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# Generic Temporal and Fuzzy Ontological Framework (GTFOF) for Developing Temporal-Fuzzy Database Model for Managing Patient's Data

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**Abstract:** A generic temporal and fuzzy ontological framework (GTFOF) is presented, specific to the task of designing temporal and fuzzy database system. The framework includes both time and fuzzy dimension in deigning patient information system in a hospital environment. The proposed framework is essential for developing knowledge management systems (KMS) in healthcare environments. The importance of ontological models in the development of patient information system is well established and it provides the logical and formal mechanism for building KMS. Healthcare information systems may include complex data such as time stamped data and fuzzy data about patients. This paper highlights the importance of identifying the key concepts for building an ontological framework to manage both temporal and fuzzy information content. The proposed generic framework is capable of integrating and mapping the proposed ontological model into an effective database design for implementation.

**Keywords:** Temporal and fuzzy ontological framework, knowledge management systems, healthcare systems, patient information system, temporal and fuzzy database system
**Categories:** I.2.4

## 1 Introduction

Use of information and communication technology (ICT) is significantly increased in managing healthcare information systems, in recent years, which rapidly changes the concepts of maintaining patient's health data in a hospital/clinic environment, ([Dick *et al.* 1997]; [Fagan and Shortliffe 2001]). Electronic patient health records [Ghani *et al.* 2008] are maintained in hospitals using database management systems and can be accessed and managed using query language support.

Time related data is of immense importance in developing an effective patient database system in a hospital or clinical system. Most of the clinical data has a temporal dimension whether it relates to diagnosis, treatment or patient monitoring. Adding temporal dimension to the clinical data changes the definition of facts and the relationships between facts, changing the complete semantics. For example, patient's blood pressure (BP), and body temperature fluctuates during the day ($10^{th}$ Nov. 2010) or during days ($10^{th}$ Nov. 2010 to $12^{th}$ Nov. 2010). Thus patient's historical information is of utmost importance for an effective, appropriate and timely patient care, which can be later used for any reasoning paradigm for better decision support.

Temporal database management for healthcare services in hospitals is a complex task and it is the combination of many disciplines such as artificial intelligence, formal logic, databases, medicine and health services and communication technology. Classical relational database model is the most widely used model in the industry but it doesn't provide inherent structure for time management. There are many extensions to the relational model to incorporate temporal information and some of these extensions are also implemented [Jensen and Snodgrass 1999]. Research community with diverse backgrounds has done lot of work to come up with solutions of the problems in the area of health informatics in general and health management systems in particular ([Augusto (2005)]; [Combi and Shahar 1997]; [Shahar and Combi 1998]). Researchers have proposed models for time oriented clinical databases such as ([Das and Musen 1997]; [Das and Musen 2001]; [Nigrin and Kohane 2000]).

Developing ontology for patient data for healthcare systems is another important concern. Ontology helps to identify the important concepts, entities and relationships that exist in healthcare system. This information includes: patients, diagnosis, treatments, diet plan and patient monitoring. Healthcare systems also includes information regarding physicians, specialties, duties, para-medical staff, and many other related activities such as pharmacy, OT/ICU (intensive care unit) management and billing system.

Time has a very important factor in the process of patient data management and therefore a temporal patient care framework is desirable in accordance with standard clinical guide lines. Maintaining data in healthcare settings is important in many perspectives. However, it is significantly important for knowledge management of supporting practitioners in decision making. It is vital for better treatment and resource optimization. Ahsan *et al.* (2009) presented a context based knowledge management concept in healthcare. 'Context' itself has various viewpoints such as duration, time, location and reasons for treatment decisions. If 'context' is maintained comprehensively through information system (IS) then it provides enhanced support to healthcare stakeholders for providing improved services [Ahsan *et al.* 2010a]. The services, applications (including application domain and data domain) and technological layers are categories for referencing healthcare [Ahsan *et al.* 2010b].

Mobile technology is used to integrate contextual aspects of healthcare components with healthcare application [Ahsan *et al.* 2010c]. These contexts are volatile in nature. If these volatility/temporal factors are maintained appropriately then it could provide better support for contextualization of healthcare viewpoints. Proper maintenance of temporal dimensions can enable decisions based on the most appropriate information. The 'context' of knowledge (based on environment data/variable) is an abstract view [Ahsan *et al*. 2010c] while temporal dimension of this data is an objective view [Burney *et al.* 2010b]. In the present paper it is intended to explore the objective view and present a model for fuzzy temporal aspect of patients' data management.

Another important issue for a large set of healthcare applications is that of

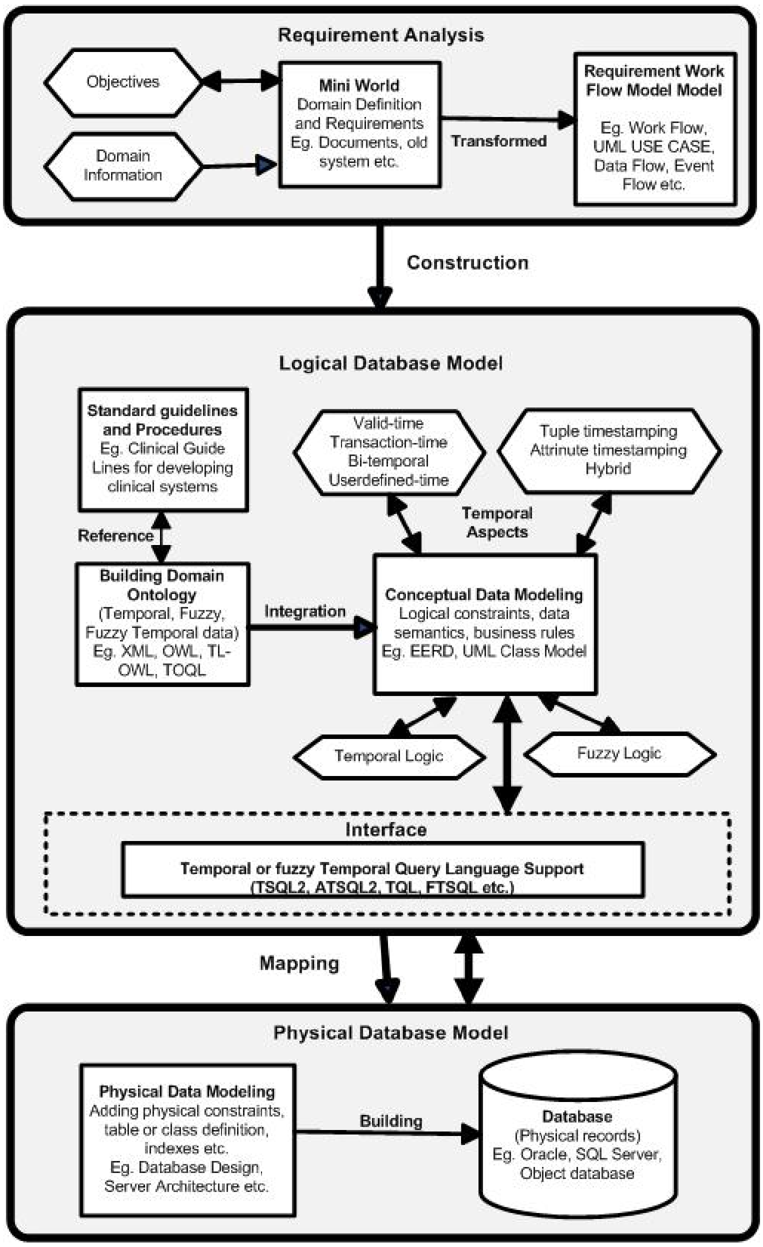


*Figure 1: Generic Temporal and fuzzy ontological framework (GTFOF)*

handling fuzzy data. Patient's data can be categorized as crisp and non-crisp data or fuzzy data. For example patient's condition in an ICU is normal, stable, critical or severe. These characteristics can be represented using fuzzy logic paradigm and fuzzy set theory. There are important contributions in the area of fuzzy databases [Nadeem and Burney, 2011]. There is a need for integrated handling of time and fuzzy dimensions for patient's data. The proposed framework (GTFOF) (figure 1) provides architecture for the development of fuzzy and temporal database systems in a relational database environment.

This paper is organized as follows. The next section presents the investigation structure followed by related work in section 3. Section 4 provides an overview of temporal and fuzzy data abstraction task followed by section 5 i.e., temporal reasoning. Section 6 explores the major components of proposed framework GTFOF. Section 7 is the conclusion which describes the important accomplishments of the proposed framework with its limitations.

## 2 Related work

Fuzzy Ontology Generation Framework (FOGA) proposed by [Tho *et al*. 2006] is considered to be a useful framework for the generation of fuzzy ontology based on fuzzy theory and formal concept analysis. Another fuzzy ontological framework was proposed by Abulaish and Dey in (2006) which uses the idea of a concept descriptor. Ma *et al.* (2008) presented a fuzzy ontology generation framework from the fuzzy relational databases, in which the fuzzy ontology consists of fuzzy ontology structure and instances. Most of the proposed ontological frameworks lack the representation of semantics between fuzzy objects or entities especially in the form of relationships.

Fuzzy database model is also an important research area over the years. Attempts have been made to extend the relational model to incorporate the non-crisp nature of data ([Chen, 1985]; [Zvieli and Chen, 1986]; [Petry, 1996]; [Chaudhry *et al.*, 1999]; [Vert *et al.* 2000]). However there are few successful implementations ([Medina *et al.* 1994 & 1995; Galindo, 2005]). Generic ontological frameworks for building fuzzy temporal databases are not found in the literature. GTFOF (figure 1) highlights the importance of such ontological framework and integrates with the conceptual data model.

In reality most of the application domains involving temporal semantics also involve fuzzy semantics. Work on the integration of the temporal and fuzzy dimensions in the context of relational model has been carried out ([Kurutach, 1998]; [Deng and Zhang, 2008]; [Deng *et al*., 2008]). GTFOF includes the capacity to identify and represent fuzzy and temporal data concepts in a relational database model.

This framework is being incorporated into the healthcare environment, which allows users to design databases for hospitals for managing patients. Modeling of huge healthcare database applications [Gold and Ball, 2007] involving both temporal data and fuzzy data is a great challenge for database researchers ([Combi, *et al.*, 2007]; [Chi and Horng, 2008]). The research has investigated the patients' data with respect to time and fuzzy nature of data, and proposed a conceptual fuzzy temporal relational model [Burney *et al.*, 2010b].

## 3 Investigation Structure

This research uses structured data for implementation of the proposed framework. Patient's data can be classified as temporal, non-temporal, fuzzy and fuzzy-temporal in a hospital environment. Data has been collected from various hospitals and interacting with healthcare professionals the necessary requirements for developing patient information system have been determined.

The analysis of the data is accomplished with the help of a requirement analysis work flow model and the study highlights the generic data requirements on the basis of mini world. The other important task was the development of patient data ontology in line with the standard clinical guidelines and procedures. Patient ontology model is then integrated to patient database model with the help of logical paradigms.

The integration of temporal and fuzzy abstraction task for building ontological model has been accomplished. The ontology is developed using domain information with the help of domain experts such as doctors, medical staff, hospital administration and patients. We have also included the existing ontological models for patient data for this purpose ([Jurisica *et al.* 2004]; [Wache *et al.* 2001]; [Parry (2005)]).

## 4 Temporal and Fuzzy Data Abstraction

Temporal abstraction is a process to identify the concepts associated with time-stamped data. The Temporal data abstraction ([Shahar (1994)]; [Stacey and McGregor (2007)]) task is a key to developing an ontology based on a specific domain. Temporal abstraction is an approach for reasoning about historical databases that allow multiple abstraction levels. The use of temporal abstraction is important especially for decision support applications which consume abstract concepts [Balaban *et al*. 2003].

Temporal abstraction can be classified as simple or complex. The former refers to the raw temporal facts defined over an interval whereas the later refers to the relationships which exist between different temporal abstractions over different intervals. For instance a medical domain where patient's sugar level is monitored over a time period is an example of simple temporal abstraction and the sugar level of the same patient monitored over different time intervals is an example of complex temporal abstraction. In contrast, fuzzy abstraction is a process to identify the concepts associated with non-crisp or imprecise data.

Most real world applications require temporal information such as stock market analysis, inventory management, portfolio management, insurance applications, monitoring systems, health care applications etc. Significant contributions in use of time oriented data in clinical and medical domain have been made by ([Chittaro and Dojat 1997]; [Combi *et al.* 2010]; [Terenziani *et al.* 2005]). Shahar (1994 & 1997) developed methods and systems for visualization of domain specific temporal abstractions.

Domain knowledge is very essential for developing knowledge base systems. It provides an interface between the temporal abstraction task and the domain expert. Temporal and fuzzy data abstraction in a medical domain based on the model proposed by [Zhou and Hripcsak 2007] as shown in figure 2. The temporal abstraction task for a new domain relies totally on a predefined set of four knowledge categories [Shahar (1994)].

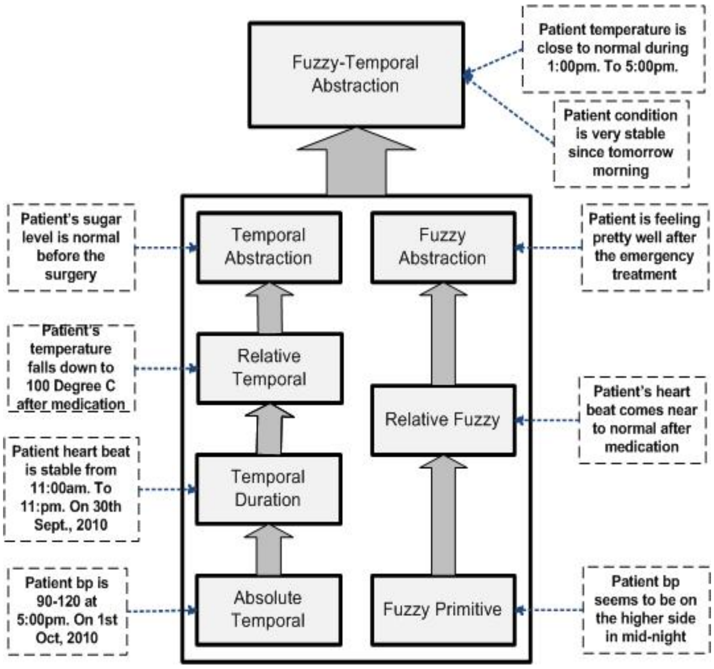


*Figure 2: Fuzzy-temporal abstraction*

1. Structural knowledge: Interrelationship of different data items or to define relationships between them such as generalization-specialization or composite structures. For example patient is classified as critical or a patient might have multiple diagnoses.
2. Classification knowledge: grouping of different entities on the basis of criteria such as blood platelet counts that ranges from normal, low or very low.
3. Temporal semantic knowledge: Recording of temporal facts and the relationships between these temporal facts over a period of time such as comparing blood pressure of a patient at midnight for one week or comparing it with other patients in the same group.
4. Temporal dynamic knowledge: Persistence of the value of a parameter over time.

## 5 Temporal Reasoning

Patient's data is captured for a hospital/clinical database can be considered as structured data and unstructured data [Zhou and Hripcsak 2007]. Structured data refers to the data that is stored in a row/column position in a relation such as patient's personal details (id, name, address, age, gender, etc), patient's billing detail (OPD cost, room charges, medicine cost, etc.). Unstructured data refers to the data which cannot be easily defined in tables and it requires other methods to store in the database such as pictures, X-rays, Magnetic resonance imaging (MRI), computed tomograpphy (CT) scan, ultra sonography and test reports, documents etc. Time oriented clinical systems have a very complex nature and it can be further divided into two classes, data for routine clinical and medical tasks and data for temporal inference and mining procedures. [Combi and Shahar 1997].

The clinical time oriented data is not only important for recording historical information regarding events but in fact it is used to improve the critical decision making process, which involves physicians and other healthcare professionals. The temporal data captured is extremely useful for physicians to abstract such results into meaningful and broad concepts and to detect significance between the data items and the abstract concepts. The temporal abstraction task [Shahar (1997)] is further extended to discover interrelationships between different abstractions over an interval of time. For example, monitoring the blood pressure of a patient having diabetes over a period of time (two or three days) and to compare it with a group of patients having high blood pressure.

The temporal reasoning process ([Keravnou (1996)]; [Lavrac *et al*. 2000]) cannot be accomplished without effective and robust query language support which may require multiple instances of a patient record (history) for the decision making process. These decisions must be in line with the treatment protocols and clinical guidelines [Dazzi *et al.* 1997]. Examples of such processes which require temporal data abstractions are patient diet plan, patient care, ICU management, patient monitoring etc.

Temporal reasoning process may involve uncertain, vague and imprecise information. Temporal data may itself articulate in a fuzzy way and vice versa [Dubois *et al.* 2003]. Historically the temporal reasoning task and fuzzy set based reasoning process were the main focus of research for the last two decades ([Keravnou (1996)]; [Lavrac *et al.* 2000]). Unfortunately there is not much literature available dealing with managing fuzzy information in a temporal reasoning process [Dubois *et al.* 2003].

## 6 GTFOF Architecture

The basic idea for proposing GTFOF is develop a generic approach for the design of fuzzy and temporal database system. GTFOF combines different approaches for managing fuzzy and temporal data. It consists of three layers i.e. the requirement analysis layer, logical layer and physical layer as described in figure 1.

### 6.1 Requirement Analysis Layer

The requirement analysis layer is fundamental in the GTFOF framework. Requirements are gathered with respect to a specific domain with the help of existing data and domain experts. The knowledge engineer is responsible for identifying the key requirements with the help of work flow models.

The first step towards efficient requirement analysis workflow management is to identify and understand the various aspects of the workflow with the help of domain information. There are some useful conceptual tools available for analyzing and modeling workflow such as UML and data flow diagrams. The choice of tools depends on the application and development methodology. Requirement analysis tools provide the complete and comprehensive analysis of the domain in all its aspects: data, processes, categories and applications.

The development of requirement analysis workflow model is helpful in identifying the important temporal and fuzzy concepts and different data items associated with patients in a hospital environment ([Aalst and Kumar 2001]; [Dazi (1997)]). Patient's history is of utmost importance in medical information system, and it is only possible if we include temporal dimension. For example, patient's sugar level was recorded on Jan 10, 2010 or the sugar level was administered during Jan 15 to Jan 30, 2010. Similarly, other important characteristics are recorded on a single time point, multiple time points or time intervals. There are data items related to patient where we have non-crisp nature of data called fuzzy data. For example the patient heart beat which is continuously monitored and it may be normal, low, fast or very fast that can be handled by a fuzzy attribute.

### 6.2 Logical Database Model

The logical layer has two important tasks. First, the development of an ontological model, second an integration of the ontological model with the conceptual data model. In this paper we are using a healthcare application of patient's database and thus we have developed patient's data ontology. Domain ontology can be built by using standard guidelines and procedures in line with the requirement analysis work flow model ([Dazzi *et al.* 1997]; [Nadeem *et al.* 2010]). The development of the conceptual data model is essential for the development of a temporal or fuzzy temporal database system.

The GTFOF solution used the logical layer to organize the view of the framework structure. Requirement analysis work flow model and the ontological model are used to describe the functional requirements of a patient database system. Therefore, the proposed framework provides openness and flexibility for allowing the systems to evolve independently, as new technologies and healthcare system functionalities arise [Ghani *et al.* 2008].

#### 6.2.1 Ontology

Ontology is the categorization and classification of the concepts and semantics related to entities, events, things, terms, roles, associations and relationships related to a specific domain such as ontology for business processes, banking, engineering applications, web ontology and medical domain etc. Ontology is a representation of concepts and visualization of domain knowledge, [Gruber (1993)]. The role of ontology is to provide a comprehensive set of terms, definitions, relationships and constraints for domain. Domain ontology helps in understanding a specific domain in a particular context such as development of information system or designing database applications.

Formal ontology has a long history; it was introduced for the first time by [Husserl (2001)]. ([Bunge (1977)]; [Carnap (1967)]). Guarino *et al.,* (1994) summarizes different definitions of the term ontology. An imporatnt definition comes from the W3C consortium which states that, "Ontology is a term borrowed from philosophy that refers to the science of describing the kinds of entities in the world and how they are related", [McGuinness and Harmelen 2004]. Important contributions in the recent past regarding the classification of ontologies include, ([Gómez-Pérez *et al.* 2004]; [McGuinness (2003)]). Wache (2001) described an excellent survey of ontology based integration of information for KMS.

Database hold data of different forms and multiple data representations are there to store data in a database. The organization of data is itself a great challenge, which determines the importance of a concept and the hierarchy that exists between these concepts. There is a dire need for a formal representation of ontological concepts and the mappings that exist between different heterogeneous data representations. Different languages are used for formal representation of ontological concepts such as OWL [Antoniou and Harmalen 2004], XML [Bedini *et al.* 2008] and TOQL [Baratis (2009)].

#### 6.2.1.1 Time Ontology

Time is not only an issue for philosophers or mathematicians but it has great significance in designing real time information systems [Guarino (1998)]. Time is of utmost importance in monitoring applications, reasoning systems, transaction management systems, planning & control applications etc. Different notions of time have been introduced in the literature ([Etzioni *et al.* 1998]; [Date *et al.* 2003]). These include transaction time, valid time, recording time, execution time, compilation time, booting time, processing time etc.

#### 6.2.1.2 Absolute Time Vs Relative Time

Time has a dual nature, it is absolute and at the same time relative. For instance temperature of a patient recorded at 5:00 p.m. or the duration of a surgery is 5 hours (1:00 p.m. to 6:00 p.m.). Moreover time has a relative nature such as at sunset, day before yesterday, weekend etc. In the medical domain there are many examples of relative time such as patient's blood pressure remains low in the morning as compared to the evenings. It is always difficult to absorb relative nature of time in developing KMS. The exact translation of relative temporal concepts in a medical domain is still in question.

#### 6.2.1.3 Notions of Time

Valid time corresponds to the effective time; it refers to the time when the fact is true in reality. Valid time is always independent of the recording time of the fact in the database [Jensen and Snodgrass 1999]. For example the time at which patient has been admitted to a ward or the time when the medicine will take effect. Valid time databases are also called historical databases. Transaction time corresponds to the recording time of a fact, it has a specified duration which includes start and end times for a particular fact. The transaction time interval normally represents the update operations (insert, delete, change) performed on the data. The database having transaction time dimension is called rollback databases. Research community in general agrees that the complete temporal semantics is represented with the inclusion of both the time dimensions, usually called bi-temporal. Valid time and transaction times are orthogonal in nature.

#### 6.2.1.4 Time Granularity

A granule is a set of time instants perceived as a non-decomposable temporal entity when used to describe, in terms of the granularity G, the symbol is generally used to timestamp a set of data [Bittini *et al.* 2000]. It involves tasks of representing and storing time points and time spans with different and mixed granularities, converting a temporal primitive from one granular level to another, and handling granularity mismatches between two sets of data [Euzenat and Montanari 2004].

Definition of each temporal aspect has some time granularity associated with it and usually different granularities are associated with different temporal attributes. For instance blood pressure of a patient may be required every hour but sugar level is recorded twice a day. Patient's stay in the hospital is recorded in terms of days. Time granularity may be defined in terms of years, months, weeks, days, hours, minutes, seconds etc. Handling of multiple granularities in a database system is a complex task. [Bettini and Ruffini 2003] presents generic user defined granularities along with abstraction level for effective data modeling .

### 6.2.2 Fuzzy Ontology

**F**uzzy ontology [Parry (2005)] is based around the concept that each index object is related to every other object in the ontology, with a degree of membership assigned to that relationship based on fuzzy logic [Zadeh (1975)]. A fuzzy ontology can be defined as consisting of fuzzy concepts, such as fuzzy attributes which may have crisp or imprecise values ([Nagyp'al and Motik 2003]; [Quan *et al.* 2006]). Existing formalisms of ontological frameworks lack in conceptualizing uncertain, vague and non-crisp nature of the objects. Fuzzy logic provides a complete formalism to represent non-crisp or imprecise nature of data. Fuzzy concepts are very much evident and important in many application domains including patient information system in the medical domain. For example a patient's blood pressure, which can be categorized as "very low", "low", "normal", "high", or "very high". The fuzziness regarding blood pressure attribute may be defined using fuzzy set theory.

> Patient(ID) = {z | z is a patient's ID}Patient's
> (BP) = {(90,110),(80,110),(70,100),(80,130), (90,150),…}U {very low, low, normal, high, very high}.

### 6.2.3 Ontologies for Medical Applications

It is very important to develop ontology for health care and medical application regarding healthcare services or clinical procedures in line with the standard clinical guidelines. The medical ontology includes patients, diseases, symptoms, medicines, lab findings & reports and their treatment. There must be a generic ontological framework where health related ontology can be built and is integrated with existing libraries. One such example is ONIONS, [Gangemi *et al*. 1999] which integrates the domain ontology using a library of generic ontological theories. Another example is DOLCE [Masolo *et al.* 2002]) which is based on ON9.2 library. For conceptual development an ontology which covers medical and hospital information is required to develop the patient data management (PDM) system ([Payne and Metzler 2005]; [Salem and Alfonse 2008]). Figure 3 represents temporal ontology for patient's data.

### 6.3 Conceptual Data Modelling

There are many extensions to the classic entity relationship model incorporating time dimension found in the literature [Gregersen and Jensen 1999]. However, there are few extensions of ER model for handling imprecise data and are presented in [Nadeem and Burney, 2011]. The proposed framework GTFOF, describes the two essential components for designing conceptual data model. First is the time-stamping approach i.e. either attribute time-stamping or tuple time-stamping. Second, the choice of time attributes valid time, transaction time or user defined time attributes. Figure 4 represents an extended entity relationship model to incorporate fuzzy and temporal aspects for patient's database [Burney *et al.* 2010b].

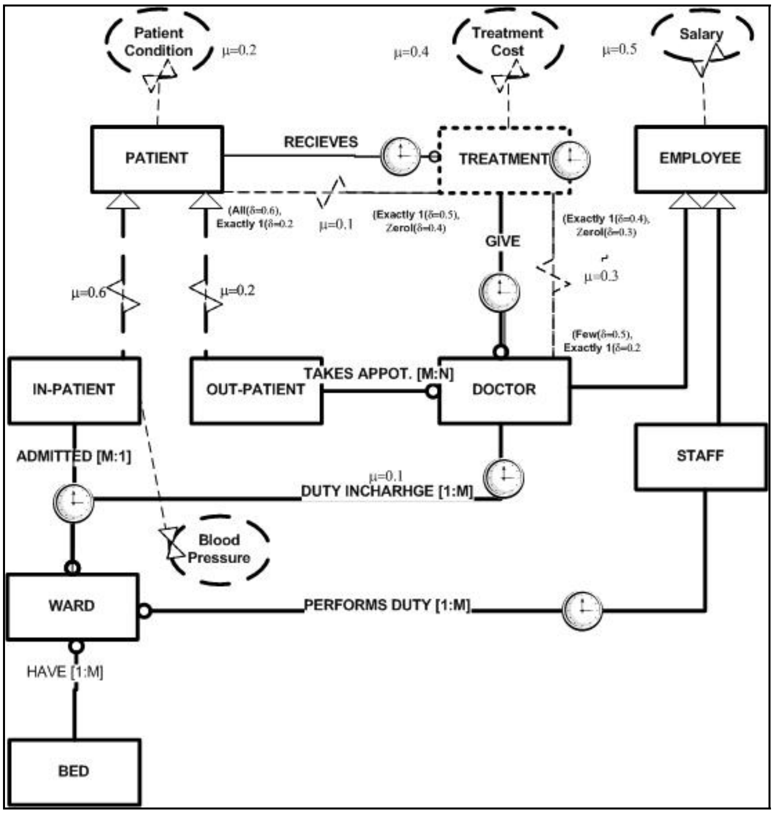


*Figure 4: Conceptual model for patient data*

### 6.3.1 Temporal Logic for Databases

Temporal logic is derived from a branch of applied modal logic. Temporal logic is focused on defining propositions changing with time and it gives formal representation of propositions or facts whose truth value changes with time [Chomicki and Toman 1998]. Temporal logic is successfully used in many applications including, reasoning in natural languages, verification and validation of concurrent programs, monitoring applications, temporal planning and in temporal knowledge representations. Temporal logic has been successfully used in databases [Gabbay and McBrien 1991] and also in the development of a formal query language for temporal databases [Chomicki and Toman 1998].

Temporal logic, by virtue of its internal semantics provides the basis for developing temporal query language. TQuery, Templog, TSQL2, ATSQL2 and TQL are examples of temporal query languages developed using temporal logic [Chomicki and Toman 1998]. First order temporal logic provides an effective mechanism for the development of query language for temporal database.

Research conducted in temporal logic, was influenced by research in computer science and specifically in the field of artificial intelligence. Any attempt to simulate an intelligent agent must incorporate some notion of time. Any system that implements a model of plans and actions must deal with several nontrivial issues relevant to the concepts of time and action.

### 6.3.2 Fuzzy Logic

Fuzzy logic in contrast with the binary logic provides the possibility of intermediate values instead of rigid and crisp boundaries [Zadeh (1970)]. For instance the patient condition can be normal, stable, critical and severe and it also gives the degree of flexibility that how close to these values. In binary logic there are no middle values either the patient is stable or unstable. Fuzzy logic deals with uncertain and imprecise information in a much flexible and organized manner.

#### 6.3.2.1 Fuzzy Relation [Chaudhry et al. 1999]

Let U be the Cartesian product of n universes of discourse $U_1$, $U_2$, $U_3$,….$U_n$. Then and n-ary fuzzy relation r in $U$ is a relation which is characterized by a n-variate membership function ranging over $U$, i.e. $\mu_r : U \rightarrow [0,1]$. A tuple of the fuzzy relation r can be expressed as $t_j = ( u_{j1},u_{j2},\ldots,u_{jn}, \mu_r(u_{j1},u_{j2},\ldots,u_{jn}))$ with $u_{j1} \in U_1,\ldots,u_{jn} \in U_n$.

#### 6.3.2.2 Fuzzy Data Representation: Example

Fuzzy data has its own dynamics and there are many approaches for the representation of fuzzy data reference. The traditional relational data model cannot represent fuzzy data in the form relations due to 1NF assumptions and fuzzy data is many valued. There is no concept of fuzzy data types in the relational model and as well the fuzzy relational operators. However there are proposed extensions of the relational model to incorporate fuzzy data [Nadeem and Burney 2011]. Patient database requires both temporal and as well as fuzzy concepts. In this section we present the representation criteria for our proposed system from conceptual schema to implementation. The fuzzy data definition may have different representation based on the fuzzy membership function value ($\mu$) and the criteria for its implementation. Table 1 represents an example fuzzy temporal relation. Figure 5 represents fuzzy membership function graph for fuzzy attribute blood pressure (BP) using a trapezoidal membership function.

### 6.4 Physical Model

The physical model provides the detailed design of the proposed model and deals with implementation issues pertaining to data storage and accessibility based on the logical model. The physical storage consists of temporal relational data (physical records), base relations, data access methods and physical constraints. Base relations are either temporal or non-temporal, physical constraints are the constraints defined on those relations related to implementation strategy. Data access methods ensure the retrieval of data from the physical medium in an efficient and effective manner. Physical storage retrieves query plan from the logical layer and search the required data in the physical storage and return back to the logical layer.

## 7 Conclusions

This research propose GTFOF framework, which is useful for the specification, design and implementation of fuzzy and temporal databases. This framework is flexible because it is independent of any specific technology and product. Any new model and technology can be integrated to manage and retrieve the desired data. Secondly, it is not restricted to specific temporal or fuzzy features. New features either temporal or fuzzy may be integrated. Another advantage of our proposed framework is the integration and mapping of fuzzy and temporal ontology model with the conceptual database model. We have based on the knowledge integration system built on the ontology model and the work flow model for temporal and fuzzy database design. The mapping of temporal, fuzzy and fuzzy-temporal ontology is well defined and integrated with the conceptual model. The paper presents different ontological approaches specifically in the context of temporal database management with respect to the representation, mappings and relevance with the system.

GTFOF is different from other models by providing a generic approach for designing temporal and fuzzy database systems. There are few limitations of the proposed framework. First, GTFOF mainly deals with structured data and does not define techniques for the management of unstructured data or multimedia content. Secondly the framework is limited to the extension of relational database model and there are other approaches such as object oriented database model. This research uses the healthcare domain to demonstrate the temporal abstraction process for patients and related entities which is necessary for hospital environment.

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