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Abstract

This document represents the final behavioural representation and virtual individual modelling (VIM) of the PRECIOUS system. It expands on Deliverable <u>D3 1 Interim report on behavioral representation and Virtual Individual Modeling 1 0</u>, which introduced the VIM parameters whose utilization we will now more closely inspect in this report. Its three main objectives are:

- To provide details about each of the variables that make up the VIM and give information about how each will be obtained/assessed within the PRECIOUS system.
- To specify rules, based on the values of variables within the VIM, that guide user journeys through the system. More concretely, this deliverable will answer the question: 'Under which circumstances will a user be suggested to each of the apps within the PRECIOUS system?'
- To provide some examples of the novel capabilities within the PRECIOUS system that will target difficult to reach user groups and improve upon existing digital behavior change and preventative care interventions.

Abbreviation	Meaning
API	Application Program Interface
FB	Firstbeat
GPS	Global Positioning System
HRV	Heart Rate Variability
IEQ	Indoor Environment Quality
JITAI	Just In Time Adaptive Intervention
MQTT	Message Queuing Telemetry Transport
PA	Physical Activity
PPD	Predicted Percentage of Dissatisfied
PMV	Predicted Mean Vote
PRECIOUS	PREventive Care Infrastructure based On Ubiquitous Sensing
RMSSD	
UCA	User Context Awareness
VIM	Virtual Individual Model
WHO	World Health Organization

List of Acronyms

Executive Summary

The PRECIOUS system aims to promote healthy lifestyles, based on three main components: 1) transparent sensors for monitoring user context parameters and health indicators such as food intake, sleep, stress and physical activity 2) the development of a virtual individual model (VIM) representing users' variables and different parameters collected (both directly from the user and with sensors) for inferring health risks and desired behavior changes, and 3) application of a motivational service design framework combined with gamification principles to trigger, monitor and sustain mid-to-long term behavior change.

This deliverable presents the deliverable products of task 3.1 of the PRECIOUS project. To this end, it provides a detailed description of the variables which the virtual individual model will include, and an initial set of rules that will govern its function and guide users' interactions with the system. As a final step, this document will trace possible user interactions with PRECIOUS by providing a number of cases, and describing how the system will behave differently for various types of users.

Task 3.1 Behavioral representation of the individual

The PRECIOUS system is a model-driven personal guidance system (enabling formulation of motivational feedback) that relies on the Virtual Individual Model (VIM). The VIM is constantly updated by the individual's behavior data and related actions. This task focuses on the parameterization of the user's behavior and development of a combined VIM that takes into account all the considered risky behaviors (e.g. physical inactivity) and produces a reliable risk profile for the individual. This task is especially divided into modelling effects of:

- Task 3.1 a Stress
- Task 3.1 b Sleep
- Task 3.1 c Physical activity
- Task 3.1 d Food intake

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1. Background and objectives

Previous research and previous deliverables within this project indicate that, in order to optimally promote motivation and healthy behavioral patterns, preventative care systems should continually adapt to users' identities, approach and needs in real-time. This is a burgeoning area of interest for both researchers and private sector enterprises, but as yet, there is no consensus on the optimal way in which this tailoring can be accomplished. Building such responsive and tailoring-based systems or "Just In Time Adaptive Interventions" (JITAI; Nahum-Shani et al, 2014) requires at least two major components: 1) collecting real-time data about users from a variety of sources, and 2) a set of rules based on this data which tailor the user experience based on his or her needs at a given point in time.

The first of these components, real-time data collection, includes acquiring information about the state of a user, including data on behavioral, positional, social, cognitive, motivational and environmental variables. Traditionally, these types of data have been collected with questionnaires or ecological momentary assessment instruments, but this limits the real-time validity of such data. It also places a considerable burden of data collection on the user, as completing questionnaires, keeping behavioral diaries and completing cognitive tasks all require cognitive resources on the part of users. As cognitive resources are limited, extended data collection therefore leaves users with fewer resources to expend on pursuing actual behavioral changes, and may also result in reduced reliability of the data collected. One key challenge within PRECIOUS, therefore, is to develop a system which collects information from users in an unobtrusive, or even undetectable way and organizes it for the purpose of subsequently tailoring user interactions. Within PRECIOUS, data collected in real-time from ubiquitous sensors, social platforms, users' psychological and motivational states, and previous user interactions with the system will be combined to produce a list of prevention-relevant variables, which we refer to henceforth as the Virtual Individual Model (VIM).

The second component of JITAIs is a collection of rules through which user interactions with the system are tailored. As the values of variables contained within the VIM change, PRECIOUS will constantly execute a set of algorithms and rules, based on boolean operators, that will personalize user experiences with the system. This includes adjustments to the order in which various components are presented (e.g. presenting unmotivated users with motivating content, and presenting motivated users with action-focused content), accurately reflecting a user's current motivational profile in order to build a sense of relatedness with the system, and using a range of location and social variables to provide push notifications or reminders when users enter potentially high-risk situations for unhealthy behaviors. As the range of sensors and user assessment variables present within PRECIOUS go beyond what has been done in past preventative care interventions, the VIM rules in PRECIOUS can also go beyond what has been done in order to provide users with highly personalized and tailored user interactions that are unprecedented up until now.

The present document will accomplish the following main objectives:

1. It will provide details about each of the variables that make up the VIM and give information about how each will be obtained/assessed within the PRECIOUS system.

- 2. It will specify rules, based on the values of variables within the VIM, that will guide user journeys through the system. More concretely, this deliverable will answer the questions:
 - a. Under which circumstances will the user be suggested to each of the apps within the PRECIOUS system? and
 - b. What triggers will cause tailored responses within each of the individual apps in the PRECIOUS system?
- 3. It will provide examples of the novel capabilities within the PRECIOUS system that will target difficult to reach user groups and improve upon existing digital behavior change and preventative care interventions.

2. Overview of the Virtual Individual Model (VIM)

The Virtual Individual Model (VIM) consists of parameterizations of the user's personal characteristics, behaviour, motivation, and previous engagement with PRECIOUS. At any given time, the state of the VIM for a particular user can be read by PRECIOUS, and specific algorithms (VIM rules) will tailor PRECIOUS' outputs and 'Suggested Apps' to meet the needs of the user at that point in time. This highly personalised and real-time approach to tailoring users' behavior change journeys within PRECIOUS will increase user engagement and motivation for behavior change, and goes beyond the level of tailoring present in nearly all existing behavior change applications. Furthermore, modification of the VIM rules will allow for toggling various components on and off during the n-of-1 evaluation process, in order to examine the effect of each in combination and in isolation.

The high-level diagram of the current PRECIOUS system implementation is depicted Figure 1. The implemented PRECIOUS system an integration of distribution system components worn (or carried) by users (e.g. smartphones) or deployed by different PRECIOUS partners at their respective testbed (living-lab) sites. At the heart of the system is the PRECIOUS cloud server that includes modules for interacting, collect and process data from different user sensors (for user activity, context, health, environmental etc.). The PRECIOUS server also includes interfaces towards other servers (e.g. Firstbeat Heart Rate Variability (HRV) data analytics server) that are used to provide domain-specific analysis for some of the sensor data and forward the results to the PRECIOUS server. All the data gathered in the PRECIOUS server is then used to generate the user's VIM using the VIM processing modules within the server.



Figure 1: High-level diagram of PRECIOUS system implementation

3. Descriptions of variables in the VIM, and how their values will be obtained

This section details the variables that will be collected from users, the PRECIOUS system and external sensors in order to inform the rule-driven behavior of the PRECIOUS system. Identifying a complete set of variables through which the system can be tailored and adapted to user needs is an ongoing task, and one which can only be completed after first monitoring and obtaining data from real user interactions with PRECIOUS. Over time, this will allow the system to learn and identify new variables or parameters through which the system can be further tailored. We therefore consider this list to be a work in progress, as it will continue to grow based on data obtained from real user interactions with the PRECIOUS system. While the project aims to collect user data from as many sources as possible, in this document we will focus primarily on VIM variables which will be integrated into the first version of PRECIOUS' rule engine. This allows us to create a well-defined initial system that is adaptable and able to adjust to user needs following the integration of additional variables in the future.

3.1. Personal characteristics

- 3.1.1. Signing in and privacy status
 - Permissions given to PRECIOUS
- 3.1.2. Personal physical and psychological characteristics

- Age/birthdate
- Nickname
- [Gender]
- [Height] (in cm)
- [Weight] (in kg) Can be input by users manually, or drawn from connected scales or other sensor inputs automatically. The [Weight] variable will be gathered automatically with xAAL and forwarded to the PRECIOUS backend with MQTT as described in D4.1.
- [BMI] = [weight]/([height]*[height])

3.1.3. Variables from social networks

Variables from social networks will be derived from the Facebook profile of the user and later on may also be extended by other social networks (e.g. Twitter). The Facebook Graph API enables the readout of a wide range of user data. However it is necessary to get the permission of the user to access his Facebook profile.

- [Permission to access facebook] yes/no
- Facebook check-in locations
- Facebook post content
- Mood

The outcome of the variables from social networks strongly correlates with the social media usage behaviour of the user. Users who use social media platforms to a large extent will yield more meaningful data outcome of social networks than users who rarely use this platforms.

In the context of PRECIOUS the focus will be on status messages of the user. The Facebook Graph API can access not only messages texts (type: String) but also locations (type: Page) and events (type: Event) associated with the status message. Since the year 2013 Facebook allows users to express their feelings in status messages by adding what he or she is doing or feeling in the moment (see figure 2), but it is not yet possible to access those feelings and additional information via the Facebook API.

Feeling How are you fe	eeling?		
U happy			
excited	happy		
loved			
blessed			
fantastic			
sad sad			
cco relaxed			
amused			

Figure 2: Users can express feelings in Facebook

While there is no direct way to access these emotions through Facebook API, methods exist in scientific literature to classify text into predefined emotion categories. For instance in a web-based tool called 'MoonPhrases' (de Choudhury et al, 2013a) was created to enable Twitter users to reflect about their mood and well-being. A similar approach was taken in (Hagen et al, 2015), it was investigated to improve the classification of Tweets in either positive, neutral or negative sentiment. Moreover in (de Choudhury et al, 2013b) and (Minsu Park et al, 2013) messages of Twitter users were interpreted to find out how it is talked about depression in Tweets and how the usage of sentiment words of a depressed person differ from a not depressed person.



Figure 3: Mood Classifier: Overview

Therefore our primary hypothesis is that it is possible to leverage mood/emotions from social media messages. As a first step it is necessary to collect emotionally classified messages to build a classifier. As the range of possible emotions is very wide it is important to choose predefined emotion classes to limit the resources needed for data collection and processing of the classifier. For example the emotion stress is very important in context of cardiovascular diseases, which are in the focus of the PRECIOUS project. Therefore a big focus is on collecting messages classified as stressed or not stressed. These classified messages are used to train a statistical model, which can be used to tell if the writer of the message was stressed (See Figure 3). Furthermore as a general indicator for well-being the emotions happy and sad, which correlate well with the pleasure dimension of the circumplex affect model, are in the focus here for emotion recognition.

- 3.1.4. Variables based on time of day and location data
 - [Current GPS location]
 - [Current Time/Date]
 - [Location area of 'HOME']
 - [Daily time spent at 'HOME']
 - [Location area of 'WORK']
 - [Daily time spent at 'WORK']
 - Location areas of 'HIGH PA'

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- Location areas of 'LOW PA'
- Location areas of 'HEALTHY diet'
- Location areas of 'UNHEALTHY diet'
- Location areas of 'HIGH STRESS'
- Location areas of 'LOW STRESS'

3.2. Behavioural variables

3.2.1. Physical Activity (PA) subcategories

Physical Activity (PA) variables will all be derived from readings of the smartphone's onboard accelerometer, and at a later date may also be combined with data from wearable devices to create a richer level of detail with the PA data. The accelerometer sensors present in nearly all smartphones are a reliable, low-power and efficient way to track PA. They can be used for step counting or even, by applying complex machine learning algorithms, for PA recognition. On the other hand, the gyroscope sensor is several times less power-efficient but it offers some additional data which can be used to measure, for instance, the rotational velocity of a human being wrist.

The PRECIOUS application offers very power-efficient 24/7 PA tracking by processing continuously the device accelerometer sensor data. The processed data is used in the in-app step counter algorithm and the PA is obtained from advanced algorithms that are part of the Google Services API. The API sends broadcast with the PA information every 20 seconds and the PRECIOUS app receives them and processes the data. Furthermore, the PRECIOUS step counting algorithm is also applicable for the PRECIOUS wristband because of its low-processing power requirements.

Moreover, the wristband built-in gyroscope sensor can be used for bite counting when food intake activity takes place. The bite counting algorithm is based the tracking of the rotational speed of the roll axis of the wrist, illustrated in Figure 4. The filtered data of a food intake activity is available in Figure 5 (Dong, 2012).



Figure 4. This illustration shows how a 3-axis gyroscope situated on a wrist is able to track its rotational speed in the three axis called yaw, pitch and row.



Figure 5. This is the roll axis data of the gyroscope when eating an apple. This illustration is reproduced from Dong (2012).

Presenting PA Data to Users. Once the PA detection is done, the data must be presented to the user in a very illustrative and easy to understand way. The algorithm is able to detect whether the user has been walking, running or riding a bike and also estimate the duration of these PA exercises and count the number of steps. However being very specific does not mean that the user will understand better the data detected by the algorithm. For that reason, all the physical activity data is converted into a unique unit, such a number of steps, walking distance or burned calories. This will also allow the user to set the goals in the unit that he or she prefers. Thus, any exercise done by the user will be automatically translated in this unit, optimizing user input to the process (autonomy) and increasing relatedness to the system.

In case that the GPS is not available, knowing the gender and height of the user and the number of steps, it is possible to estimate how much distance has the user been walking in the following way (Crosby, 2015):

- Men, walking: distance[m]=0.415*height[m].
- Women, walking: distance[m]=0.413*height[m].

Furthermore, from the walking distance and its duration, one can calculate the average speed and it is also possible to estimate the burned calories if the user's weight is known in the following way:

Where Cal is the estimated burned calories, V the average walking speed in miles per hour and W the weight in kg (equation obtained by nonlinear regression of the data available in http://calorielab.com/burned/).

For activities such as biking, the physical activity can be converted, for example, in equivalent walking steps at speed of 3 mph by multiplying the duration of the biking activity in minutes by 270 steps/min.

- [Current PA Daily Sedentary Time] A total time in minutes, which indicates the amount of time spent sedentary and not asleep.
- [Current Sedentary Bout] When a bout of sedentary behavior is detected, its duration in minutes will be logged.
- [Current PA Daily Steps] A number which indicates the number of steps taken from the last time the system clock read 03:00 until the current time.
- [Last 7 days daily step average] A number which indicates the average of the last 7 Daily Step totals.
- [Last 30 days daily step average] A number which indicates the average of the last 30 Daily Step totals.
- [Lifetime PA steps taken] A number which indicates the cumulative total of steps achieved
- [PAHealthIndex] An index number (0-100) revealing the health enhancing effects of physical activity during the measurement period from heartbeat data. The index takes into account both intensity and duration of PA.
- 3.2.2. Dietary subcategories
 - Dietary variables logged via manual entry, photo and barcode scanning methods will be combined on a daily basis and compared to existing nutritional guidelines. This includes information for the following variables: Calories, Fat, Protein, Sodium, Sugar, Total Carbohydrates, Fiber, Vitamins A-E, Iron, Zinc and others deemed appropriate. The total number of categories for which an individual meets the guideline will also be logged.
- 3.2.3. Sleep subcategories
 - [FB Report Ready] Indicates receipt of report from Firstbeat servers.
 - [AverageRMSSDSleep] Average value for heart rate variability parameter describing parasympathetic activity of the autonomic nervous system (RMSSD) during sleep period, taken from Firstbeat sensors.
 - [RelaxationSleepTime] Time spent in physiological recovery state, i.e. parasympathetic domination over sympathetic activity of the autonomic nervous system during sleep period, taken from Firstbeat sensors.
 - [RelaxationSleepTimePercentage] Proportion of physiological recovery state, i.e. parasympathetic domination over sympathetic activity of the autonomic nervous system, from the sleep period, taken from Firstbeat sensors.
 - [SleepDuration] Sleep duration can easily and accurately be estimated by the movement of the user, measured by an accelerometer sensor. The location of the sensing device can be on the user's wrist in a form of a wristband, but a smartphone can also be used for such measurement (the accuracy in this case will be lower).
 - [SleepDepth] This parameter is directly related to how much the user moves while sleeping, which can be measured by an accelerometer

sensor. Thus, a wearable can easily distinguish between light and deep sleep.

- [NocturalAwakenings] Can be measured by an accelerometer sensor, calculating the duration of the awakening and the activity of the user when awake.
- 3.2.4. Stress subcategories
 - [StressTime] Time spent in physiological stress state, i.e. sympathetic domination over parasympathetic activity of the autonomic nervous system without physical activity during the measurement, taken from Firstbeat sensors.
 - [StressPercentage] Proportion of physiological stress state, i.e. sympathetic domination over parasympathetic activity of the autonomic nervous system without physical activity from the measurement, taken from Firstbeat sensors.

3.3. **Motivational variables** (referred to in D3.4)

3.3.1. Outcome goals

Each outcome goal in the PRECIOUS system will have the following parameters stored for it on the backend of the system. These include the following:

- [Current State of Outcome Goal] A variable to indicate user input from the outcome goal setting tool described in D3.4. For each outcome goal, the variable can be either 'Selected,' 'Top5,' or 'Unselected'
- [Progress Toward Outcome Goal] A variable to indicate user's self-perceived progress toward the outcome goal.

3.3.2. Behavioral Targets

- [Current behavioral target] PA, Diet, Sleep or Stress
- [Current behavioral target 2] only becomes active once user achieves Level ##, which allows for pursuing multiple behaviors simultaneously.
- 3.3.3. Motivational Status

[Motivational Status for XXX] (stage of change) - 4 Motivational status variables will indicate how ready a user is to begin pursuing behavioral changes for each of the 4 choosable behavioral targets denoted by XXX (PA, diet, sleep, stress).

3.4. Action variables

3.4.1. **Physical Activity**

• Each physical activity present in the system will have a number of parameters stored for it in the backend of the system. These include the following:

- [Is PA favorite activity?] In the choose favorite PA sub-app, users indicate the extent to which they like (or might like) each of the individual PA modalities in the system.
- [PA steps per minute] Number of steps accrued during 1 minute of this exercise. This data comes from the compendium of physical activities (Ainsworth et al, 2011), which specifies a MET value for 1000s of PA types, which can subsequently be converted to steps knowing a user's height and weight.
- [Current PA Goal Number] Specifies a counter variable which increases by 1 each time a goal is set.
- [Current PA Goal Content] Specifies the number of steps needed to accumulate to achieve the daily goal.
- [Current PA Goal Achievement] Specifies the percentage of steps accumulated in relation to the PA Goal.
- [Current PA Plan] Specifies the type of plan the user has selected to pursue their current PA goal
- [PA Goal Achievement Streak] Specifies the current number of goals achieved consecutively.
- [PA Goal NON Achievement Streak] Specifies the current number of consecutive goals a user has failed to achieve.
- [PA Importance] A number 0-10 which specifies the momentary importance of PA for a user. Taken from the importance ruler exercise.
- [PA Importance Ruler Response] A variable which specifies the outcome goal a user cites in part 2 of the importance ruler exercise. This will be one of the user's 'Top5' rated outcome goals, or no choice.
- [PA Confidence] A number 0-10 which specifies the momentary confidence to change PA for a user. Taken from the PA confidence ruler exercise.
- [PA Confidence Ruler Response] A variable which specifies the tool/component a user cites as helpful in increasing confidence in part 2 of the PA confidence ruler exercise.

3.4.2. **Diet**

- [Current Diet Challenge Number] Specifies a counter variable which increases by 1 each time a challenge is initiated.
- [Current Dlet Challenge Type] Specifies whether the chosen challenge is in relation to a 'Start' or a 'Stop' behavior.
- [Current Diet Challenge Target] Specifies the threshold of behavioral counts to be achieved to complete the challenge. This will be a minimum number to achieve for 'Start' challenges and a maximum number allowable for 'Stop' challenges.
- [Current Diet Challenge Progress] Specifies the number of behavioral accounts logged during the current challenge.
- [Diet Challenge Achievement Streak] A counter variable which specifies the consecutive number of challenges successfully achieved.

- [DIET Importance] A number 0-10 which specifies the momentary importance of DIET for a user. Taken from the DIET importance ruler exercise.
- [DIET Importance Ruler Response] A variable which specifies the outcome goal a user cites in part 2 of the DIET importance ruler exercise. This will be one of the user's 'Top5' rated outcome goals, or no choice.
- [DIET Confidence] A number 0-10 which specifies the momentary confidence to change DIET for a user. Taken from the DIET confidence ruler exercise.
- [DIET Confidence Ruler Response] A variable which specifies the tool/component a user cites as helpful in increasing confidence in part 2 of the DIET confidence ruler exercise.
- 3.4.3. Sleep
 - [FB Report Viewed] yes/no
- 3.4.4. Stress
 - [FB Report Viewed] yes/no

3.5. **Process and 'User Journey' variables**

- 3.5.1. Previous engagement with PRECIOUS sub-apps
 - [#Times Completed XXX] Indicates several variables, wherein XXX represents the name of one component of the system. There will be one such variable for all 'suggestable' components within PRECIOUS.
 - [Last completed app] The last component completed by the user.
- 3.5.2. System time-related variables
 - [System first opened]
 - [System last opened]
- 3.5.3. Reward variables
 - [Total 'Points' achieved] Points are accumulated for interacting with PRECIOUS and engaging in healthy behaviors. Points are earned each time [Last completed app] changes state, and the amount of points earned specifically has yet to be determined.
 - [Current 'Level'] Level are obtained by users accumulating points. Different point thresholds will be set for achieving each level, and these will be specified later during the build phase.

3.6. Indoor environmental quality variables

To assess well-being of occupant in dwelling the indoor environmental quality (IEQ) is important to follow. Consequently, the user context awareness (UCA) at home is a key

objective of a system trying to assist user in its daily life. The PRECIOUS project defined the following environmental variables within deliverable 3.1:

- Thermal comfort (temperature and humidity)
- Noise quality
- Light quality

To achieve the UCA, a transparent sensors/actuators layer will be used. A new protocol, xAAL, has been proposed to fight interoperability issues in the home automation domain and it will be used to gather sensor data characterizing the PRECIOUS home user space. The xAAL infrastructure deployed at the PRECIOUS user home offers also the access to the PRECIOUS services. Indeed a gateway allows to store home user data in the PRECIOUS database in order to provide inputs to the VIM. But the gateway also offer the possibility to dispatch PRECIOUS user feedback to the home environments on multimodal interfaces. The VIM is the heart of the PRECIOUS system. Indeed, it processes data, analyzes context and finally allows to deliver specific user feedback.

The process offering feedback on environmental quality to PRECIOUS users will be based on rules (see section 4.6). Concerning the home, messages or alerts delivered to the user are based on standards, norms or guidelines (European or country specific).

Each indoor environmental quality variable present in the system will be stored in the backend of the system with MQTT. These will be gathered automatically with xAAL according to the location of the sensors in various rooms (e.g. bedroom, living room) and include the following:

- Temperature (in °C), measured by the thermometer sensor
- Humidity (in %), measured by the hygrometer sensor
- Noise (in dB(A)), measured by the sound meter
- Light (in lux), measured by the light sensor

4. VIM algorithms (Rules) for suggestion of each app and notification within PRECIOUS

The VIM algorithms will guide users' journeys through the system, but at the same time allow users some flexibility in pursuing the components that they want to at a given time. A simplified skeleton outline of potential user journeys is presented in Figure 6 below for the sake of clarity, but there are additional feedback loops not pictured which will suggest that users revisit certain components, or jump to adjacent paths depending upon previous inputs. This outline also fails to capture the extent of tailoring present in the algorithms and interactivity of the various components, so is presented only to give a broad overview. It should be noted as well, that within the field trials described in sections 5 and 6 of deliverable 5.1, the VIM rules will be altered further to turn various components of the PRECIOUS system on or off, depending on the research questions being addressed.



Figure 6 - Broad, simplified overview of potential user journeys

4.1. Onboarding and general motivation apps

4.1.1. Welcome, Mini-game and Onboarding.

-Initiate IF: [#Times completed onboarding] = 0

4.1.2. Setting outcome goals.

<u>-Suggest IF</u>: ([#Times completed onboarding] > [#Times completed outcome goal setting]) OR ([Time since last completed outcome goal setting] > 2 weeks)

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<u>-Upon Launch</u>: IF [#Times completed outcome goal setting] > 0, THEN show prelude screen. The <u>prelude screen</u> will assess user progress toward their current active outcome goal, and provide brief information about selecting a new active outcome goal.

4.1.3. **Choose behavior** to achieve outcome goals.

<u>-Suggest IF</u>: [Last completed app = Setting outcome goals] OR [#Times completed outcome goal setting] > [#Times completed choose behavior]

4.1.4. **Risk Information**

<u>-Suggest IF:</u> ([Selected outcome goal] = 'Feel Healthier') AND ([Last completed app = Choose behavior])

4.1.5. **Rewards**

<u>-Show:</u> After returning to the home page following all new points accruals, level increases or badge awards.

4.2. **PA-specific apps**

4.2.1. **PA - Importance ruler**.

<u>-Suggest IF</u>: ([Current chosen behavior] = PA) AND ([#Times completed PA Importance ruler] < [#Times PA has been chosen behavior]) OR [Last completed app = Choose Behavior] <u>-Upon Launch</u>: Multiple choice responses populated from user's top 5 outcome goals.

4.2.2. PA - Identifying favorite modalities

<u>-Suggest IF</u>: ([Current chosen behavior] = PA) AND [#Times completed PA Importance ruler] > [#Times completed PA identifying favorite modalities] OR [Last completed app = PA Importance ruler]

4.2.3. PA - Linking Activities to active outcome goal

<u>-Suggest IF</u>: ([Current chosen behavior] = PA) AND [#Times completed PA identifying favorite modalities] > [#Times completed PA Linking Activities] OR [Last completed app = PA identifying favorite modalities]

4.2.4. PA - Identifying motivational Status (stage of change)

<u>-Suggest IF</u>: ([Current chosen behavior] = PA) AND [#Times completed PA PA Linking Activities] > [#Times completed PA Motivational Status] OR [Last completed app] = PA Linking Activities <u>-Suggest IF 2</u>: ([Current chosen behavior] = PA) AND ([Motivational status for PA] = Low) AND ([Last completed app] = PA Normative information) OR ([Time since PA Motivational Status last completed] > 1 week)

4.2.5. **PA - Big Feedback #1**

<u>-Suggest IF</u>: ([Current chosen behavior] = PA)

AND ([#Times completed PA Importance ruler] > 0 AND [#Times completed PA Identifying favorite modalities] > 0 AND [#Times completed PA Linking activities] >0 AND [#Times completed PA Motivational status] >0)

AND ([#Times completed PA Importance ruler] + [#Times completed PA Identifying favorite modalities] + [#Times completed PA Linking activities] + [#Times completed PA Motivational status] - 3 > [#Times completed PA Big Feedback])

4.2.6. PA - Confidence ruler

<u>-Suggest IF</u>: ([Current chosen behavior] = PA) AND ([Motivational status for PA] = Low) AND ([Last completed app] = PA Big feedback)

4.2.7. PA - Past success

<u>-Suggest IF</u>: ([Current chosen behavior] = PA) AND ([Motivational status for PA] = Low) AND ([Last completed app] = PA Confidence ruler)

4.2.8. PA - Problem solving

<u>-Suggest IF</u>: ([Current chosen behavior] = PA) AND [PA Goal NONAchievement Streak] > 2] AND [Last completed app] != PA Problem Solving <u>-Suggest IF 2</u>: ([Current chosen behavior] = PA) AND [PA Confidence Ruler Response] = 'overcome barriers'

4.2.9. PA - Data report

<u>-Suggest IF:</u> ([Current chosen behavior] = PA) AND ([Motivational status for PA] = Low) AND ([Date system first opened] > 1 week ago) AND ([Date last PA data report] > 1 week ago) <u>-Suggest IF 2</u>: ([Current chosen behavior] = PA) AND ([Date last PA data report] > 1 week ago)

4.2.10. **PA - Normative information**

<u>-Suggest IF:</u> ([Current chosen behavior] = PA) AND ([Motivational status for PA] = Low) AND ([Last completed app] = Past success)

4.2.11. PA - Goal setting

<u>-Suggest IF:</u> ([Current chosen behavior] = PA) AND ([Motivational status for PA] = 'Moderate' OR 'High') AND ([Last completed app] = PA Big Feedback #1 OR [Last completed app] = PA Action Planning) OR ([Current PA Goal Target] = 'undefined')

4.2.12. PA- Action planning

<u>-Suggest IF</u>: ([Current chosen behavior] = PA) AND [#Times completed PA Goal Setting] > [#Times completed PA Action Planning] OR [Last completed app = PA Goal Setting]

4.2.13. PA - Self-monitoring and logging

<u>-Suggest IF:</u> ([Current chosen behavior] = PA) AND ([Current PA Goal Target] != 'undefined') AND ([Last completed app] = PA Action Planning)

4.2.14. PA - Conquer the City Game Suggest IF: ([Current chosen behavior] = PA) AND ([Current State of 'Competition'] = 'Top5' or 'Selected') AND ([Current PA Goal Number] > 1)

4.3. **Diet-specific apps**

4.3.1. Diet - Importance ruler

<u>-Suggest IF</u>: ([Current chosen behavior] = DIET) AND ([#Times completed DIET Importance ruler] < [#Times DIET has been chosen behavior]) OR [Last completed app = Choose Behavior] <u>-Upon Launch</u>: Multiple choice responses populated from user's top 5 outcome goals.

4.3.2. Diet - Confidence ruler

<u>-Suggest IF</u>: ([Current chosen behavior] = DIET) AND [Last completed app = DIET Importance Ruler] OR ([#Times completed DIET Importance ruler] > [#Times completed DIET Confidence ruler])

4.3.3. Diet - Identifying motivational status (stage of change)

<u>-Suggest IF</u>: ([Current chosen behavior] = DIET) AND [Last completed app = DIET Confidence Ruler] OR ([#Times completed DIET Confidence ruler] > [#Times completed DIET Motivational status])

4.3.4. Diet - Big feedback

-Suggest IF: ([Current chosen behavior] = DIET)

AND ([#Times completed DIET Importance ruler] > 0 AND [#Times completed DIET Confidence ruler] > 0 AND [#Times completed DIET Motivational status] >0)

AND ([#Times completed DIET Importance ruler] + [#Times completed DIET Confidence ruler] + [#Times completed DIET Motivational status] - 2 > [#Times completed DIET Big Feedback])

4.3.5. Diet - Home page

<u>-Suggest IF</u>: ([Current chosen behavior] = DIET) AND ([# Diet Challenges Active] < 1)

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4.3.6. Diet - Challenges

-Suggest IF: ([Current chosen behavior] = DIET) AND ([# Diet Challenges Active] > 0) -This will give users the ability to view and log progress toward their challenge directly from the system Home screen.

- 4.3.7. **Diet Learning modules** No suggestion rules, directly accessible through the Diet Home Page
- 4.3.8. **Diet Tracking tools** No suggestion rules, directly accessible through the Diet Home Page

4.3.9. **Diet - Problem solving**

-Suggest IF: ([Current chosen behavior] = DIET) AND [DIET Challenge NONAchievement Streak] > 2] AND [Last completed app] != DIET Problem Solving

4.4. Sleep-specific apps (FB)

4.4.1. **Display of sleep-related information** <u>-Suggest IF</u>: ([Current chosen behavior] = SLEEP)

AND ([FB Report Ready] = TRUE)

4.5. Stress-specific apps (FB)

4.5.1. **Display of Stress-related information** <u>-Suggest IF</u>: ([Current chosen behavior] = STRESS) AND ([FB Report Ready] = TRUE)

4.6. Indoor environmental quality

The VIM Engine described figure 7 is part of the "Domain knowledge VIM processing module" in the high-level diagram of PRECIOUS system implementation depicted figure 1. The remote rules (VIM processing modules) are based on domain-specific knowledge. The rules for home environmental variables will be mainly driven by European (or international) standards, norms or recommendations from World Health Organization (WHO) and/or European guidelines if standards/norms do not exist.

The PRECIOUS system will interact with users thanks to the notification system. According to VIM data related to home environmental sensors and rules, the system will deliver notification messages (multimodal interface): text, vocal, etc.

Moreover, we could also propose to PRECIOUS user the opportunity to define their own rules. Nevertheless a rule defined by a user should not be in conflict with the PRECIOUS recommendations. If it is the case, the PRECIOUS system should alert the user and ask to confirm its choice or canceled the rule.



"IF (Rule) then (deliver notification : recommendation/alert)"

Figure 7: Overview of PRECIOUS system: IEQ variables - VIM - notifications

Indoor ventilation plays a role in the control of indoor air quality and thermal comfort. However, we suppose here that the airflow system at PRECIOUS user home is working correctly and it is well designed. In other words, the PRECIOUS system will not manage the airflow system. The PRECIOUS system will only deliver notification according to predefined rules to deliver user recommendations. User feedbacks will be confirmed and/or defined with questionnaires during the testing phases described in deliverable 5.1. In the following, we will describe the IEQ variables and the corresponding standard in order to establish the rules for VIM model.

4.6.1. Thermal comfort

For thermal comfort, the European standard EN15251 (European committee for Standardisation) will be the reference. The system delivering specific feedback to user will be based on the VIM engine and domain-knowledge rules. The rule is based on the PMV-PPD (ISO). The Predicted Mean Vote (PMV) index is defined by :

$$PMV = [0.303. e^{(-0,036.M)} + 0,028] \cdot \{(M-W) - 3,05*10^{(-3)} \cdot [5733 - 6,99.(M-W) - p_a] - 0,42.[(M-W) - 58,15] - 1,7.10^{(-5)} \cdot M \cdot (5867 - p_a) - 0,0014. M \cdot (34 - t_a) - 3,96,10^{(-8)} \cdot f_{cl} \cdot [(t_{cl} + 273)^4 - (t_r + 273)^4] - f_{cl} \cdot h_{c.}(t_{cl} - t_a)\}$$

 $t_{cl} = 35,7 - 0,028.(M - W) - I_{cl}.\{3,96.10^{-8} f_{cl}[(t_{cl} + 273)^4 - (t_r + 273)^4] + f_{cl}.h_{c.}(t_{cl} - t_a)\}$

$$h_{c} = \begin{cases} 2,38. |t_{cl} - t_{a}|^{0.25} & \text{for } 2,38. |t_{cl} - t_{a}|^{0.25} > 12, 1\sqrt{v_{ar}} \\ 12,1\sqrt{v_{ar}} & \text{for } 2,38. |t_{cl} - t_{a}|^{0.25} < 12, 1\sqrt{v_{ar}} \\ f_{cl} = \begin{cases} 1,00+1,290. l_{cl} & \text{for } l_{cl} \le 0,078 \, m^{2}. K/W \\ 1,05+0,645. l_{cl} & \text{for } l_{cl} > 0,078 \, m^{2}. K/W \end{cases}$$

with :

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- \circ M , the metabolic rate in watts per square metre (W/m^2)
- \circ ~W , the effective mechanical power (W/m²)
- $_{\circ}$ $f_{\rm cl}$, the clothing area factor
- \circ t_{d} , the clothing surface temperature (°C)
- h_{c} , the heat convective transfer coefficient (W/m²/°C)
- $_{\circ}$ p_{a} , the partial water vapor pressure in the air (Pa)
- \circ t_a , the air temperature (°C)
- $_{\circ}$ $I_{\rm cl}$, the thermal resistance of clothing
- t_r , the mean radiant temperature (°C)

The PMV values are described in the Table 1, where each value is link to thermal comfort.

PMV value	Human meaning
+3	Hot
+2	Warm
+1	Slight Warm
0	Neutral
-1	Slight Cold
-2	Cool
-3	Cold

Table 1: PMV values and thermal comfort meaning

The Predicted Percentage of Dissatisfied (PPD) allows to estimate the percentage of a large group of user related to the thermal sensation scale (PMV) :

$$PPD = 100 - 95 \cdot e^{(-0,03353 \cdot PMV^4 + 0,2179 \cdot PMV^2)}$$

Virtual Individual Model



Figure 8: Overview of VIM & rules for thermal comfort

According to humidity and temperature data, the rule allows to have an estimation of the thermal comfort of the user context at home. Using this estimation, the notification generator will propose a dedicated feedback to the user. The message will be in the form of recommendation in order to advise the user about his thermal comfort. The message will also be deliver to multimodal interfaces: text on TV, text on smartwatch, text on tablet, pc, voice, etc.

4.6.2. Noise comfort

The ambient sound level will be monitor and specially in bedrooms during night. Indeed, the sleep disturbance is one risk factor that PRECIOUS try to reduce. The EN15251:2007 defines recommendation for indoor noise level (figure 9) if specific rules in countries are not defined. Noise affects human activities : sleep, rest, work, etc. Noise level recommendations are not the same according the user activity. For instance, there is a special noise level when the user is sleeping.

Virtual Individual Model



Figure 9: Overview of VIM & rules for noise comfort

The WHO guidelines for night noise recommends less than 40 dB(A) of annual average (Lnight) outside of bedrooms to prevent adverse health effects from night noise (Hurtley, 2009). The rules will be based on the "Equivalent continuous sound pressure level, (LAeq)" and Leq:

$$Leq = 10\log(\frac{1}{T}\int_{0}^{T}\frac{p^{2}(t)}{p_{0}^{2}}dt)$$

with

 $T\,$, the measurement duration

p(t), the sound pressure

 p_0 , the reference sound pressure of 20µPa.

Thus, the LAeq will be compute as the average energy of the A-weighted sounder during a period T (e.g., T = 8 hours for the night period).

- Daytime & evening: LAeq = 35 dB, 16 hours
- Night time: LAeq = 30 dB, 8 hours
- Rules will be based on the following personal noise exposure:
 - user daytime & evening
 - user night time.

The first one will be more complicated to monitor because we will only measure the noise context of the user at home, thus we suppose here that the user is present at home all the day (which is not realistic). The night noise level will be easier to monitor at home and is more related to sleep disorders.

It is to be noticed that the World Health Organisation is currently revising the community noise European guidelines. The PRECIOUS rule engine will, however, be adaptive enough to change rules according to new recommendations.

4.6.3. Light comfort

There is not a specific reglementation for the lighting quality in dwelling. Consequently, the rules for light quality will be driven by the EN 15251:2007, EN 12464-1 and EN 12193 as depicted figure 10.



Virtual Individual Model

Figure 10: Overview of VIM & rules for light comfort

Standards for light quality are more dedicated to work tasks and visual comfort. For example, typical recommendation according the user tasks:

- 500lx on workplane
- 750lx for drawing (Europe)

In the bedroom, the light exposure should be also measured. Indeed, exposure to light during the night can affect the quality of the user sleeping activity [Kim et al]. But there is no standards, european recommendations concerning this rule. Nevertheless, a rule not based on standard and related to bedroom environment quality will be defined to favorise a good sleep.

5. Use case examples

5.1. Unhealthy, unmotivated individuals with little experience of a healthy lifestyle.

Users from this category who interact with the PRECIOUS system will be those least likely to change their behavior, and the main focus will be on getting members of this user group to engage with the system at all. Users from this category have probably also had failed attempts to change health behaviors in the past. Therefore, to avoid a focus on these past failures, a future-focused intervention is warranted. In early interactions with the system, this group of users will be asked what is their primary target, what they most want to achieve out of a list of options including health, fun, stress management, etc. This 'outcome goal setting' can be a powerful motivator of behavioral change, and it is hypothesized that these future-facing outcome goals will also increase engagement with the system. After setting outcome goals, these users will progress through the next steps of digitized motivational interviewing, which will use creative, novel methods to link changes in their health behavior to helping them achieve their outcome goals, strengthen individuals sense of relatedness to the system, and support their autonomy and choice for behavior change. It is thought that these techniques will prepare individuals for taking action, or in other words that they will cause the users to form intentions to change their health behavior.

For individuals who do not form an intention to change behavior after engagement with these initial motivational components, additional motivation enhancing components will be suggested. This includes visualization exercises aimed at getting people to think about how a behavioral change might affect their future outcomes, and offering normative information about health behaviors should users so desire. If, after engaging with all motivation-enhancing components a user has still not established an intention to change one or more health behaviors, then he or she will be prompted to perhaps reconsider their chosen outcome goals and behaviors to something that he or she is more inclined to want to do. As mentioned, this is the most difficult target group for any behavior change intervention, and as such, the use of gamified reward mechanisms will be crucial to increasing engagement with the system.

5.2. Healthy individuals with unhealthy behavioral patterns

Within this group of users, motivation for health behavior changes may also be quite low, but for different reasons than the group of potential users described in section 5.1. Users in this category have no diagnosed health problems, but rather a slight overweight, possible unhealthy diet or inactive lifestyle which could lead to health problems in the future. As users within this category are likely to see themselves as similar to others in this age group with similar characteristics, their perceived social norms might be incongruent with what constitutes a healthy lifestyle. Additionally, as they perceive no imminent risks to their health, taking a directive and health-focused approach with this group of users (as is often done in healthcare settings and in existing behavior change apps), may not be in line with what users desire, and might therefore be perceived as too controlling or directive. To avoid this situation, PRECIOUS will approach behavior change within these individuals differently, by tapping into their desired outcomes, and recognizing that these may not be health related. Research has indicated that age is related to individuals motives for health behavior change, and that health is not typically cited as a motive for health behaviors until after the age of 50 (Quindry et al, 2011). Up until that time, social connectedness, enjoyment, competition and appearance-related motives are more commonly cited (Biddle & Mutrie, 2007). For this reason, the earlier described approach with outcome goals and future-focus is again used to initiate behaviour change within this group of users. By focusing on what users want, as opposed to instructing them how to behave more healthily, a greater sense of autonomy and relatedness will be achieved. Also,

by focusing on health behaviors only as a means to achieve desired future outcomes, instead of as the main focus of the system, users will work toward healthier behavioral patterns without having to focus on health itself. This is a unique approach within behavior change interventions, especially in mobile systems, and one which could be of great interest to industry and public health agencies if found to have effects on engagement with the system and/or preventative health behaviors.

5.3. Individuals who have disengaged with the PRECIOUS system.

A key problem with many lifestyle and behavior change interventions is discontinued use. This is also true for apps in general, as only 26% of all apps downloaded from the app store are ever opened more than once (Leger, 2011). Discontinuation of use creates particular problems for behavior change apps. Several meta-analyses have shown that core self-regulation techniques (e.g. self-monitoring, feedback, goal setting and action planning) are crucial to the effectiveness of behavior change interventions (Michie et al 2009), and further to that, increased engagement and enactment of these behavior change techniques mediate the effectiveness of interventions (Hankonen et al 2014; Knittle et al 2015; Janssen et al 2014). In other words, interventions that contain self-regulation techniques are effective, but only when they are actually used by individuals. For these reasons, PRECIOUS will contain a number of mechanisms to encourage continued use of its self-regulation components and to support re-engagement with the service after periods of disuse.

The first of these mechanisms involves gamification of the self-regulation process. By rewarding engagement with the process of setting goals and making plans, as well as behavior itself, users will be more likely to persist with this over time. Stepped difficulty of goals and challenges, and novel aspects of self-regulation that are unlocked as users gain experience with the system will also contribute to this. Another tool which aims to get users to re-engage with the system is tailored push notifications, which will ask users about progress toward their outcome goals in the absence of activity with the app. Supportive notifications such as this to nudge users toward reengagement, will foster a sense of ownership and relatedness within users and contribute to sustained engagement with the system. Within this feature, it will of course be necessary to establish the optimal timing and content of such notifications, and preliminary pilot work with end users will be done to inform these aspects. This might also include news briefs, information about activities or other relevant notes. Another feature to enhance engagement with the service is a real-time feedback option, which will allow users to offer suggestions for improvements to the system as they are encountered. This will be done by offering users the chance to record messages which will be sent directly to the development team. Taken together, we expect that these features will contribute to low rates of disuse of the system.

6. Future directions for the VIM

6.1. **3rd party health/fitness apps and wearables**

Passing data between PRECIOUS and the Application Program Interfaces (APIs) provided by 3rd party apps and wearables would enrich the data sources from which the VIM and VIM rules draw. This could lead to greater tailoring of intervention suggestions and would provide users with a wider range of options to pursue

behavioral changes. However, it also presents several challenges, including creating a coherent way to integrate and present data from various sources which may have been calculated differently, the absence of an API for many 3rd party applications, and the 'closed' nature of many wearables which do not allow data sharing across platforms. Within the present project, we therefore elected not to pursue 3rd party integration initially, and instead to focus on the creation of motivation. This choice was made because our target groups consist mainly of users who are new to the world of health and fitness apps and wearables, and who would not likely benefit much from this enriched data. We have therefore included components within PRECIOUS that are included in most behavior change apps (i.e. self-regulation techniques), and supplement this with novel ways to increase engagement and motivation for the process of behavior change. 3rd party integration will be a focus of any subsequent iterations of PRECIOUS, so that it also appeals to users who already use activity trackers or health and fitness apps.

6.2. Integration with healthcare sector/medical records

A future challenge for PRECIOUS will be integrating the system into healthcare settings. To do this, it will need to draw information directly from medical records held in databases which use different naming mechanisms, contain different variables, and which are managed and upkept with varying degrees of completeness. It will also necessitate that PRECIOUS be able to write to this database so that the information it collects can provide direct feedback about users' behavioral patterns to healthcare professionals. Accomplishing this will require programmers with resources dedicated to developing APIs to pass data between these different medical records systems and PRECIOUS, and include ways to accomplish this working across linguistic and administrative differences. It would also require that special attention be paid to the ethical considerations of handling potentially sensitive medical information. Within the present development and evaluation of PRECIOUS there were not sufficient resources to accomplish these tasks, and instead, within the context of the MI field trials, users' physical and medical characteristics will be input to the system manually before users begin interacting with the app. This will simulate what it would be like if data were passed from medical records to PRECIOUS automatically, creating a sense of connectedness between users, PRECIOUS, and medical care teams. For the purpose of the field trial, it will also be possible for medical professionals to view users' progress on motivational and behavioral variables within PRECIOUS so that subsequent face to face interactions can be facilitated around the PRECIOUS system.

6.3. Implementing machine learning algorithms

Machine learning algorithms are capable of working with big data to find correlations between variables adaptively, where human beings would not be capable of doing so. The VIM parameters (such as physical activity, diet, environment information, etc) compose a data set with very rich information about the user. This data set can be used to detect diseases in early stage, by linking unhealthy habits with symptoms. For a human being, this linking is very difficult and sometimes impossible. For a machine, finding the correlation between two data sets is easy task once the algorithm has been implemented and it can be easily applied to anyone. It also allows

for investigation of links between variables that had not previously been connected. Therefore, machine learning not only offers a new way for disease and risk detection, but it also makes it available to a lot of people at the same time, because no human being is involved in detection.

7. Conclusions

This document provides the foundations upon which the architecture of the virtual individual model (VIM) within PRECIOUS will be built. The VIM variables and rules will create personalized user interactions with the system, and aim to increase user engagement with the process of behavior change. The VIM will take into account behavioral, motivational and engagement variables from users, and via theory-derived algorithms deliver information, notifications, customizations and behavior change tools at the times when they are most needed. These rules will also allow for the customization of user experiences based on the research questions to be tested in the field trials described in deliverable 5.1, and will continue to be adapted and improved based on user feedback. By introducing novel methods for targeting behavior change via the pursuit of distal outcome goals, PRECIOUS represents a step forward for fostering greater autonomy and relatedness for users of digital preventative care platforms.

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