ICT4Depression

User-friendly ICT Tools to Enhance Self-Management and Effective Treatment of Depression in the EU

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Deliverable 3.3: Report with formal specification of meta-reasoning techniques to select therapy

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Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services).	
RE	Restricted to a group specified by the consortium (including the Commission Services).	
CO	Confidential, only for members of the consortium (including the Commission Services).	

Executive Summary

In the previous two deliverables within WP3 abstraction techniques to measure the progress (D3.1) and a virtual patient which can make predictions with respect to the development of the patient (D3.2) have been developed. In order to utilize the combination of these two elements, this deliverable will show how the predictions are compared with the actual observations of the patient, how they trigger a reasoning process, and how the models are used to give advice about a possible switch of therapy. In order to allow for a tailored model of the patient parameter estimation techniques are also utilized to tune the parameters of the model towards the observed patient functioning. Based upon the conclusions, feedback and advice can be generated, which will be treated in D3.4.

Contents

1. Introduction

In the previous deliverables of WP3 techniques have been introduced to monitor the current progress of the patient based upon the current measurements (D3.1) as well as models that can make predictions of the progress of the patient following a certain therapy based upon a virtual patient model and compare this prediction with the observed progress (D3.2). In this deliverable, the outcome of the comparison as mentioned under D3.2 will be used to trigger a process to look for alternative therapies that could potentially be more effective. Essentially, when the current comparison with the predicted outcome signals that the therapy is not as successful as anticipated, the expected response of the patient for the different alternative therapies that can be selected (i.e. activity scheduling (abbreviated to AS, sometimes also referred to as behavioral activation), cognitive behavioral therapy (CBT), problem solving therapy (PST), and exercise therapy (ET), note that this terminology follows the terminology used in D3.2) will be simulated using the virtual patient, and the system will then perform reasoning about these predictions and possibly advise a modification of the therapy.

The process of making these simulations using the virtual patient is not a trivial matter: the simulations should take it into account if the human patient responds different on the therapy than expected. Therefore the parameters used in the simulation need to be modifiable to make the predictive power of the simulations themselves more reliable and more tailored towards the patient. Approaches for this are introduced in this deliverable as well.

This deliverable is organized as follows. First, the triggers for the meta-reasoning process will be shown in Section 2. Thereafter, Section 3 expresses how the parameters of the simulation will be adjusted based upon the previous experiences. In Section 4 the actual comparison between the different therapies is addressed, including advice based upon the information which will be provided. Section 5 addresses related work and shows the innovativeness of the research presented, and finally Section 6 concludes the deliverable.

2. Trigger for Reasoning about Therapies

In the previous deliverable (D3.2) a comparison between the trends within the virtual agent and the trends as observed by means of the aggregated measurements was discussed. The comparison was summarized by means of Table 1 (whereby 'o' indicates approximately as predicted; '-' expresses that patient is performing slightly worse than predicted, '--' signifies that the patient is performing significantly worse than predicted; '+' specifies that the patient is performing slightly better than predicted, and finally, '++' represents that the patient is performing significantly better than predicted

.

Table 1. Comparison between trends

	Virtual patient state trend	good			bad		
Patient state trend		increasing	stable	decreasing	increasing	stable	decreasing
good	increasing	o	+	++	++	++	++
	stable	-	o	+	+	+	++
	decreasing	--	-	o	o	o	o
bad	increasing	o	o	o	o	+	++
	stable	--	-	-	-	o	+
	decreasing	--	--	--	--	-	o

It is assumed that the reasoning mechanism is triggered in case the patient performs significantly worse than expected (i.e. ‘--' in Table 1).

In Figures 1-4 graphical examples are shown that express the comparison between the observed patient state and the predictions using the virtual patient (i.e. the average between the levels of *mood*, *thoughts*, and *appraisal*). The x-axis shows the time line (whereby each point represents 4.8 hours as five patient state rating calculations are assumed per day for the *observed patient state (PS)*, each represented by a single time point). Note that in this case it is assumed that the ratings come in on a regular basis, but such regular measurements are not required for the algorithms. The y-axis indicates the level for the *observed patient state* and the *virtual patient state (VPS)*. The blue line represents the VPS whereas the green line represents the PS. The trends are also shown in these figures. The red x’s are the trends of 1 day with respect to the VPS: 0 is decreasing, 1 is increasing, 0.5 is stable. These values are also used for the other trends that are explained below. For the precise definition of the calculation of these trends, see D3.1. The parameter for stable (following the definition in D3.1) has in this case been set to a maximum difference of 0.02 between first and last VPS of the day, excluding deviant values of more than two standard deviations from the average of the week. Furthermore, a good VPS (or PS) is defined as an average value of 0.6 during the calculated period and bad as the opposite. The daily trend of the PS is not calculated per day as merely 5 measurements do not give a sufficiently reliable trend. A trend per week is however calculated for the PS, represented by a purple asterisk. For the VPS this weekly trend is represented by a blue circle. The parameter for the weekly trends has been set to a maximum deviation of 0.05 between the first and last virtual patient state of the week. Finally, a red triangle shows whether the reasoning mechanism is triggered (i.e. whether

the comparison in the trends falls under the significantly worst performance in Table 1), whereby a red triangle with a value 0 indicates that the mechanism is not triggered, and a 1 represents a triggered reasoning mechanism.
All simulations are run with the same characteristic: medium levels for openness for therapy, coping skills and vulnerability and the patient is currently assumed to be following the activity scheduling intervention.

Figure 1 shows a bad and increasing VPS. The PS trend is the same; therefore, this situation will not trigger the reasoning process.

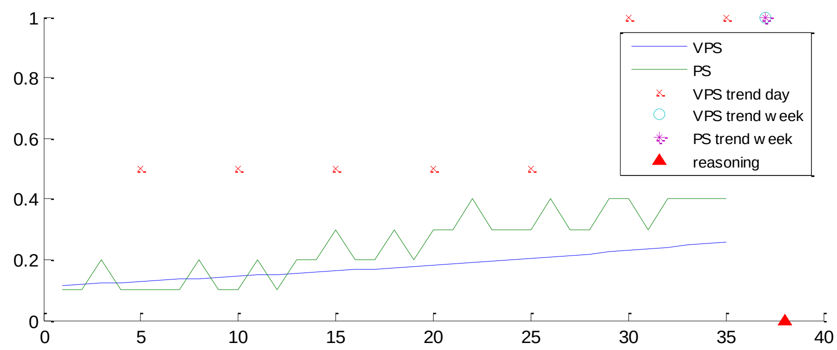

Figure 1. VPS and PS comparison in week 1 of AS; the PS is bad and increasing.

In Figure 2, the VPS is again bad and increasing. The PS however, is bad and decreasing. Following the comparison of trends in Table 1, this situation triggers the reasoning process.

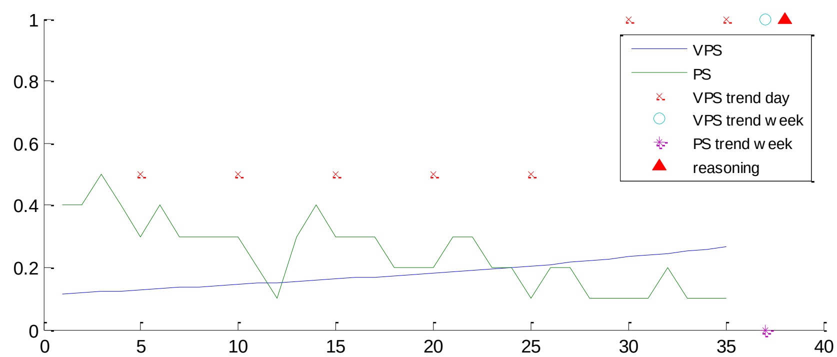

Figure 2. VPS and PS comparison in week 1 of AS; the PS is bad and decreasing.

The next two simulations (shown in Figure 3 and 4) show the same person during week three of the intervention. The prediction of the VPS is a good and increasing patient state.

In Figure 3, it is shown that the actual PS is bad and increasing. According to the comparison table, this difference is not significant enough to trigger the reasoning process.

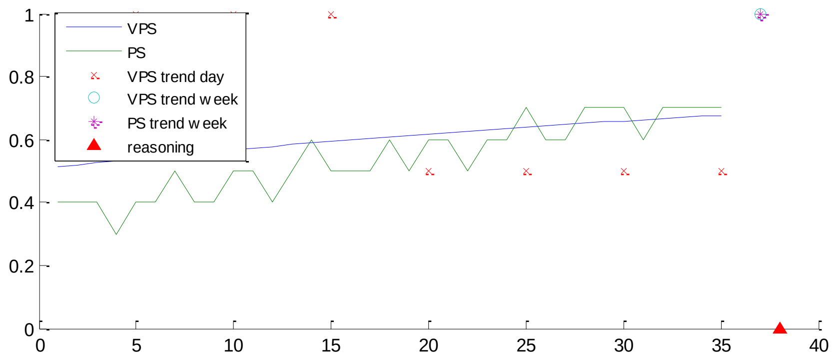

Figure 3. VPS and PS comparison in week 3 of AS; the PS is bad and increasing.

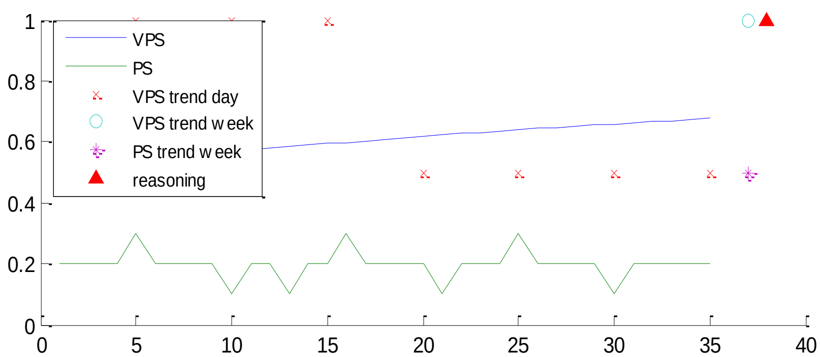

Figure 4. VPS and PS comparison in week 3 of AS; the PS is bad and stable.

Figure 4 again shows the good and increasing VPS, but now the PS is bad and stable. This situation will lead to a triggering of the reasoning process. Based upon the mechanism that has been exemplified above the overall reasoning process to evaluate other potential therapeutic options can be triggered. The first step in this process is to tailor the parameters of the virtual patient to the actual patient behavior. The next step is to use the virtual patient to evaluate the effectiveness of the other types of therapies.

3. Parameter Adaptation

Within the therapeutic models, several parameters are present that are tailored towards the specific human being supported. These are (cf. D3.2):

- Openness for therapy (low/medium/high)
- Initial level of mood (value between 0 and 1)
- The coping skills (low/medium/high)
- The vulnerability (low/medium/high)

Given that the process to look for alternative therapies is started (and hence, the predictions differ significantly from the actual behavior of the patient) the parameters of the model might actually not be the best to describe the patient. Therefore, a first step before running comparative simulations with other therapies is to adjust the parameters of the model so that the predictions are more in line with the actual behavior. For this purpose, the parameters are adjusted in the following manner:

Openness

The value of the openness for the current therapy is made dependent upon the current therapeutic state that has been signaled based upon the measurements obtained from the patient (following the therapeutic involvement), and set to a value representing *low*, *medium* or *high* openness. For the other (alternative) therapies that have not been followed yet, the same state as the initial openness for the therapy is assumed. For the ones that have already been followed but are not the current therapy, a stored value for the openness is used.

Initial level of mood

Because the initial level of mood is simply taken directly from patient input (or by means of the patient state in case the patient has not provided a mood rating yet), the initial level of mood will not be a parameter that will be adjusted in the process.

Coping skills

The coping skills parameter is an element which is generic and a parameter across multiple therapeutic models, and should be adjusted to the most appropriate value. To make sure that the model exhibits desired and predictable patterns, three settings for this parameter are allowed: *low*, *medium*, and *high* (which map to the numerical value 0.1, 0.3 and 0.5 respectively). The parameter adaptation algorithm for this adjustment is expressed in more detail below.

Vulnerability

The vulnerability parameter is similar to the parameter for coping, and values of *low*, *medium*, and *high* are allowed for this parameter. Parameter adaptation will also take place for the specific parameter value.

Note that for each of the parameters only a limited number of values are allowed. This choice has been made to guarantee the robustness of the model (for each of the allowed values the model shows correct behavior) and also to reduce a too time consuming process of parameter adaptation. Below, the parameter adaptation algorithm is given.

3.1 Parameter Adaptation Algorithm

In order to adjust the two parameters to the best possible value to describe the current patient state, simulations with different settings for these parameters are performed, and a comparison with the observed patient behavior is made. As a measure of error, the mean squared error is used. Note that due to the limited number of possibilities, the running of all options is feasible, in case a continuous scale would have been used, other parameter adaptation techniques could have been utilized, such as Genetic Algorithms (cf. Kirkpatrick, 1983), or a more mathematical based approach (see e.g. Koch, 1999). Below the algorithm to determine the best parameters is shown.

Algorithm 1. Parameter adaptation

```
current_best_value_coping = low;
current_best_value_vulnerability = low;
current_best_mse = 1; // maximum value

for all settings for coping
        for all setting for vulnerability
                current_mse = mse(current_value_coping, current_value_vulnerability,
                                        current_therapy);
                if (mse(current_mse < current_best_mse) {
                        current_best_mse = current_mse;
                        current_best_value_coping = current_value_coping;
                        current_best_value_vulnerability = current_value_vulnerability;
               end
        end
end
```

In order to determine the mean squared error for different parameter values, a daily value for the patient state (calculated using the sensory data) is compared with the daily average as calculated during the simulations.

3.2 Parameter Adaptation Example

A person has started with the AS intervention. From the questionnaire filled out before the intervention follows that this person has medium coping skills and vulnerability. After the third week of the intervention, the VPS and PS are compared (see Figure 5). The actual patient state appears to be worse than predicted and is stable instead of the predicted increase. This triggers the reasoning process, and therefore initiates the parameter adaptation mechanism.

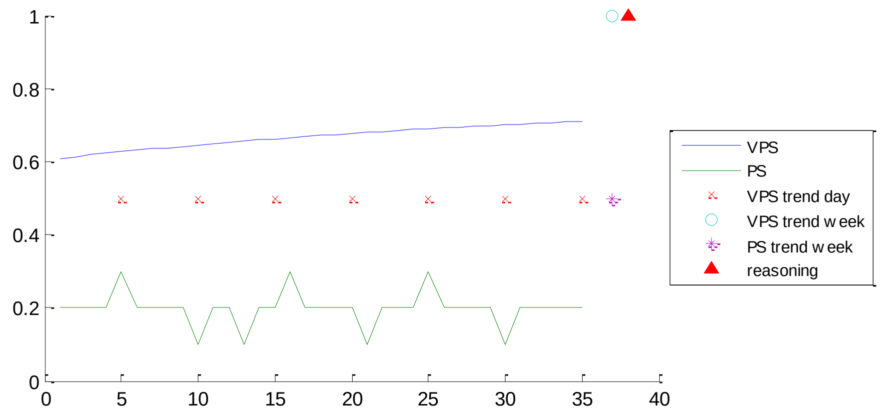

Figure 5. VPS and PS comparison in week 3 of AS; the person has medium coping skills and vulnerability.

As a result of the start of this process, the different alternatives for parameter values for coping skills and vulnerability are tried, and the mean squared error for each of the values is calculated. The mean squared errors for the different coping skills levels are 0.004 (low) 0.202 (medium) and 0.257 (high). For the vulnerability the best value was shown to be high. The best fitting coping skills and vulnerability levels are low and high respectively, resulting in a smaller difference between the VPS and PS. Figure 6 shows the VPS calculated using these new values.

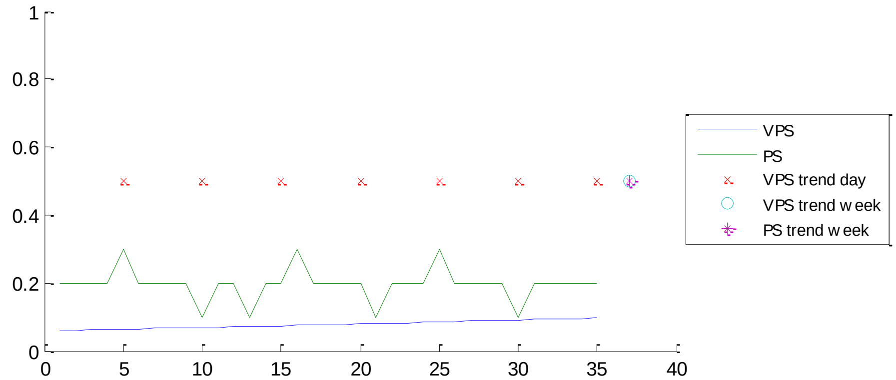

Figure 6. VPS and PS comparison in week 3 of AS with low level of coping and high vulnerability.

4. Comparison between Therapy Effectiveness

Given that the parameters have been adjusted to maximize the accuracy of the predictions of the model(s), a true comparison between the predictions of the various models can be made. Hereby, it is assumed that switching has an initial positive effect on the patient state (an increase of 0.1 on a scale from 0-1) due to the fact that the patient feels that the therapy is really being tailored towards him/her.

Consider the example as shown in Section 3.2 again. Using the parameter adaptation process, a new set of parameters has been determined: low coping skills and high vulnerability (thereby replacing the previous values of medium coping skills and medium vulnerability). For each therapy, a prediction is made about the future patient state based on the current patient state (including the values for each of the states of the model, these are simply copied) and the (adapted) parameters. Figure 7 shows the predicted mood levels for the three therapies. The patient states are calculated for each week using mood, thoughts and appraisal.

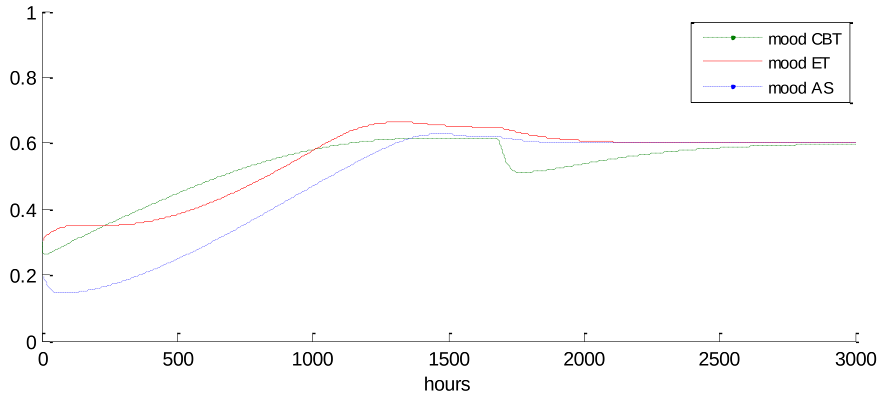

Figure 7. Predicted mood levels for therapies CBT, AS and ET.

Once the comparison has been made, an advice can be given to the patient. In this case, an advice can consist of switching between therapies. Hereby, the crucial element to come to such an advice is the expected recovery time. This expected recovery time is the predicted amount of days before the mood is structurally above a certain threshold (i.e. the patient is feeling better again). In case the predicted recovery time of the best therapy simulation is shorter than the predicted recovery time of the current therapy (given the adjusted parameters), then an advice is given to start following the alternative module.

In the example, the predicted recovery time is 46 days for CBT, 53 days for AS and 45 days for ET. The advice to switch to exercise therapy can be given to the person.

5. State of the Art and Beyond

Within several disciplines, work related to the approach described in this deliverable can be found. In order to show how the scientific research presented in this deliverable relates to this existing work, and moves beyond the current state of the art, this section gives an overview of relevant other work. First, work related to modeling of psychological processes and interventions is described, followed by model-based reasoning approaches that allow to reason about the effectiveness of such therapies. Finally, alternative parameter estimation techniques will be presented that tailor the models towards the observed human behavior.

5.1 Computational Modeling of Psychological Processes and Interventions

Ambient Intelligence and Ubiquitous Computing are fields in which devices are utilized to support humans by means of an intelligent environment (see e.g. Aarts *et al*, 2001, Weiser 1999). A key element within these techniques is that the environment really comprehends the human and supports him in an intelligent way (see e.g. Bosse *et al*, 2008). This should of course also hold for people suffering a depression for which a support system is designed in this project. Within the domain of Artificial Intelligence, techniques have been developed to create models of such human behaviour, and to reason about such models. Examples of architectures are for instance ACT-R (Andersen and Lebiere, 1998) and SOAR (Laird *et al.*, 1987) for cognitive models. Besides such architectures which are designed for a subset of human models, also approaches have been created which are independent of the domain of application, including for instance default logic (Reiter, 1980) and temporal logic. These all allow the reasoning with models to derive conclusions, for instance what support should be given to the human. Since the above approaches are generic approaches, they commonly do not include specific concepts such as emotions (which is very relevant for depression), but they can be used to express models which describe how such concepts relate to each other. When it comes to specific models dedicated to the role of emotions in agents, ample research is available. For instance, in (Bates, 1992) an example model which involves emotions and the influence thereof upon the behaviour of an agent. Other examples of models include (Dastani and Meyer, 2006) in which agents are programmed which involve emotions in their deliberation process, and many more exist. Although these are all very interesting, they do not involve all major internal concepts that play a role in depression, such as for instance appraisal and thoughts, which is a necessity to truly understand the current state of the patient. Furthermore, the modelling of the precise influence of certain interventions is also an element that has not been previously modelled in a computational fashion. Of course, the influences of the therapies upon the state of the patient have been investigated within Clinical Psychology (see e.g. Lewinsohn *et al.*, 1986; Lazarus and Folkman, 1984; Beck, 1972; Gross, 2007; Zubin and Spring, 1977), but they have never been expressed in a computational manner.

5.2 Model-based Reasoning Techniques

A second important aspect which is the main element introduced in this deliverable is that the progress information should be used to reason about the various therapies that can be selected in order to advise the best possibility at the current moment. Hence, reasoning on a meta-level should take place about the various models which include the therapeutic influence. Meta-reasoning is a topic which has been under investigation for many years, see e.g. (Russel and Wefald, 1991). (Bowen and Kowalski, 1982) for example propose a dedicated logic for meta-reasoning. In this deliverable, an approach has been taken which performs so-called what-if simulations, thereby making predictions of the development of the patient based upon running the model with dedicated parameters. By itself, performing what-if simulations is not a new phenomenon (see e.g. Fone *et al.*, 2003; Paranjape, R. and Sadanand, 2009) for what-if simulations used in health care), but the utilization of such simulations to select a therapy for mental health-care is something which has not been done before. In the literature on clinical psychology, little evidence has been found to indicate which therapy can be selected best, however due to the usage of these more sophisticated models that are well grounded in psychological theory the idea is that a more knowledgeable advice can be given to the patient. The validation of the model will be performed by means of initial pilots with real patients.

5.3 Parameter Estimation Techniques

Within the models that represent the mental state of the patient, a variety of parameters are present that are unique for the patient. Initially, such parameters are set to an appropriate value based upon answers received from an initial questionnaire. Of course setting the parameters based upon these answers can result in a very rough estimate of these parameters, which might not be sufficient. Therefore, parameter estimation techniques can be utilized to tailor the parameters towards the patient once more information is available concerning the actual behavior of the patient. In the past, many techniques have been proposed for such parameter estimation, ranging from mathematical based approaches (see e.g. Koch, 1999) to Artificial Intelligence learning techniques such as Genetic Algorithms (see e.g. Kirkpatrick, 1983). The aforementioned techniques have mainly been introduced to improve the scalability of the parameter estimation process in a large search space. In the case of the parameters which will be tuned in the process described above only a limited number of values will be allowed, and only two parameters will be tuned. Hence, the scalability is not an issue in this case, so therefore an exhaustive search can take place to find the appropriate parameter settings. For future work, it is envisioned to allow more freedom in the parameter settings of the model, and in that case more sophisticated parameter estimation techniques are crucial. For the current scenario however, robustness of the outcomes of the model is given priority over the highest possible accuracy to describe the behavior of the patient.

6. Conclusion

In this deliverable, the next step to come towards a tailored advice and feedback system for depressed patients has been presented. This step encompasses the reasoning about the effectiveness of therapies and potential alternatives. Hereby, the reasoning is triggered based upon a comparison of the predicted progress (cf. D3.2) and the actual observed progress (cf. D3.1). Based upon these triggers, the parameters of the model are tuned towards the observed patient behavior, and predictions for alternative therapies are made. The patient is thereafter advised when an alternative therapy is expected to be significantly more effective. The next step (D3.4) is to determine what feedback to provide to the patient based upon the measurements (D3.1), predictions using the virtual patient model (D3.2), and alternative therapies that have been derived (this deliverable).

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