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Title: Designing Adaptive Hypermedia for Internet Portals: A Personalization Strategy Featuring Case Base Reasoning With Compositional Adaptation

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Keywords: Case Based Reasoning, Case Adaptation, Adaptive Hypermedia, Compositional Adaptation

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Abstract. In this paper we propose that the *Case Based Reasoning (CBR)* paradigm offers an interesting alternative to developing adaptive hypermedia systems, such that the inherent analogy-based reasoning strategy can inductively yield a 'representative' user model and the case adaptation techniques can be used for dynamic adaptive personalization of generic hypermedia-based information content. User modeling is achieved by applying an *ontology-guided CBR retrieval technique* to collect a set of similar past cases which are used to form a global user-model. Adaptive personalization is accomplished by a novel *compositional adaptation technique* that dynamically authors a personalized hypermedia document—a composite of multiple fine-grained *information 'snippets'*—by selectively collecting the most relevant information items from past matched cases (i.e. not the entire past solution) and systematically amalgamated them to realize a component-based personalized hypermedia document. We present a *Personalized Health Information Generation and Delivery System* that leverages case based reasoning techniques to dynamically author a *Personalized Health Information Prescription* based on an individual's current health profile.

1. Introduction

Web-mediated information portals routinely suffer from their inability to satisfy the heterogeneous needs of a broad base of information seekers. For instance, web-based education systems present the same static learning content to learners regardless of their individual knowledge of the subject; health information portals deliver the same generic medical information to consumers with different health profiles; and web e-stores offer the same selection of items to customers with different preferences and needs. The underlying approach adhered by most web-portals is that 'one-size-fits-all', which in a realistic setting is not necessarily the case—on the contrary individuals have heterogeneous needs and preferences, which even change with time and location.

A solution to this overly-simplified approach for 'generic' information delivery is the development of *adaptive hypermedia systems*—web-based systems that belong to the class of user-adaptive software systems—that have the ability to adapt their behavior to the goals, tasks, interests and needs of individual users and group of users [1]. Put simply, adaptive systems develop a user model, using a combination of explicit questioning and implicit observation techniques, that is used for dynamically adapting generic information to personalized information in line with the user's need and interest profile [2]. Hence, an adaptive hypermedia system involves two distinct activities: (a) development of a user model and (b) adaptation of static generic information content to user-specific personalized content [3]. Adaptive personalization technology involves a multitude of intelligent techniques for user modeling and content adaptation [4, 5].

In this paper we argue that the *Case Based Reasoning (CBR)* paradigm [6, 7] offers an interesting alternative to developing adaptive hypermedia systems [8], such that the inherent analogy-based reasoning strategy can inductively yield a 'representative' user model and the case adaptation techniques can be used for dynamic adaptive personalization of generic hypermedia-based information content. User modeling is achieved by applying an *ontology-guided CBR retrieval technique* to collect a set of similar past cases which are used to form a global user-model. Adaptive personalization is accomplished by a novel *compositional adaptation technique* that dynamically authors a personalized hypermedia document—a composite of multiple fine-grained *information 'snippets'*—by selectively collecting the most relevant information items from past matched cases (i.e. not the entire past solution) and systematically amalgamated them to realize a component-based personalized hypermedia document.

Based on the above ideas, this paper features a CBR-mediated approach for developing adaptive hypermedia systems. For concept explication purposes, we have chosen the healthcare sector and present an adaptive hypermedia system designed to dynamically author personalized healthcare information hypermedia content based on an individual's current health status/profile. The choice of the application domain is driven by the need for information personalization in the healthcare sector [9, 10, 11, 12], as personalized and adaptive health maintenance information is deemed to have a significant impact in ensuring wellness maintenance both at the individual and community level.

The forthcoming discussion will provide a technical overview of CBR-based user modeling and adaptive personalization vis-à-vis our compositional case adaptation strategy. A detailed description of operational and evaluation issues pertaining to the implemented adaptive hypermedia system is beyond the scope of this paper.

2. CBR-Mediated Adaptive Personalization: Problem Specification & Solution Strategy

Adaptive personalization of generic healthcare information, as per an individual's 'local' user model provides an interesting opportunity to apply CBR [8], in particular the application of *case adaptation* techniques [13]. Our CBR-mediated adaptive hypermedia system development approach builds on a corpus of past *cases* specified by medical practitioners. Each case depicts a situation-action construct, such that (a) the situation component defines the local user-model—i.e. an individual's *Health Profile (HP)*—in terms of attribute-value pairs (ideally originating from the individual's medical record); and (b) the action component comprises a corresponding *Personalized Healthcare Information Prescription (PHIP)* that is composed of a number of fine-grain, *Problem-focused (hypermedia) Document (PD)*. Each PD is designed to contain health maintenance information pertaining to a specific medical problem. Note that the PHIP is a composite of multiple PDs, whereby each constituent PD is prescribed by a medical practitioner in response to some facet (i.e. an attribute-value) of an individual's HP.

2.1. Problem Specification

We argue that one limitation of traditional CBR approaches is that the recommended solution/action to a new problem-situation—i.e. a case—is taken as the entire solution of the matched past case. This approach works well for many applications which require coarse-grain, estimated solutions. However, in a healthcare information delivery context where information accuracy is paramount it would be rather naive to assume that heterogeneous individuals may have a similar HP or user model! Notwithstanding the possibility that a set of features may be common between two (or more) individuals thereby satisfying some coarse-grain CBR similarity criteria, yet there may certainly exist some features that are idiosyncratic to an individual. Hence, the entire PHIP associated with matched past cases (i.e. existing user-profiles) can not be accurately regarded as the inferred solution to a new user-model.

In this scenario, adaptive personalization is characterized as the problem of selective collection of only the relevant information 'snippets' from the multiple matched past PHIPs, as opposed to selecting the entire PHIP (which may potentially contain irrelevant or damaging information for a particular individual). We believe that a *component-based* information representation and compilation strategy will ensure that the healthcare content disseminated to an individual is specifically selected and is focused towards an individual's prevailing healthcare needs, akin to the kind of personalized service one enjoys from a visit to a medical practitioner [9].

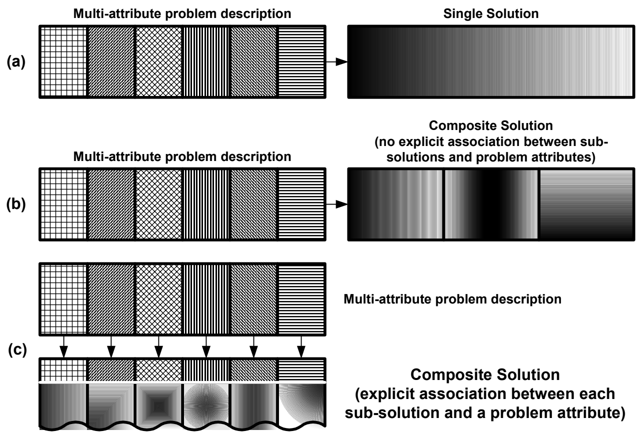

Figure 1: An illustration of different case structures. Case structures (a) and (b) are quite typical, however we have devised a composite structure (c) that links the solution components to the problem features.

2.2. Compositional Adaptation Strategy

The above-mentioned problem specification implies that the solution component of a case cannot be structured as a single information unit. Rather the solution component need to be designed as a 'composite' of multiple *sub-solutions*, where each sub-solution addresses a particular feature of the problem (Figure 1 shows the possible and proposed case representation schemes).

In the realm of CBR, we have devised a case adaptation strategy—based on the notions of compositional adaptation [14]—that is applicable to the adaptation of a specialized class of cases, whereby the case solution is a composite of individual *sub-solutions*; each sub-solution is associated with a problem-defining attribute of a case as shown in Figure 1 (c). Solution adaptation is achieved via similarity-guided selection of multiple 'relevant' sub-solutions from a number of parent cases.

Our compositional adaptation strategy is quite applicable to the problem of dynamic adaptive personalization of hypermedia documents as it allows the tailoring of a personalized document via user-profile driven selection of 'generic' information snippets (analogous to sub-solutions) from an ensemble of past-compiled hypermedia documents. The systematic amalgamation of 'relevant' information snippets yields a unified personalized document corresponding to a particular user-model. Figure 2 shows our CBR-mediated compositional adaptation strategy for adaptive hypermedia personalization.

The rationale for our approach is grounded in the principle that since inter-case similarity is determined at an attribute-level, therefore fine-grained solution adaptation should also be conducted at the attribute-level. By adapting the attribute-specific sub-solutions based on the attribute's similarity measure we ensure that the best matching attribute values impact the most on a selected a segment of the solution—i.e. the sub-solution component associated with the attribute—as opposed to impacting the entire solution component [14]. In this way we are able to generate a solution that contains components that reflect the best features—i.e. most relevant information—of similar past solutions.

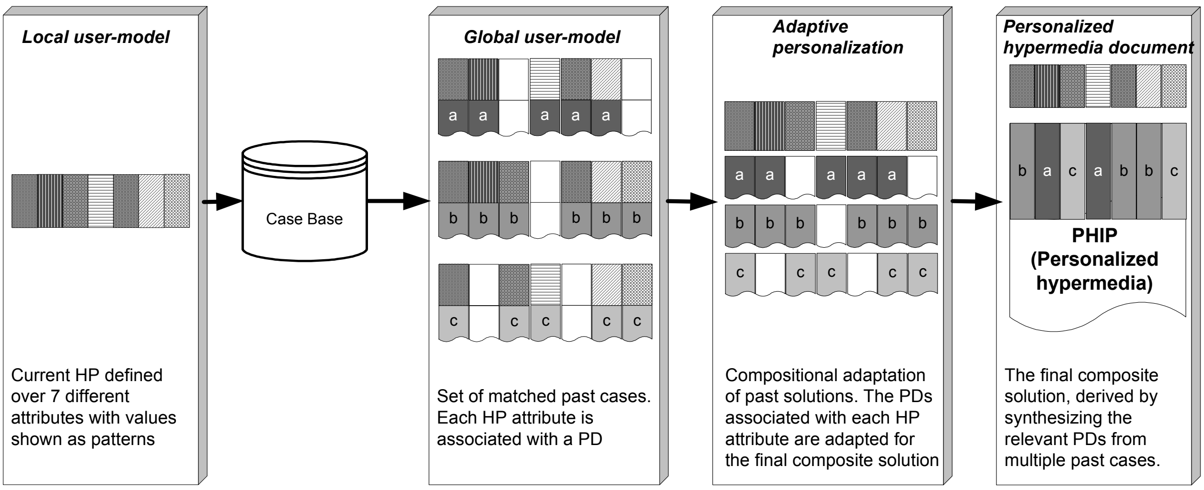

Figure 2: A pictorial illustration of our CBR-Mediated compositional adaptation based strategy for generating adaptive personalized hypermedia documents.

3. CBR-Mediated Adaptive Personalization of Hypermedia Documents: An Algorithm

In this section we will discuss, at an algorithmic level, our overall strategy for performing adaptive personalization of hypermedia documents. We will continue with the exemplar application of generating a personalized health information package based on a specific user-model (i.e. an individual's HP). The below discussion identifies the sequence of operations in CBR-mediated personalization of generic information.

3.1 Case Representation Scheme

In the context of adaptive systems, the HP depicts a 'local' user-model. In a CBR context, the HP serves as the problem description and is defined in terms of a list of health specific attributes as shown in Table 1. The first five attributes of the HP—i.e. AD, SI, S, D, A—are regarded as the *medical attributes* as they describe medically-relevant facts. Whereas the last two attributes of the HP—i.e. DD and LD—are deemed as *description attributes* as they contain values that describe an individual, for instance age, gender etc (shown in

Table 1). The HP contains multi-valued attributes, where the domain of attribute-values is determined from standard medical resources. For instance, the values of the attribute AD is derived from the *International Code of Diseases* (ICD-10) that suggests a taxonomic classification of diseases (as shown in Table 2).

Table 1. An exemplar HP illustrating the 7 HP information groups and HP values.

CORE ATTRIBUTES					DESCRIPTION ATTRIBUTES	
Acute Disease (AD)	**Short-Term Illness (SI)**	**Current Symptoms (S)**	**Current Drugs (D)**	**Allerg-ies (A)**	**Demographic Data (DD)**	**Lifestyle Data (LD)**
Diabetes-Mellitus Hypertension	Fever	High Temp. Cough Breathlessness	Panadol Bendryl	Allergic Rhinitis	Age : 56 y Sex : Male Edu.: High	Fitness: Normal Diet : Healthy Smoking: Yes

Table 2. The representation scheme for the classification of the HP attribute-values for the attribute *Acute Disease* (AD)

Acute Disease (AD) Super-Class	AD Sub-Class	AD Name	AD Code
INFECTIOUS AND PARASITIC DISEASES (1)	**Intestinal Infectious Diseases (1)**	Paratyphoid Fever A (001)	1-1-001
		Paratyphoid Fever B (002)	1-1-002
		Paratyphoid Fever C (003)	1-1-003
		…	…
		Typhoid Fever (020)	1-1-020
	Zoonotic Bacterial Diseases (2)	Spirillary Fever (021)	1-2-021
		Streptobacillary Fever (022)	1-2-022
		…	…
		Unspecified Rat-Bite Fever (029)	1-2-029
	…..	…	…
DISEASES OF THE CIRCULATORY SYSTEM (2)	**Acute Rheumatic Fever (1)**	Acute Rheumatic Pericarditis (001)	2-1-001
		…	…
		Acute Rheumatic Heart Disease (009)	2-1-009
	…..	…	…

In a CBR-context, the PHIP is deemed as the solution component of a case. Structurally, the PHIP is a composite of multiple PDs. Conceptually, each HP attribute is related to at least one PD in the solution component. The logical structure of the PHIP is similar to that of the HP; it comprises of five information groups, where each information group contains information corresponding to a core attribute in the current HP.

3.1 User-Modeling: Case Retrieval Procedure

In a CBR context, user modeling involves the generation of a *global user-model* derived based on the similarity between the local user-model (i.e. the HP) and a set of past user-models. Given a local user-model, we retrieve a set of similar past user-models based on similarity measures—referred as ***Total Weighted Distance*** **(TWD)**. In principle, the value of the TWD is derived as the sum of the individual ***Total Distance*** (TD) between the corresponding attributes in the current and past user-models. The set of past user-models, retrieved based on the local user-model, are modified to realize an individual's global user-model that is relative to existing user-models. This process is akin to the case retrieval process in the CBR formalism. To illustrate our case retrieval strategy we present Table 3 that shows an exemplar current HP and a set of past cases available in the case-base. For illustration purposes we will focus on a single HP attribute, namely Acute Disease (AD). In Table 3, the HP section shows that the AD attribute has 3 values (given in uppercase) encoded according to the scheme presented in Table 2—each HP attribute-value code is derived as a combination of the *class-code*, *sub-class-code* and the *element-code*. The disease code 1-1-002 corresponds to *Paratyphoid Fever B* (see Table 2). In response to the given HP the case retrieval mechanism retrieves four past cases. Table 3 illustrates the attribute-values (given in lower case) of existing past cases.

Table 3. An exemplar current HP shown in the shaded area and past cases (4 in total) in the case-base.

	Cases	Acute Disease	Short-Term Illness	Current Symptom	Current Drugs	Allergies
Current Case	**HP**	**AD_1 = 1-1-002_1** **AD_2 = 1-3-035_2** **AD_3 = 2-1-004_3**	SI_N	S_1 S_2 S_N	D_1 D_N	A_1 A_N
Past Cases (PC)	**PC_1**	**ad_1 = 1-1-002_1** **ad_2 = 1-3-035_2** **ad_3 = 2-1-004_3**	si_1 si_m	s_1 s_2 s_m	d_m	a_1 a_m
	PC_2	**ad_1 = 1-2-021_1** **ad_2 = 2-1-003_2** **ad_3 = 1-1-002_3**	si_m	s_1 s_2 s_m	D_1 d_m	a_1 a_m
	PC_3	**ad_1 = 1-1-020_1** **ad_2 = 1-3-035_2** **ad_3 = 2-1-004_3**	----	----	----	----
	PC_{total} *total = 4*	**ad_1 = 3-1-002_1** **ad_2 = 3-1-004_2**				

A domain-specific *similarity matrix* (as shown in Table 4) is used to determine the attribute-level *Degree of Similarity* (DS)—the DS spans from *perfect match* to *close match* to *weak match* and *no match*—between the current and past HP attribute-values belonging to the same attribute. For instance, the attribute values 1-2-2001 and 1-2-2002 will result in a DS of 'close match' as the class and sub-class codes match, whereas the DS between the attribute values 1-2-2001 and 1-3-3004 is a 'weak match' because only the class code is similar.

Table 4. Similarity Matrix used to determine DS between the current HP and past HP attribute values.

Degree of Similarity (DS)	Class Code	Sub-Class Code	Element Code	Numeric Value
Perfect Match	√	√	√	**1**
Close Match	√	√	×	**75**
Weak Match	√	×	×	**25**
No Match	×	×	×	**100**

We trace below the steps involved in the calculation of TWD between a current HP and a set of past HPs, leading to the retrieval of similar past cases.

Step 1 : Determine attribute-level *Distance*

The idea is to establish equivalence between the current HP and a past case's HP at the attribute level. We calculate the DS between each current HP attribute-value with respect to corresponding attribute-value(s) in each past case's HP. Since each HP attribute can have multiple values, we need to individually determine the DS for each current HP attribute-value. The pseudo code for performing the same is given below; for illustration purposes we consider matching the values for the current HP attribute of 'AD' with the corresponding retrieved past case attribute of 'ad_x'.

```
For P = 1 to PC_total {total is the no. of past cases}
      For J = 1 to AD_N {N is the number of AD values in current HP}
           For K = 1 to ad_m {m is the no.of ad values in a past HP}
              compare each AD_J with all ad_K in PC_P using the similarity matrix
              given in table 5such that
              DS[AD_J, ad_K^P] = similarity_matrix(AD_J, ad_K^P )
```

Step 2 : Find the best matching attribute-value in the past HP

For each current HP attribute-value, we proceed to find the best matching attribute-value(s) in the past cases based on the value of DS(AD_x , ad_y). AD_x is deemed to best match ad_y if it has the least DS as compared to all other *ad* values in the same past case. Hence, we select the DS(AD_x,ad_y) that has the minimum value. This is achieved by determining the *Distance* (D) as shown in the pseudo code below:

```
For P = 1 to PC_total
        For J = 1 to AD_N
              For K = 1 to ad_m
```

$$D_{AD_J}^{ad_K^P} = \min(DS[AD_J, ad_K^P])$$

where $D_{AD_J}^{ad_K^P}$ implies that AD_J best matches with the attribute-value ad_K in the past case P, and the variable D holds the distance measure between AD_I and ad_K which would be the minimum for all ad values in the past case P. Note that we individually calculate $D_{AD_J}^{ad_K^P}$ for all the past cases. Using the current HP 3and the set of past cases given in Table 3, we present a trace of the calculation of DS as shown in Table 5.

Table 5. An exemplar trace of the calculation of DS for the current HP and the set of past cases. The minimum DS value for each *AD* against the *ad* attributes is indicated in bold typeface in the shaded cell. The ad_k values given in bold are deemed to best match the corresponding AD_J. The legend ($AD_1 \rightarrow ad_1$) implies that the attribute value AD_1 matches with value ad_1.

P	J	K	DS[AD_J,ad^P_K]	P	J	K	DS[AD_J,ad^P_K]
1	1	**1**	**1 ($AD_1 \rightarrow ad_1$)**	3	1	**1**	**25 ($AD_1 \rightarrow ad_1$)**
		2	75			2	75
		3	100			3	100
	2	1	75		2	1	75
		2	**1 ($AD_2 \rightarrow ad_2$)**			**2**	**1 ($AD_2 \rightarrow ad_2$)**
		3	100			3	100
	3	1	100		3	1	100
		2	100			2	100
		3	**1 ($AD_3 \rightarrow ad_3$)**			**3**	**1 ($AD_3 \rightarrow ad_3$)**
2	1	1	75	4	1	1	100
		2	100			2	100
		3	**1 ($AD_1 \rightarrow ad_3$)**				
	2	**1**	**75 ($AD_2 \rightarrow ad_1$)**		2	1	100
		2	100			2	100
		3	100				
	3	1	100		3	1	100
		2	**25 ($AD_3 \rightarrow ad_2$)**			2	100
		3	100				

Table 6. Calculation of TD for the current HP attribute of AD (considering the shaded cells in Table 5).

	AD_1		AD_2		AD_3		
Past Case	**Matches With**	**DS**	**Matches With**	**DS**	**Matches With**	**DS**	**TD_{AD} (N = 3)**
PC_1	ad_1	1	ad_2	1	ad_3	1	**1.00**
PC_2	ad_3	1	ad_1	75	ad_2	25	**33.67**
PC_3	ad_1	25	ad_2	1	ad_3	1	**9.00**
PC_4	--	100	--	100	--	100	**100.00**

Step 3 : Calculate the *Total Distance* for each current HP attribute

For each current HP attribute, we calculate its distance with the corresponding attribute in a specific past case. Since each attribute can have multiple values, the TD is derived via an average of the individual matching D's associated with the multiple attribute-values. Note that a D_{AD} value of 100 refers to a non-match and hence it will not included in the calculation of the TD. We calculate a separate TD for each current HP attribute for all past cases as follows:

```
For P = 1 to PC_total
```

$$TD_{AD}^{P} = \sum_{K=1}^{N} D_{AD_K}^{ad^P} / N$$

where TD_{AD}^{P} refers to the total distance of the current HP attribute of AD with the same attribute in the past case P, and N is the number of non-zero D_{AD}. Note that the same procedure is applied to calculate the TD for the other four attributes in the current HP, given as TD_{SI}, TD_S, TD_D and TD_A. In Table 6, we illustrate the calculation of TD for the current HP attribute of AD as per the procedure mentioned above.

Step 4 : Calculate the *Total Weighted Distance* for each past case

We use the individual TD values for all the current HP attributes with respect to a specific past case to calculate the TWD between the entire current HP and the HP component of a specific past case. Recall, that earlier we were calculating distances at a attribute level but now we calculate distance at the case-level. The case-level distance is weighted—i.e. the user can modulate the influence of each attribute in the determining the similarity between the current and past HPs. The pseudo code to calculate the TWD between the current HP and a specific case P is given as follows:

For P = 1 to PC_{total}

$$T1 = TD_{AD}^{P} * W_{AD} + TD_{SI}^{P} * W_{SI} + TD_{S}^{P} * W_{S} + TD_{D}^{P} * W_{D} + TD_{A}^{P} * W_{A}$$

$$T2 = W_{AD} + W_{SI} + W_{S} + W_{D} + W_{A}$$

$$TWD^{P} = T1 / T2$$

where TWD^P is the weighted distance between the current HP and the past case *P*. Using the TD values calculated for the attribute AD (as shown in Table 6), in Table 7 below we illustrate the calculation of the TWD of the current HP with the HP component of the four past cases given in Table 3. Since we have performed calculations for the AD attribute only, we give hypothetical TD values in Table 7 for the remaining HP attributes to facilitate the calculation of TWD for each past case.

Step 5: Retrieve similar past cases to form global user model

Finally, we retrieve all past cases that have a TWD less than a pre-defined threshold. In Table 8 below, for illustration purposes we have set the threshold to 55 and we apply the same threshold over the TWD values calculated earlier to retrieve past cases. It may be noted that PC_1, PC_3 and PC_2 have TWD less than the threshold and hence are retrieved, whereas PC_4 with a TWD of 100 is not retrieved.

Table 7. Calculation of the TWD of the current HP with the HP component of the past cases. It may be seen that past cases 1, 2, and 3 have a TWD below the threshold and hence are retrieved, whereas past case 4 is not retrieved.

Past Case	TD_{AD}	TD_{SI}	TD_S	TD_D	TD_A	TWD	Case Retrieved (TWD < 55)
PC_1	**1.00**	*50*	*50*	*50*	*50*	**40.20**	√
PC_2	**33.67**	*50*	*50*	*50*	*50*	**46.73**	√
PC_3	**9.00**	*50*	*50*	*50*	*50*	**41.80**	√
PC_4	**100.00**	*50*	*50*	*50*	*50*	**60.00**	×

3.3 Adaptive Personalization Via Compositional Adaptation

The outcome of the user modeling stage is the generation of a global user-model in terms of a set of past user-models (i.e. past cases) that have a high degree of similarity with the current user-model. From Table 7, it can be concluded that the *global user-model* is based on *PC_1, PC_2 and PC_3.*

Next, in the adaptive personalization stage (also regarded as the solution generation stage in a CBR context), we proceed to personalize the solution component of the retrieved past cases to generate an individual-specific PHIP. As per our compositional adaptation approach, for each current HP's attribute-value we select the most relevant past sub-solution (given in terms of a specific PD) from the entire solution of the retrieved past cases. The sequence is as follows: (i) Each attribute-value of the current HP is mapped to a set of matching attribute-values in the retrieved past cases; (ii) the PD associated with the matching past case's attribute value is selected; and (iii) the set of selected PDs are systematically amalgamated to yield the most representative PHIP. We explain below our compositional adaptation technique. For explication purposes we will continue to use the AD attribute of the HP, however the same method is applied to all the remaining attributes of the current HP.

Step 1: Calculate the *Relative Distance* of each matched current HP attribute-value

We determine the *Relative Distance* (RD) of each current HP attribute-value with respect the attribute-level distance (calculated earlier as D) and case-level distance (calculated earlier as TWD) for each retrieved past case. We believe that only the inter-element distance between the current HP and the retrieved past case cannot determine the suitability of the associated PD, rather both the attribute-level and the case-level distance measures need to be jointly taken into account. Therefore, we calculate and use the RD (as opposed to the absolute D calculated earlier) as follows:

For P = 1 to $PC_{retrieved}$

For K = 1 to N {N = total no. of matched AD values}

$$RD_{AD_K}^{ad_x^P} = (D_{AD_K}^{ad_x^P} * W_{Field} + TWD^P * W_{TWD}) / (W_{Field} + W_{TWD})$$

where $RD_{AD_K}^{ad_x^P}$ is the relative distance between the current HP attribute-value AD_K and the corresponding attribute-value ad_x in the retrieved past case *P* (shown in Table 8). Here, we introduce two user-specified weights $W_{Attribute}$ and W_{TWD} to impact the influence of attribute-level and case-level similarity, respectively. Both $W_{Attribute}$ and W_{TWD} are inversely proportional to each other. The sum of $W_{Attribute}$ and W_{TWD} equals 1 and is set to 0.3 and 0.7, respectively. This implies that we emphasize case-level similarity when performing compositional adaptation on the retrieved past solutions to derive the new solution.

Table 8. Calculation of RD of each AD attribute-value with the corresponding attribute-values in the three retrieved cases. Next, the calculation of the NRD for each PD associated with a matching *ad* value. Since each *ad* attribute value is associated with a PD, we show the *ad* attribute-value so as to identify the associated PD which will have the same index number as the corresponding *ad* attribute-value.

K	P	TWD^P	ad_x^P	$D_{AD_K}^{ad_x^P}$	$RD_{AD_K}^{ad_x^P}$
1	1	40.20	1-1-002	1	28.44
	2		1-1-002	1	33.01
	3		1-1-020	25	36.76
2	1	46.73	1-3-035	1	28.44
	2		1-2-021	75	55.21
	3		1-3-035	1	29.56
3	1	41.80	2-1-004	1	28.44
	2		2-1-003	25	40.21
	3		2-1-004	1	29.56

AD_K	Temp	NRD^P_{ADK}
1	0.092	0.38
		0.33
		0.29
2	0.086	0.40
		0.21
		0.39
3	0.092	0.38
		0.26
		0.36

Step 2 : Calculate the Normalized Relative Distance of current HP attribute-values

To acquire a uniform range of RD's over the entire set of current-HP attribute values we normalize the RD values in the range of 0 – 1. This is achieved by calculating the *Normalized Relative Distance* (NRD) of a specific current HP attribute-value (say AD) over the entire set of retrieved past cases (i.e. $PC_{retrieved}$) as follows:

For K = 1 to AD_N

$$Temp_{AD_K} = \sum_{P=1}^{PC_{retrieved}} 1 / RD_{AD_K}^{ad_x^P}$$

Next, the NRD for the attribute-value AD for a retrieved past case *P* is calculated as:

$$NRD_{AD_K}^{ad_x^P} = 1 / (Temp_{AD_K} * RD_{AD_K}^{ad_x^P})$$

where $NRD_{AD_K}^{ad_x^P}$ is the normalized relative distance between the current HP attribute-value AD_K and the attribute-value ad_x in the past case *P*, as shown in Table 8.

Step 3 : Determine the appropriateness of available solution components

Since each current HP attribute-value can match with one or more past case attribute-value, there exist the possibility that a current HP attribute-value can be associated with multiple PDs. We select the most appropriate PDs (from the set of collected PDs) for each current HP attribute-value. This is achieved by determining the *Appropriateness Factor* (AF) of all the available PDs via the aggregation of their NRD over the entire set of retrieved cases in the following manner:

For I = 1 to AD_N

$$AF_{AD_I}^{ad_x^P} = \sum_{P=1}^{PC_{retrieved}} NRD_{AD_I}^{ad_x^P}$$

where $AF_{AD_I}^{ad_x^P}$ is the appropriateness factor for the PD associated with the attribute-value ad_x in the past case P with respect to the current HP attribute-value of AD_I.

Next, we compare the AF for each PD against a pre-defined threshold; if the AF of a PD exceeds the threshold then it is included in the final solution. Table 9 shows the calculation of the AF for the available PDs (as shown in Table 8) and the selection of the most 'appropriate' PDs.

The Final Output: A Personalized Hypermedia Document Comprising Multiple Sub-Documents

In Table 9, it may be noted that at the conclusion of the final calculations of AF for each candidate PD, we have a set of 6 distinct PDs (9 in total). For attribute AD_1, we have two distinct candidate PDs: PD 1-1-002 from two past cases—i.e. PC_1 and PC_2; and PD 1-1-020 from PC_3. Since, PD 1-1-002 is recommended by two past cases it has a stronger case for being included in the final solution, as is reflected by its AF value. The same applies for the PDs selected for the other AD values. In this way, our compositional adaptation strategy favors those PDs that are part of multiple past solutions which intuitively makes sense.

Table 9. Selection of the most appropriate PDs based on their AF values, such that the selection criteria is $AF_{PD} > 0.35$. The selected PDs represent the final solution component—i.e. a PHIP specific to the current HP.

AD_N	$ad^P \rightarrow PD^P$	NRD	AF_{PD}	Selected PDs as the FINAL SOLUTION
AD_1 **(1-1-002)**	ad^1 = 1-1-002 ad^2 = 1-1-002	0.38 0.33	**0.71**	√ **(1-1-002)**
	ad^3 = 1-1-020	0.29	0.28	×
AD_2 **(1-3-035)**	ad^1 = 1-3-035 ad^3 = 1-3-035	0.40 0.39	**0.79**	√ **(1-3-035)**
	ad^2 = 1-2-021	0.21	0.21	×
AD_3 **(2-1-004)**	ad^1 = 2-1-004 ad^3 = 2-1-004	0.38 0.36	**0.74**	√ **(2-1-004)**
	ad^2 = 2-1-003	0.26	0.26	×

The adaptive personalization of the final solution is evident in the composition of the final PHIP which comprises three PDs, one each for AD_1, AD_2 and AD_3. More interestingly, the selected PDs originate not necessarily from just one past case, rather they are collected over the entire set of retrieved cases on a attribute-level similarity basis. For instance, the solution for AD_1 is collected from past cases 1 and 2, whereas the solution for AD_2 is collected from past cases 1 and 3. This is in accordance with our compositional adaptation approach that posits the collection of the most appropriate sub-solutions from all the retrieved past cases as opposed to the selection of the entire solution of the most similar past case.

4. A Personalized Health Information Generation and Delivery System

We have implemented an intelligent info-structure that incorporates the above-mentioned compositional adaptation based adaptive hypermedia development technique for the generation of personalized healthcare information (as shown in Figure 3).

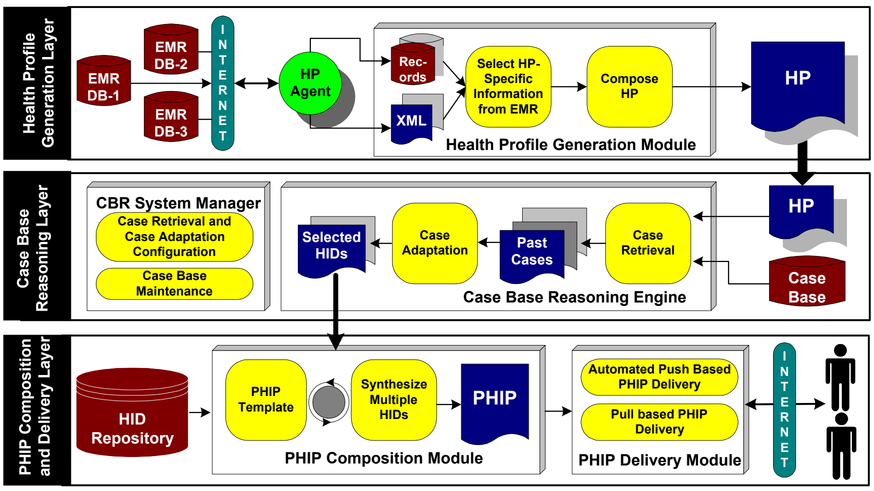

Figure 3. The functional architecture of our Personalized Healthcare Information Generation and Dissemination System (PHIGDS)

5. Concluding Remarks

When considering the design of a hypermedia system for supporting the customized information needs of individuals, the use of adaptive hypermedia appears as an interesting paradigm for tailoring generic information to personalized information in line with the user's needs and interests. Central to any hypermedia system is a user model derived using a number of techniques. We have demonstrated that CBR provides an interesting alternative to developing user models, in which the user model is adaptively derived based on a corpus of existing user models; and the adaptive hypermedia development aspect corresponds well with CBR's analogy-based solution generation.

In this paper, we have presented an interesting compositional adaptation technique that is applied to problem of adaptive hypermedia design in the healthcare domain. We conclude that our compositional adaptation approach is well-suited personalized hypermedia document generation, whereby the hypermedia document is a composite of multiple fine-grained *information 'snippets'*. In this scenario, we design a personalized hypermedia document by selecting the most appropriate sub-solutions (or information snippets) from all the retrieved past cases. From our experiments, we have determined that (a) the higher the frequency of occurrence of a particular sub-solution across the various retrieved past cases, the higher its appropriateness towards the current solution; and (b) the appropriateness of a particular sub-solution is more accurately determined by taking into account both its individual appropriateness factor (vis-à-vis some problem defining attribute) and the similarity measure of the entire past case with the current problem description.

Finally, we believe that the said compositional adaptation mediated personalization approach can be used for a variety of applications such as education material personalization based on academic performance, stock market reporting and advice based on user-specific portfolio, tourist information based on user-specific criterion and so on; with the only constraint being the availability of a large volume of past cases. The work presented here is a successful 'proof of concept' and a trial version of our *Personalised Health Information Generation and Delivery System* is currently deployed for use by a small set of users. The quality of personalization and the impact of the personalized hypermedia document are open questions, which will be addressed at the next stage.

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