Quality scores are used to weight data appropriately in analysis algorithms and ensure that high-quality data has greater influence on system decisions.

5.2 Data Normalization and Standardization

Temporal Alignment: Data from different sources is collected at different frequencies and time intervals. The normalization process aligns all data to consistent time intervals and time zones, enabling accurate correlation analysis and pattern recognition. Temporal alignment includes interpolation for missing time points and aggregation for different measurement frequencies.

Unit Standardization: Health biomarkers and behavioral metrics are standardized to consistent units and scales. This standardization enables comparison across different measurement devices, user populations, and time periods. The system maintains conversion factors and calibration data to ensure accurate standardization.

Feature Engineering: Raw data is transformed into meaningful features that support behavioral analysis and pattern recognition. Feature engineering includes calculating derived metrics, trend indicators, and composite scores that capture complex

behavioral patterns. The feature engineering process is designed to extract maximum analytical value from raw data while maintaining interpretability.

Data Schema Consistency: All data is transformed to consistent Pydantic schemas that ensure type safety and enable reliable processing across all system components. Schema consistency includes validation of data types, ranges, and relationships to prevent processing errors and maintain system reliability.

5.3 Pydantic Models for Data Quality Framework

```
class DataQualityAssessment(BaseModel):
    assessment_id: str
    user_id: str
    data_source: str = Field(description="sahha, firebase, or application")
    assessment_date: datetime
    data_completeness: float = Field(ge=0.0, le=1.0)
    data_accuracy: float = Field(ge=0.0, le=1.0)
    data_consistency: float = Field(ge=0.0, le=1.0)
    anomaly_count: int = Field(ge=0)
    quality_flags: List[str]
    overall_quality_score: float = Field(ge=0.0, le=1.0)

class DataAnomalyDetection(BaseModel):
    anomaly_id: str
    user_id: str
    data_source: str
    anomaly_timestamp: datetime
    anomaly_type: str = Field(description="outlier, inconsistency, or
missing_data")
    anomaly_description: str
    severity: str = Field(description="low, medium, or high")
    confidence: float = Field(ge=0.0, le=1.0)
    handling_action: str = Field(description="flag, exclude, or investigate")

class DataNormalizationResult(BaseModel):
    normalization_id: str
    user_id: str
    source_data_type: str
    normalized_data_type: str
    normalization_timestamp: datetime
    transformation_applied: List[str]
    quality_impact: float = Field(ge=-1.0, le=1.0, description="Impact on data
quality")
    confidence_adjustment: float = Field(ge=0.0, le=1.0)

class CrossSourceValidation(BaseModel):
    validation_id: str
    user_id: str
    validation_timestamp: datetime
    data_sources: List[str]
    consistency_score: float = Field(ge=0.0, le=1.0)
    discrepancies: List[str]
    validation_confidence: float = Field(ge=0.0, le=1.0)
    recommended_actions: List[str]
```

6. Metrics and KPI Framework

6.1 Behavioral Analysis KPIs

The KPI framework defines the specific metrics that enable sophisticated behavioral analysis and adaptive decision-making. These KPIs are designed to capture both quantitative behavioral patterns and qualitative engagement indicators that inform personalized optimization strategies.

Engagement Quality Metrics: Beyond simple usage statistics, the system tracks engagement quality indicators including session depth, feature exploration patterns, proactive behavior frequency, and user-initiated customizations. These metrics distinguish between passive and active engagement, enabling more sophisticated adaptation strategies.

Behavioral Consistency Indicators: The system tracks consistency across multiple dimensions including routine adherence, timing consistency, completion quality consistency, and engagement pattern stability. Consistency indicators help identify user capacity for structured approaches and optimal routine complexity levels.

Adaptation Response Metrics: The system monitors user responses to adaptations including acceptance rates, engagement changes following adaptations, and success rates of different adaptation strategies. These metrics enable optimization of adaptation timing and approach for different user types.

Progress Velocity Indicators: The system tracks the rate of progress across multiple dimensions including goal achievement velocity, skill development rate, and health improvement trajectory. Velocity indicators help calibrate challenge levels and identify optimal progression rates for different users.

6.2 System Performance KPIs

Data Processing Performance: The system monitors data processing performance including ingestion latency, processing throughput, and analysis completion times. Performance KPIs ensure that the system can deliver real-time adaptation while maintaining comprehensive analysis capabilities.

Prediction Accuracy Metrics: The system tracks the accuracy of behavioral predictions, adaptation outcome predictions, and success probability assessments.

Accuracy metrics enable continuous improvement of prediction algorithms and confidence calibration.

User Satisfaction Indicators: The system monitors user satisfaction through direct feedback, engagement patterns, and retention metrics. Satisfaction indicators help evaluate system effectiveness and identify improvement opportunities.

System Reliability Metrics: The system tracks reliability indicators including uptime, error rates, data quality scores, and recovery times. Reliability metrics ensure consistent system performance and user experience quality.

6.3 Pydantic Models for KPI Framework

```python
class EngagementQualityKPI(BaseModel):
    user_id: str
    measurement_date: datetime
    session_depth_score: float = Field(ge=0.0, le=1.0)
    feature_exploration_rate: float = Field(ge=0.0, le=1.0)
    proactive_behavior_frequency: float = Field(ge=0.0, description="Proactive behaviors per week")
    customization_engagement: float = Field(ge=0.0, le=1.0)
    overall_engagement_quality: float = Field(ge=0.0, le=1.0)

class BehavioralConsistencyKPI(BaseModel):
    user_id: str
    measurement_period: str = Field(description="weekly or monthly")
    period_start: datetime
    period_end: datetime
    routine_adherence_consistency: float = Field(ge=0.0, le=1.0)
    timing_consistency: float = Field(ge=0.0, le=1.0)
    completion_quality_consistency: float = Field(ge=0.0, le=1.0)
    engagement_pattern_stability: float = Field(ge=0.0, le=1.0)
    overall_consistency_score: float = Field(ge=0.0, le=1.0)

class AdaptationResponseKPI(BaseModel):
    user_id: str
    adaptation_id: str
    response_measurement_date: datetime
    adaptation_acceptance_rate: float = Field(ge=0.0, le=1.0)
    engagement_change: float = Field(ge=-1.0, le=1.0, description="Change in engagement post-adaptation")
    success_rate: float = Field(ge=0.0, le=1.0)
    user_satisfaction_change: float = Field(ge=-1.0, le=1.0)
    adaptation_effectiveness: float = Field(ge=0.0, le=1.0)

class ProgressVelocityKPI(BaseModel):
    user_id: str
    measurement_date: datetime
    goal_achievement_velocity: float = Field(ge=0.0, description="Goals achieved per month")
    skill_development_rate: float = Field(ge=0.0, le=1.0, description="Rate of skill improvement")
    health_improvement_trajectory: float = Field(ge=-1.0, le=1.0, description="Health improvement trend")
    optimization_sophistication_growth: float = Field(ge=0.0, le=1.0)
    overall_progress_velocity: float = Field(ge=0.0, le=1.0)

class SystemPerformanceKPI(BaseModel):
    measurement_timestamp: datetime
    data_ingestion_latency_ms: int = Field(ge=0)
    processing_throughput: float = Field(ge=0.0, description="Records processed per second")
    analysis_completion_time_ms: int = Field(ge=0)
    prediction_accuracy: float = Field(ge=0.0, le=1.0)
    system_uptime: float = Field(ge=0.0, le=1.0)
    error_rate: float = Field(ge=0.0, le=1.0)
    user_satisfaction_score: float = Field(ge=0.0, le=1.0)
```

---

7. Real-Time Processing Requirements

7.1 Real-Time Data Pipeline Architecture

The real-time processing system enables immediate response to user actions and physiological changes, supporting adaptive optimization that responds to user needs as they emerge. The architecture balances real-time responsiveness with comprehensive analysis capabilities.

Stream Processing Infrastructure: The system employs stream processing technology to handle real-time data from all sources. Stream processing enables immediate detection of significant changes, behavioral anomalies, and adaptation opportunities. The infrastructure includes automatic scaling, fault tolerance, and quality assurance mechanisms.

Event-Driven Processing: Real-time processing is organized around events that trigger specific analysis and adaptation workflows. Events include user actions, biomarker changes, engagement pattern shifts, and system-generated insights. Event-driven processing enables efficient resource utilization and rapid response to significant changes.

Adaptive Threshold Management: The system employs adaptive thresholds that adjust based on user patterns and system learning. Thresholds determine when real-time events trigger adaptation decisions, ensuring appropriate sensitivity to user changes while avoiding over-adaptation.

Quality-Aware Processing: Real-time processing includes quality assessment mechanisms that ensure adaptation decisions are based on reliable data. Quality-aware processing prevents inappropriate adaptations based on data anomalies or measurement errors.

7.2 Real-Time Decision Making Framework

Immediate Adaptation Triggers: The system identifies specific conditions that trigger immediate adaptation decisions including significant biomarker changes, engagement drops, completion pattern shifts, and user-initiated modifications. Immediate triggers enable proactive response to user needs.

Confidence-Based Decision Making: Real-time decisions include confidence assessments that determine the appropriate level of adaptation. High-confidence decisions enable immediate significant adaptations, while lower-confidence situations trigger monitoring and gradual adaptation approaches.

Risk Assessment Integration: Real-time decision making includes risk assessment mechanisms that evaluate the potential negative consequences of adaptations. Risk assessment prevents adaptations that could disrupt established patterns or overwhelm users during challenging periods.

User Context Consideration: Real-time decisions consider current user context including stress levels, life circumstances, and recent adaptation history. Context consideration ensures that adaptations are appropriate for user current state and capacity.

7.3 Pydantic Models for Real-Time Processing

```
class RealTimeEvent(BaseModel):
    event_id: str
    user_id: str
    event_timestamp: datetime
    event_type: str = Field(description="biomarker_change, engagement_shift, or
user_action")
    event_data: Dict[str, Union[str, int, float]]
    event_significance: float = Field(ge=0.0, le=1.0)
    processing_priority: int = Field(ge=1, le=5)

class RealTimeAdaptationDecision(BaseModel):
    decision_id: str
    user_id: str
    triggering_event: str
    decision_timestamp: datetime
    adaptation_type: str
    adaptation_confidence: float = Field(ge=0.0, le=1.0)
    risk_assessment: Dict[str, float]
    expected_impact: Dict[str, float]
    implementation_urgency: str = Field(description="immediate, within_hour, or
next_day")

class RealTimeProcessingMetrics(BaseModel):
    measurement_timestamp: datetime
    events_processed_per_second: float = Field(ge=0.0)
    average_processing_latency_ms: int = Field(ge=0)
    decision_accuracy: float = Field(ge=0.0, le=1.0)
    false_positive_rate: float = Field(ge=0.0, le=1.0)
    system_responsiveness: float = Field(ge=0.0, le=1.0)
```

This comprehensive data requirements and metrics framework provides the foundation for sophisticated behavioral analysis and adaptive optimization that can

outperform existing health optimization tools through deep understanding of user behavior, real-time responsiveness, and continuous learning and improvement.