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A Knowledge-Based Prototype to Support the Intelligent Diagnosis of High-Risk Pregnancy

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Abstract
High-risk pregnancy identification (HRP) involves data interpretation and analysis by experts of pregnancy characteristics, and similar prior experiences; this task can be complex depending on the characteristics of the pregnancy. To facilitate this task in Chile, a prototype system based on knowledge that, combining the available information (statistical data, background reported in specific papers for pregnancies in Chile and others worldwide, etc.) with the experience of experts, can support physicians in the task of identifying characteristics of risk pregnancies and can help to estimate morbidity in a neonate is proposed. This prototype of intelligent system uses symbolic representation, rules of inference and knowledge (from the expert and previous cases available in the literature), logic programming and a Java interface to generate interpretations of neonatal morbidity. Knowledge of the system is separated into knowledge bases: (i) factors (pathologies) of the mother that influence a pregnancy and (ii) factors related to the evolution of pregnancy. This paper shows how using the development technology of a knowledge-based system with the statistical analysis of data of the Chilean population and expert knowledge has generated a valid tool that can be useful in in the labor of the specialists working with high risk pregnancies.

Keywords: Knowledge-based system; High-risk pregnancy; Neonatal morbidity; Pregnancy risk factors

Introduction

Current society and particularly the domain of health have experienced an increasing influence of Information and Communication Technologies (ICT). Specifically, in the medical field ICTs are being widely used [1], e.g. hospitals and health research centers are using data and expert knowledge in determining the evolution of certain cancers [2]. Chile is no stranger to this evolution in medicine and specifically in the area of control of pregnancies, births, and diseases that may develop around the first months after childbirth, data is being collected (reported for example in [3]), Perinatal Guide or documents such as [4–6].

Despite of the efforts being made by the Chilean government, it has not been possible to identify in the bibliographic review an expert system to support specialists in the task of identifying risk pregnancies. These specialists have and use protocols and statistical data from previous experiences to support the task of identifying risk pregnancies and possible neonatal morbidity. Making available to specialists a system of prediction of morbidity in neonates, by interpreting characteristics of such situations [2,7], may help better control a risk pregnancy and decrease cases of neonatal morbidity.

A pregnancy[1] can lead to a high-risk pregnancy at any time during its gestation or just before delivery. It can be understood as a high-risk pregnancy (HRP) when it represents potential complications (illness) for the mother, the fetus, or both [3]. When HRP-type pregnancy is suspected, special care is required to attempt to control the factors that have generated this situation, delivery in an HRP should also be attended by specialists [3].

An HRP can occur for several reasons, for example:

(1) caused by characteristics of the mother: mother's age (women younger than 15 years or older than 42 represent a risk segment [3,5].
(2) pre-existing diseases in the mother or conditions that develop during pregnancy or that appear during childbirth (such as pre-gestational diabetes, lupus, alterations in the blood pressure, heart problems, preeclampsia, etc.) and these elements can affect the neonate [3,6].
(3) preterm birth, understanding preterm birth as birth before week 36 [8], and multiple pregnancies that are considered in some Latin American countries as a high-risk pregnancies [3,4]. If it is a high-risk pregnancy, the woman can also be affected during childbirth. Approximately 15% of pregnant women can develop health disorders such as hypertension or kidney damage or proteinuria (postpartum) at first pregnancy [9]. However, the most affected in a high-risk pregnancy situation is the neonate [7].

Two pregnancy processes typically occur in health centers, pregnancy control and delivery. An intelligent system to aid in the diagnosis of high-risk pregnancies can help specialists to better control a high-risk pregnancy or when a woman is in labor, it may also help to identify possible risks associated with childbirth that may lead to neonatal morbidity. In this sense, the aim of this study was to describes the construction of a prototype of a knowledge-based system to help the tasks mentioned above.

Materials and Methods

In order to construct and validate the prototype, techniques such as those described in [10–13] have been followed. This prototype is an extension of one of the authors' thesis work [7], a prototype of an expert system similar but based on the expert knowledge acquired from an expert in gynecology and obstetrics in Spain and statistical documentation from Spain. The main difference in this work with respect to the previous one is that the expert knowledge used for the rules of inference is centered in the Chilean population, specifically the control of risk pregnancies on Chile (as for example papers [3,6]), as described for other populations [8]. In the construction of the prototype, a new communication has been used between the Java NetBeans[2] interface and the SWI-Prolog[3] inference engine, in order to facilitate the use of the prototype in any computer that supports software applications developed in Java.

Knowledge-Expert and Related Jobs

Cooperation between technology and typical medical tasks such as diagnosis and prediction is now visible. Expert systems provide specialists with valid solutions for tasks such as those mentioned above.

In recent years, attention in smart healthcare systems has been increasing [12,15]. For example, intelligent systems for monitoring pregnancy (such as [9]) or other types of diseases such as certain cancers are currently available. A common element in this type of applications is expert knowledge [8,17] and particularly holds great importance in intelligent systems for medicine [12,18]. In order to have an expert knowledge, it is necessary to initially perform the task of acquiring this knowledge, task known as elicitation [19,20]. After the knowledge has been elicited must be adequately

[1] http://iuhealth.org/womens-health/high-risk-obstetrics
[2] https://netbeans.org/
[3] http://www.swi-prolog.org/

represented to be able to use it [21]. Currently, there are several elicitation techniques: from the experts (with an observation of tasks, questions or protocol analysis), by reviewing documents (such as papers, theses or protocols of action), etc. But this task is time-consuming and requires costly resources such as expert time [19,22] and that such experts are able to clearly express such expert knowledge. A valid alternative in certain domains such as medicine is to use automatic learning techniques [23] or to combine elicitation techniques as described above in what are known as hybrid techniques. The hybrid techniques of elicitation, such as the use of elicits knowledge to create a model to share information and treatment to patients with ovarian cancer, from bibliographic analysis along with automatic learning has already been reported [24]. Furthermore, a proposal to elicit and share information on diseases and treatments based on the philosophy of personalized medicine has also been described [21]. In the present work, a combination of elicitation techniques has been implemented. First, the expert knowledge obtained from human experts has been represented. Second, relevant knowledge was identified in documents such as the Chilean Perinatal Guide [3], reports from the Spanish Society of Obstetrics and Gynecology, and papers particularized in Chilean studies [4,6,25,26]. With this procedure, pieces of knowledge such as the following were identified:

(1) Normal pregnancy: is one that develops during the gestation period without the need for additional treatment and results in spontaneous delivery between weeks 37 and 40.
(2) Pregnancy Risk is the one that requires additional assistance and treatment because it can cause problems/alterations during pregnancy or during childbirth (or both) and can lead to delivery before 36 weeks of gestation.
(3) Normal birth is one that occurs between weeks 37 and 40, after the physiological evolution of dilatation and ending in a normal birth with a child with abilities for extra uterine life.
(4) The remaining cases are considered High-risk pregnancies (HRP).

Usually (5) a diagnosis of a HRP is based on the analysis of some risk factors of the mother (such as biometric parameters, previous pregnancies or "parity", social or environmental characteristics), healthy habits, chronic diseases or developed during Pregnancy or risk factors associated with the fetus (such as size or size not suitable for gestational age).

Intelligent System, Concepts and Related Experiences

Knowledge-based systems (KBSs), also known as Expert Systems, are computer systems that achieve expert-level competence in task analysis and problem-solving in specific domains [20]. A KBS is a type of intelligent system of the Artificial Intelligence area that has been applied in the medical domain since the 80's [9,18,22]. In a KBS, knowledge of the problem is translated into specific data structures and domain production rules, where both are used to infer solutions to domain problems intelligently [12,21]. Artificial intelligence techniques are used in such systems to solve problems and support tasks such as decision-making, diagnosis or learning, in a manner similar to how a human would [27]. Unlike traditional computer systems, in KBS domain knowledge is explicitly represented and separated from the knowledge and algorithms used in the reasoning process, this reasoning process is also based on non-deterministic processes [17].

Currently, KBS experiences in the field of medicine report typical medical tasks, facilitating the daily work of clinical staff [22,28]. One of the tasks where experiences are reported is in the diagnosis. Basically, the diagnosis is the identification of factors that cause problems or dysfunctions, based on observable data (e.g. values of biometric variables) or symptoms described by patient [29]. Since the late 1990s researchers have identified the accuracy of KBS in medicine [15,28,30], the progressive use of such systems in medicine has aroused great interest in recent decades [31], mainly due to the potential benefits to support the diagnosis and daily tasks in medicine [32]. Such systems have also proven useful in tasks such as early warning generation or medical professional training. Concrete examples of KBS to support the diagnosis exists in the literature [2,30], some of them use genetic algorithms [33] while others used artificial neural networks for the diagnosis of breast cancer [34]. Korkmaz and Poyraz [2] also use image processing algorithms to create models and identify patterns that support the diagnosis of breast cancer. Okpor used fuzzy logic classification in an expert system to support the diagnosis of diabetes gestations [29]. A Bayesian network was applied to analyze and learn from concepts and information related to ovarian cancer found in digital documents, and to create a diagnostic support model based on the expert knowledge and learning obtained by the Bayesian network [1].

The Proposal

This proposal consists of a prototype of KBS for the diagnosis of morbidity risk, based on pregnancy control and HRP identification in Chilean women. In the construction of the prototype we follow principles of methodologies of construction of systems based on knowledge as described in [19,35]. The creation of the prototype consists of three phases: first, a knowledge representation was constructed, followed by the implementation of the prototype and validation with human experts; the last phase consists in the validation of the software product.

The knowledge regarding HRP and neonatal morbidity was obtained from experts and digital documents, as mentioned in the introduction (e.g. [3–6,8] and [25,26], to identify the processes used by the expert to Identifying HRP and possible morbidity problems also used expert knowledge, previous case analysis, analysis of Chilean statistical data.

The prototype system model is presented in Figure 1. The first "routine checkup" process is used to identify HRP characteristics in each pregnancy control, and the second "morbidity diagnoses" process is used to identify characteristics of problems in the fetus or in the fetus. A month after delivery (neonatal morbidity).

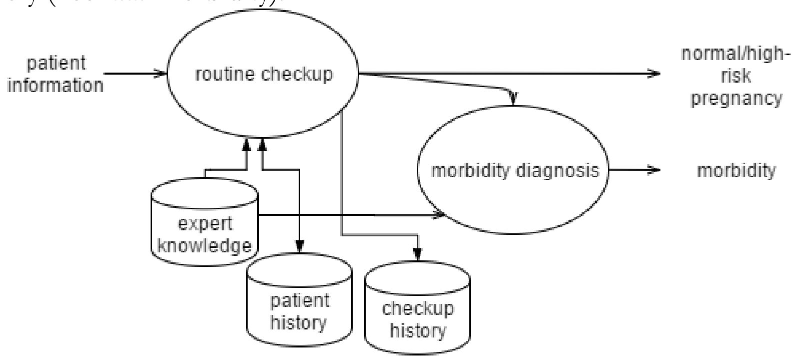

Figure 1. The proposed architecture

In agreement with CommonKADS [19], a semantic network and Frames were constructed with the knowledge acquired in the elicitation phase, Figure 2 and Figure 3 detail these structures. The concepts of the domain and the relationships between these concepts are detailed in Figure 2, usually the Frames provide detail on the concepts [17], Figure 3 details the characteristics and dependency relations of these concepts.

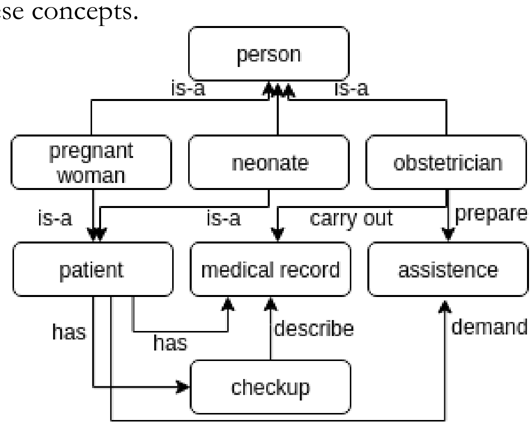

Figure 2. Semantic network

The modeled concepts (Figures 2 and 3) were incorporated into the knowledge base of the prototype. Among the main concepts in this model are:

- *Woman*, it corresponds to the woman who is pregnant. This concept is important for the diagnosis of HRP and morbidity, and the age of the mother, if she have gestational diabetes or heart problems, or preeclampsia are among the main characteristics that help the diagnosis. A synonym for this concept is the mother.
- *Fetus*, corresponds to the baby in gestation. This concept is important in the diagnosis of HRP and morbidity, among the main characteristics that help the diagnosis are the size, weight, number of weeks of gestation.
- *Control*, corresponds to the periodic check that is made to the pregnant woman to know the evolution of the pregnancy. In the Control the characteristics of the mother and the fetus are evaluated.
- *Neonate*, corresponds to a newborn. A neonate can be a term: it corresponds to a child born between week 37 and 40, or it may be premature: a child born before 37 weeks. The characteristics of the neonate, such as size, weight, the number of weeks, etc. Influence morbidity.
- *Childbirth*, corresponds to the moment of the child's birth (when it leaves the mother's body). The characteristics of childbirth (such as the type of delivery, time of delivery, etc.) influence morbidity.

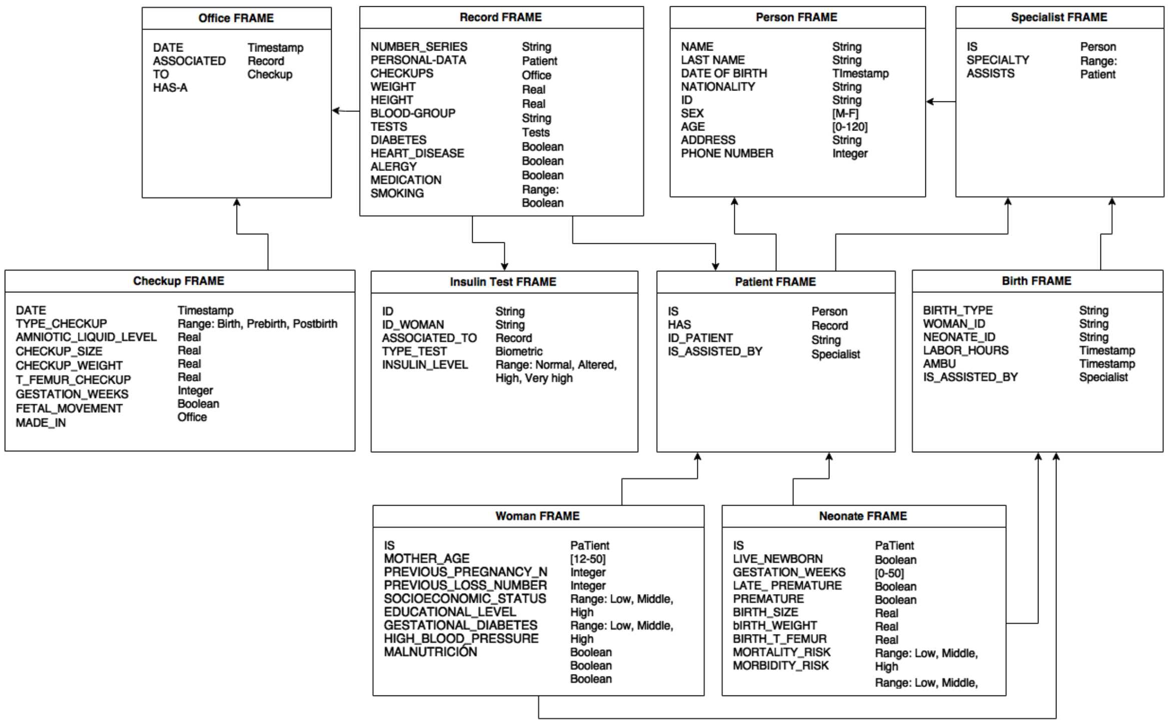

Figure 3. Frame representation of main concepts

The Implementation

The implementation of the proposal consists of two parts, the first is the process of HRP identification, which is necessary to achieve the objective set forth in this paper (generate a diagnosis of neonatal morbidity). This objective is realized in the process of the second part of the implementation. In order to perform the first process, it is necessary to have background information on the pregnant woman, i.e. personal data, data on previous pregnancies, health disorders (diabetes, heart problems, smoking, etc.), and pregnancy control data. With the information elicited production rules were generated that help to diagnose an HRP. It is convenient to emphasize that this diagnosis is done by the specialist and that this prototype serves as the basis for this diagnosis, generating expressions in natural language about the level of risk of an HRP. In total, 35 rules were developed to identify HRP during pregnancy (in controls) and 15 rules to identify HRP just before delivery, these rules are in the style of Eq. 1. Specifically, the rule in Eq. 1 relates the existence of gestational diabetes with minimum values of weight and weeks of gestation obtained from [3,5,8] and the expert's interpretation of this situation as a high risk factor for HRP.

$$\text{gestationaDiabetes}(M,D) \wedge (D=\text{true}) \wedge [\text{sizeWeeksvalue}(S,T) \wedge (T<\text{size\_weeks\_lower\_value})] \wedge [\text{weightWeeksvalue}(W,P) \wedge (P<\text{weight\_weeks\_lower\_value})] \rightarrow \text{hrpRisk}(M, \text{high}) \quad \text{(Eq. 1)}$$

Figure 4 presents the two rules that are used in inference engine to establish the relation of normality between number of weeks and weight of the fetus and between number of weeks and size of the fetus. Both rules support the inference process of the diagnosis of HRP during pregnancy and may also be part of the inferred facts that will be made initial for the inference of a state of morbidity at birth or after childbirth.

```
normal_semana_peso(S, P) :- PesoLimiteInferior =
 [(22,516),(23,560),(24,618),(25,688),(26,772),(27,868),(28,976),(29,1096),
        (30,1233),(31,1384),(32,1552),(33,1756),(34,1986),(35,2211),(36,2443),(37,2682),
        (38,2880),(39,3033),(40,3133),(41,3261),(42,3323)],PesoLimiteSuperior =
        [(22,632),(23,704),(24,792),(25,893),(26,1011),(27,1143),(28,1290),(29,1452),
        (30,1627),(31,1815),(32,2017),(33,2245),(34,2493),(35,2734),(36,2974),
        (37,3216),(38,3424),(39,3595),(40,3746),(41,3871),(42,3966)],
        lookup(S,PesoLimiteInferior,PesoInf),lookup(S,PesoLimiteSuperior,PesoSup),
        PesoInf =< P,P =< PesoSup.
normal_semana_talla(S, T) :- TallaLimiteInferior =
        [(22,27.8),(23,28.9),(24,30),(25,31.2),(26,32.4),(27,33.6),(28,34.9),(29,36.3),(30,37.6),(31,39),(32,40.3),
      (33,41.7),(34,43.1),(35,44.4),(36,45.6),(37,46.8),(38,47.7),(39,48.5),(40,49.2),(41,49.7),(42,50)],
     TallaLimiteSuperior [(22,30.7),(23,32),(24,33.4),(25,34.7),(26,36.1),(27,37.5),(28,38.8),
     (29,40.2),(30,41.5),(31,42.8),(32,43.9),(33,45.1),(34,46.2),(35,47.2),(36,48.2),
    (37,49.2),(38,50.1),(39,50.8),(40,51.3),(41,51.8),(42,52.1)],
    lookup(S,PesoLimiteInferior,PesoInf),lookup(S,PesoLimiteSuperior,PesoSup),
    PesoInf =< P,P =< PesoSup.
```

Figure 4. Example of rules used in the HRP inference engine

The values used in the rules correspond to those described in Table 1, which correspond to the results of studies in the Chilean population.

Figure 5 shows an example of a production rule used to calculate the level of influence of (chronic) pathologies of the mother in the state of pregnancy morbidity.

```
patologias_cronicas(Dpg,C,N,E,M,Enp,Total) :-
      scores = [( diabetesPregestational,3),(cardiopatias,3), (nefropatias,3),(endocrinopatias,3),
              (mesenquimopatias,3),(enfermedadesNeuropsiquiatricas,2)],
              lookup(diabetesPregestacional,score,PtjDpg),...,
              lookup(enfermedadesNeuropsiquiatricas,score,PtjEnp),
       Total is Dpg*PtjDpg + C*PtjC + N*PtjN + E*PtjE + M*PtjM +
       Enp*PtjEnp.
```

Figure 5. Example of rule used in the morbidity inference engine

Table 1. Relationship threshold values: weeks-weight and weeks-height centered on Chilean population [3,5]

weeks-height		weeks-size	
lower limit	upper limit	lower limit	upper limit
(22,516)	(22,632)	(22,27.8)	(22,30.7)
(23,560)	(23,704)	(23,28.9)	(23,32.0)
(24,618)	(24,792)	(24,30)	(24,33.4)
(25,688)	(25,893)	(25,31.2)	(25,34.7)
(26,772)	(26,1011)	(26,32.4)	(26,36.1)
(27,868)	(27,1143)	(27,33.6)	(27,37.5)
(28,976)	(28,1290)	(28,34.9)	(28,38.8)
(29,1096)	(29,1452)	(29,36.3)	(29,40.2)
(30,1233)	(30,1627)	(30,37.6)	(30,41.5)
(31,1384)	(31,1815)	(31,39)	(31,42.8)
(32,1552)	(32,2017)	(32,40.3)	(32,43.9)
(33,1756)	(33,2245)	(33,41.7)	(33,45.1)
(34,1986)	(34,2493)	(34,43.1)	(34,46.2)
(35,2211)	(35,2734)	(35,44.4)	(35,47.2)
(36,2443)	(36,2974)	(36,45.6)	(36,48.2)
(37,2682)	(37,3216)	(37,46.8)	(37,49.2)
(38,2880)	(38,3424)	(38,47.7)	(38,50.1)
(39,3033)	(39,3595)	(39,48.5)	(39,50.8)
(40,3133)	(40,3746)	(40,49.2)	(40,51.3)
(41,3261)	(41,3871)	(41,49.7)	(41,51.8)
(42,3323)	(42,3966)	(42,50)	(42,52.1)

Results

Figure 6 shows the main menu of the Interface with the main options (in the Spanish language) of the prototype. This interface has four main options: the first corresponds to the window for entering personal data (Figure 7), with this window you can link to other windows to enter additional information of the patient, such as entering chronic pathologies (Figure 8). Gestational diabetes, heart disease, etc. The second main option corresponds to the control of the pregnancy (Figure 9) and shows the main options (in Spanish) of the ISHpI prototype. This interface has four options; a brief description of these menus is provided. The first one is related to a new pregnancy control, this option can be used when patients have been entered for routine monitoring of the process with fresh data (for example from laboratory tests). The second option is used to activate a routine checkup 'pregnancy. The third menu option is used when a woman goes into labor, and the last menu option is used to activate the postpartum morbidity.

Figure 6. Main menu interface

Figure 7. Window for registering new patients or entering additional patient data

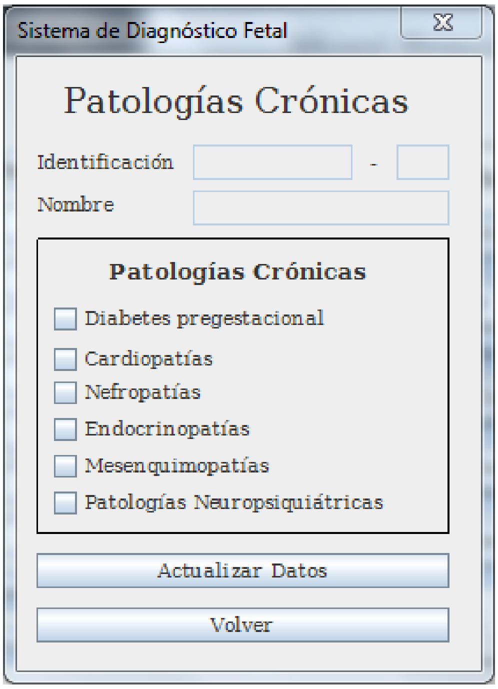

Figure 8. Window for the entry of chronic diseases

Figure 9 has a section called "Recommendations" where the HRP estimate (made by the prototype inference engine) will be shown to the specialist physician. The other two main options: *Control of preterm* and *Control of postpartum* are useful to generate the diagnosis of morbidity. If necessary, the specialist can obtain a diagnosis of morbidity just before delivery. For this, it is necessary that at least two pregnancy controls and maternal data to be stored in the system. In the case of the diagnosis of morbidity with the window of *Postpartum Control*, it is necessary to provide the aforementioned plus the data of the birth, such as birth weight and a number of weeks of pregnancy at the time of delivery.

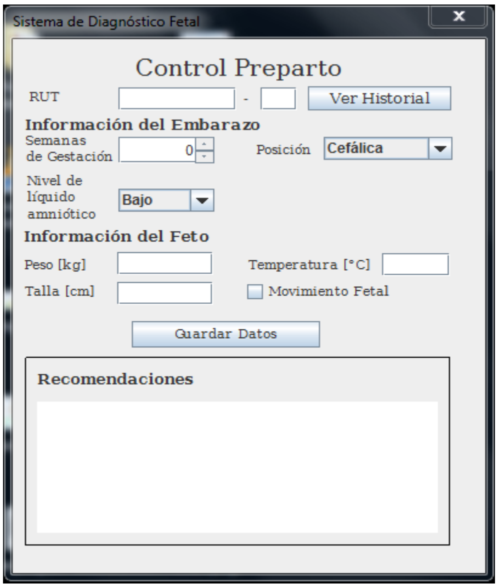

Figure 9. Birth control

Evaluation of Prototype Quality

In order to evaluate the validity of the prototype in the generation of diagnoses appropriate to the reality of Chile, expert systems validation techniques were used in [19] and another one aimed at evaluating the quality of diagnosis based partially on [1,13]. For the first case, we used a set of refining data that are detailed in Table 2. Each line (slot) in Table 2 corresponds to a type case constructed with the help of an expert and values extracted from [3–6]. Table 3 shows some examples of how to perform this first validation, the information from Table 3 was translated from Spanish for a better understanding. In Table 3, the "Expected result" row corresponds to the expert's diagnosis and the "Result obtained" column corresponds to the result of the inference of the system. Using this form of work, the expert's results were compared with the results of the system, considering that the interpretations of the expert were correct and using Eq. 2, the system achieved an accuracy of 74%.

Accuracy= ((success cases) – (failure_cases))/(total cases) * 100% (2)

A second validation was done with a universe of 400 cases extracted from the statistics published by the Department of Statistics and Health Information (DEIS) of the Ministry of Health of the Government of Chile6. The data for these new validation cases were generated using the Monte-Carlo model, the percentiles were taken for each of the parameters available in Chile's health report for the years 2013 and 2014: mother's age, number of weeks of gestation and birth weight

To perform the simulation in Monte Carlo, the ranges were obtained for the mother's age, birth weight and weeks of gestation, establishing the probabilities based on the statistics obtained from Chile in the years 2013 and 2014, these ranges were discretized by assigning ranges between 0 and 1 to generate random cases with the Monte Carlo system.

Once these data were prepared, values of diabetes, heart problems, and parity were added; when the dataset was complete, the tests were performed with the expert system and the results were compared with the statistics, this test showed an accuracy of 78%.

Table 2. Refined knowledge. Values of 0 corresponds to low risk, 1 corresponds to average risk and 2 corresponds to high risk

Id	Mother's age	Weeks	Size (cm)	Weight (Kg)	Gestational diabetes	Heart disease	Parity	Morbidity
1	16	36	45.1	2,445	yes	no	1	0
2	30	36	47.2	2,974	yes	yes	2	0
3	17	36	47.0	2,600	no	no	0	0
4	25	37	44.8	2,682	yes	yes	2	1
5	30	37	50.1	3,516	no	no	0	0
6	31	37	51.1	3,200	no	yes	1	1
7	23	38	46.1	2,880	yes	yes	0	1
8	19	38	48.0	3,224	yes	no	1	1
9	33	38	46.2	2,751	no	yes	1	0
10	41	38	50.5	3,000	no	no	3	0
11	16	38	50.7	2,900	yes	no	0	0
12	16	38	47.3	3,216	yes	yes	1	1
13	23	39	47.1	2,980	yes	yes	0	0
14	19	39	49.3	3,324	yes	no	1	0
15	33	39	51.8	3,371	no	yes	1	0
16	41	39	52.5	3,500	no	no	0	0
17	16	39	51.7	3,100	yes	no	0	0
18	16	39	47.1	3,316	yes	yes	1	0
19	17	39	46.2	2,880	yes	yes	0	1
20	41	40	39.5	3,000	yes	yes	0	2
21	22	40	47.1	3,180	yes	yes	0	0
22	18	40	49.3	3,300	yes	no	1	0
23	37	40	51.8	3,321	no	yes	1	0
24	42	40	52.5	3,500	no	no	0	0
25	16	40	50.9	3,850	yes	yes	1	0

Table 3. Case examples

Case description 1	Birth of a 31-year-old woman with 37 weeks of pregnancy, height at birth = 51.10, birth weight = 3,200, did not develop gestational diabetes, mild problems of heart disease previous delivery.
Expected result	Fetal weight in normal range. Carving weight within the normal range, normal values. It is expected that the risk during pregnancy is normal and that the risk of morbidity is nil.
Obtained result	Message from the system: "The weight of the fetus is within normal ranges for the current gestational week." Message from the system: "The size of the fetus is within normal ranges for the current gestational week." System message: "Normal pregnancy."

Case description 2	Birth of a 23-year-old woman with 38 weeks of pregnancy, height at birth = 46.10, birth weight = 2,280, developed gestational diabetes and mild problems of heart disease, she did not have previous pregnancies.
Expected result	Weight and size below the normal range. It is quite probable that there is pregnancy risk and also the risk of morbidity.
Obtained result	Message from the system: "The weight of the fetus is below normal ranges for the current gestational week." System message: "The size of the fetus is below normal ranges for the current gestational week." System message: "Moderate risk pregnancy.""

Case description 3	Birth of a 42-year-old woman with 40 weeks of pregnancy, height at birth = 52.50, birth weight = 3,500, pregnancy without complications, no previous pregnancies.
Expected result	Fetal weight within the normal range. Fetal size within the normal range. Estimated risk of pregnancy is medium or moderate by the mother's age.
Obtained result	Message from the system: "The weight of the newborn is within normal ranges for the current gestation week." System message: "The size of the newborn is within normal ranges for the current gestational week." System message: "Low morbidity risk."

Conclusions and Future Works

The proposed expert system has a knowledge base centered on the characteristics of the Chilean population and the inference integrates into its rules recent knowledge on how to identify HRP and morbidity characteristics based on Spanish, Latin American and Chilean studies. We envisage that the prototype described here may be useful in Chile but it may also be useful in South America since the peoples of South America share many genetic and customs/habits characteristics. A future line could be to incorporate facts related to risk pregnancies in other regions of Latin America (such as limit values of height, weight, pregnancy weeks for countries such as Peru, Bolivia, etc.) and rules of production specific for these populations, so that the expert system can infer states of HRP and/or morbidity in pregnancies in those countries.

On the other hand, in the public health centers of Chile, the primary care of pregnancies does not reach the treatment of an HRP, usually, in Chile, the treatment of an HRP is performed in the regional hospitals. If this prototype can be used in primary care centers (after due validation and testing) it could help doctors and midwives to identify early disorders in pregnancy and help them act more quickly in these situations.

Conflict of Interest

The authors declare that they have no conflict of interest.

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