Bayesian Model for Optimization Adaptive E-Learning Process

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***Abstract*—In this paper, a Bayesian-Network-based model is proposed to optimize the Global Adaptive e-Learning Process (GAeLP). This model determines the type of personalization required for a learner according to his or her real needs, in which we have considered both objects and objectives of personalization. Furthermore, cause-and-effect relations among these objects and objectives with the learning phases, the learner, and the Intelligent Tutorial System (ITS) are accomplished. These cause-and-effect relations were coded into a Bayesian Network (BN), such that it involves the entire GAeLP. Four fundamental phases that have a direct effect in the learner's learning process are considered: Learner's previous knowledge Phase, Learner's Progress Knowledge Phase, Learner's /Teacher's Aims and Goals Phase, and Navigation Preferences and Experiences Phase. The efficacy of the Bayesian networks is proven through the first phase, in which learners of different knowledge area were select. The main results in this work are: causal relations among objects and objectives of personalization, knowledge phases, learner and electronic system. Personalization profiles set and their probabilities in the first phase were obtained to diagnose the type of personalization of the learner.**

***Index Terms*—Bayesian networks, .e-Learning, Learning metrics.**

I. INTRODUCTION

Global Adaptive e-learning process (GAeLP) is an on-line learning-teaching system in which the knowledge phases should be adapted to learner's needs. In this system, main learner's personal characteristics can be studied in every stage of the learning-teaching process, in order to optimize the GAeLP according to his or her real requirements. This is in conjunction with aims and goals of teacher and learner relative to their educative program.

E-Learning process supposes utilization of multimedia and hypermedia technologies to develop and improve new learning's strategies [57]. This process uses information-technology tools such as: CD-ROMs, Internet, intranet, or mobile devices, to make knowledge accessible for a lot of people. Thus, the knowledge is obtained through on-line courses, e-mails, learning by computer, electronic books, CD-ROMs, virtual simulation, and another types of software, such like wikis, forum, and others collaborative spaces. On the other hand, Adaptive e-Learning is a teaching-learning process individually adjusted to the learner by mean of selecting and presenting the contents according to his or her scholar grade, personal needs, learning style, previous knowledge, and individual preferences. Therefore, the GAeLP enables to build the learning environments required [58].

Previous works on e-Learning, based on Bayesian Models (BMs), are only implemented to identify learner's characteristic. A BM is a set of previous probability distributions; a set of conditional probability distributions; and a network representing the relations of independence between its nodes. Examples of such software are: OLAE, (computer system for assessing student knowledge of physic and Newtonian mechanic), [34], [35]; POLA: Probabilistic On-Line Assessment [12], [13] ANDES: [53], [20], [54]; HYDRIVE: [42]; SIETTE: test-based intelligent evaluation system [41], CAPIT: [38], [39]; and POET: the on line reference elicitation tool [47]. The BMs used in these references, are successfully used to build and update the learner's model, but they only accomplish diagnosis of the learner's knowledge level, at most, they can diagnose only one objective of personalization, e.g. learning style [19]. Consequently, such BMs don't take into account preferences, needs, goals, interests and other information about the learner, which are very important for to determine the learner desirable profile in a more realistic manner. In [49], John Self argues that an extensive learner model must contain information about the learner's knowledge domain, the learner's progress, preferences, goals, interests and other information, which is important to the system. Likewise, there are systems like the Intelligent Tutorial Systems (ITS) [7], Adaptive Hypermedia Systems (AHS) [8], [9], [10], and Adaptive Educational Hypermedia Systems (AEHS) [11] [26], which are programs having an ample knowledge of any subject. Most of this software assumes that knowledge is given to the learners by means of a personalized interactive process. Based on the learner model, these systems try to emulate the teaching style of a human tutor or a human teacher. The learner's model represents the system's beliefs about its main target user, the learner, and provides the necessary information for tailoring the instruction to the learner's needs.

In this paper, we present an improved BM to optimize the GAeLP. This probabilistic model is developed taking into account objectives and objects of adaptivity [28] within four fundamental phases: Adaptivity for Learner's previous knowledge, Adaptivity for Learner's Progress

Knowledge, Adaptivity for Learner's /Teacher's Aims and Goals, and Adaptivity for Navigation Preferences and Experiences [27]. To optimize GAeLP in a personalized manner is necessary to collect all possible learning metrics (LM). LM are all kinds of formative and summative assessments, all class of information about learning activities/ processes, and all ways of recording development of learning [50]. Introduction of learning metrics in communication and information systems can be used to generate pedagogical and psychological research in both e-learning and e-teaching systems, which in turn could be substantially improved. Hence, a broad set of metrics are considered in this paper, such as knowledge levels (low, intermediate, and high), cognitive style (dependent, and independent), communication style (passive, assertive, and aggressive), learning style (active, reflexive, theoretic, and pragmatic), among others. The model is evaluated through a simulated curse on-line with 45 learners of several areas, such as beautiful arts, exact and natural sciences, engineering, biology and science of health, social science and economic and administrative. In addition, we include a list of objects of personalization, and objectives of personalization to determine learner's qualities and potentialities, and personal preferences. This information can be used to initialise either our Bayesian model or other similar probabilistic models.

Section 2 revises some techniques for learners modelling, whereas BN is presented in Section 3. Experiment design is described in Section 4. In addition, knowledge phases are described in Section 5, theses phases are fundamental for personalization of the GAeLP. Section 6 contains main result of this research, which are very usefully to infer join and conditional probability distribution, besides the learner's profile type for each phase and previous and posterior probability of parent and child nodes. Discussion of results and summary are contained in Section 7. Conclusion remarks are presented in Section 8.

II. LEARNER'S MODELLING TECHNIQUES

The problem of to infer and to update the learner's model to his or her preference is known as the learner's modelling problem. Learner's modelling in on-line courses undoubtedly includes uncertain data. Several methods to manage uncertainly in ITSs are mentioned in this Section.

To construct a student's model we need to infer certain characteristic, such as his or her abilities, beliefs, motives, individual preferences, personal needs, learning styles, previous knowledge, future actions, and so on. These characteristic invariably involve uncertainty when is used within an intelligent tutorial system. Uncertainty necessarily implies imprecise information or doubtful information [1], [5].

There are some techniques to deal with uncertainty: 1) Deterministic approaches, which assume that all the required information can be quantified a priori and made available in case of being necessary [2]. 2) Algorithmic and deterministic approaches extension, which assumes that some prudently algorithms could encompass all plans and its corresponding actions [30], [6]. 3) Machine learning: traditional user modelling systems have disadvantages that can be overcome with machine learning techniques for adaptive learning [21], also machine learning methods are capable of expressing a rich variety of non-linear decision surfaces [60]. These approaches, in general, process training/input data and attempt to make decision or classification based on this input. 4) Fuzzy Logic: These techniques are used for representing and reasoning with vague concepts to mimic human style of reasoning. This reasoning may be of the user, whose inferences or evaluations are being anticipated, or it may be of an expert whose knowledge constitutes the basis for the system's reasoning [51]. 5) Probabilistic Approaches: Majority of uncertainty management methodologies quantify uncertainties in form of some probabilistic measures that are propagated during reasoning [45]. Examples of these methods are: Bayesian Belief Networks, Certainty Factors, Dempster-Shafer, and so forth. Such approaches are based on the premise that assigning a certain value to plan hypothesis reflects likelihood of its being pursued by user [29]. Thus, it lends itself to some probability-like measure for representing information about user's individual preferences [59]. Key issue in using probabilistic approaches is accurate representation of probabilistic dependencies in task domain. According to Heckerman [23], a BN offers a number of advantages for data analysis, some of which are: a) The model can handle situations where some data entries are missing because it encodes dependencies among all variables or nodes, and b) It also allows us to infer causal relationships among variables or nodes. These reasons motivate our study.

III. BAYESIAN NETWORKS

Along with Friedman and Goldszmidt [16], a BN is a graphical model for efficiently representing a joint probability distribution over a set of random variables *V*. A BN is denoted by (*G*, *P*); where *G* is a Directed Acyclic Graph (DAG) defined over *V* (such graph encodes independence relationships among the variables in *V*)**;** and *P* denotes a set of local probability distributions, one for each variable conditioned on its parents. Variables are represented for *nodes* denoting "concepts" and *edges* indicating cause/effect dependencies among concepts. Final nodes can be seen as "effects" (values collected from the learning environments), while highest-level nodes can be thought as "causes". Every node can have two or more possible results; each result is named a *state* of the variable. Thus, the probability associated to certain profile of the learner is obtained from a DAG. Once the learner's profile is known, then it can eventually be used to build the personalized learning model for this pupil.

Let $V = \{x_1, x_2, \cdots, x_n\}$ be the domain, such that its associated BN represents the joint probability distribution $P(x)$ over the set of random variables x_i. This joint probability is computed from [18]

$$P(x_1, x_2, \cdots, x_n) = \prod_{i=1}^{n} P(x_i | \Pi_i). \quad (1)$$

where Π_i is a set of parents relatives to each x_i, such that $\Pi_i \subseteq \{x_1, x_2, \cdots, x_{n-1}\}$ is a subset of variables in which x_i is conditionally dependent. The pair formed by the structure (graph) and collection of local distributions $P(x_i | \Pi_i)$, for each node in the domain, constitutes the BN for that domain. Using the chain rule for random variables [44] we can rewrite the joint probability distribution (1) of V as follows

$$P(x_1, x_2 \cdots, x_n | e) = \prod_{i=1}^{n} P(x_i | x_1, \ldots, x_{n-1}, e). \quad (2)$$

where e stands for the *evidence* with respect to the variable x_i.

Now, for every x_i there will be some subset $\Pi_i \subseteq V$ such that x_i and V are conditionally independent given Π_i. That is,

$$P(x_i | x_1, x_2, \cdots, x_{n-1}, e) = P(x_i | \Pi_i, e). \quad (3)$$

The BN structure encodes the assertions of conditional independence as a directed acyclic graph such that: (a) each node corresponds to a variable; (b) the parents of the node corresponding to x_i are the nodes associated to the variables in Π_i. The pair formed by the structure (graph) and the collection of local distributions $P(x_i | \Pi_i)$ for each node in the domain, constitutes the BN for that domain.

Structural modelling for belief networks is a straightforward modification of existing knowledge engineering techniques, which are used in this paper to build the BN representing the personalization type of the learner. We could construct a BN using causal edges [44]; also we can interact with the domain to identify aspects of qualitative problem, such as direct relationships between variables. These relationships then become encoded in a network structure.

IV. EXPERIMENT DESIGN

Our experiment randomly assign a *learning style* to each of 45 simulated learners ([33], [31]; [3]), a *cognitive style* [58], a *communication style* [24], a *teaching style* preferred [22], *learning techniques* preferred [32], a *previous knowledge level* [48], *individual preferences* [17], a *curriculum* or expertise area (Exact and Natural Sciences, Engineering, Biology and Sciences of Health , Social Sciences, Economic and Administrative and, Humanities and Beautiful Arts), and *personal needs* [4]. Each characteristic represent one learner's objective of personalization in the BM. Besides, we randomly assigned to each learners the following particularities: *learning objects* choice (CD-ROM, On-line, Any combination of these two forms) [46], *input methods* choice (Mouse, Keyboard, Press button, Speech recognition system) [40], *learning devices* preferred [14] and *usability of the system level* in the learner [52]. Each characteristic represents one learner's object of personalization in the BM. Both, objectives and abject of personalization are considered as independent events among themselves. Each object or objective of personalization represents a cause having a direct effect in any one of the four learning phases mentioned above. Every phase, in turn, is considered as a cause that has a direct effect in the learner's training, and in the system's adjusting. Learner and system are taken mutually independent events as well. Thus, is possible to determine the learner's desirable profile for each phase. The BN model for optimization GAeLP is constructed as follows.

V. MODELLING THE KNOWLEDGE PHASES THROUGH BAYESIAN NETWORKS

Data analysis was realized considering higher probabilities of results obtained in each of phases of personalization. These probabilities represent credibility of electronic system used for the learning-teaching on-line process about the learner's characteristics that determine his or her type of personalization. Final result is obtained by multiplication of probabilities computed in the learner's node and the system node.

Building a BN for a domain implicates a variety of tasks [25], [44]. First task consists of to identify significant variables and their possible values. In our application domain, variables represent objects and objectives of personalization, phases of personalization, the learner and the system (computer). Table I shows the variables and its states used in this paper.

TABLE I.
VARIABLES OF THE BM AND THEIR STATES

Variables	States or possible results and notation
Objectives of Personalization	
1. Previous knowledge.	1) Low, 2) Intermediate (INT), and 3) High
2. Learning style.	1) Active, 2) Reflexive, 3) Theoretic, and 4) Pragmatic.
3. Cognitive style.	1) Dependent (DEP), and 2) Independent.(IND.)
4. Communication style.	1) Passive (PAS), 2) Assertive (ASS.), and 3) Aggressive (AGG)
5. Teaching style preferred.	1) Formal authority, 2) Demonstrator or personal model, 3) Facilitator, and 4) Delegator.
6. Learning techniques.	1) Visual, 2) Active, and 3) Collaborative (COLL).
7. Individual preferences.	1) Visuals (VIS), 2) Auditives (AUD), and 3) Kinestetics (KIN).
8. Curriculum (expertise area).	1) Exact and Natural Sciences, 2) Engineering, 3) Biology and Sciences of Health, 4) Social Sciences, 5 Economic and Administrative, and 6) Humanities and Beautiful arts.
9. Personal needs.	1) Environmental (ENV), 2) Emotional (EMO), 3) Social (SOC), and 4) Physiological (PHY).
Personalization Objects	
10. Learning objects choice.	1) CD ROM, 2) On line, and Combined.

11. Learning objects presentation.	1) Needs teaching programs, 2) Facility to access to a particular learning object suggested.
12. Input methods choice.	1) Mouse, 2) Keyboard (KYB), 3) Press button (PB), and 4) speech recognition system (SRS)
13. Learning devices preferred.	1) Intelligent objects, 2) Information infrastructures, and 3) Shared artificial environments.
14. Usability of the system for the learner.	1) Good, 2) Regular, and 3) Deficient.
Phase	
15. Personalization to the Learner's Previous Knowledge.	1) Adapt, and 2) No adapt
16. Personalization to the Learner's Progress Knowledge.	1) Adapt, and 2) No adapt
17. Personalization Learner's /Teacher's Aims and Goals.	1) Adapt, and 2) No adapt
18. Personalization Navigation Preferences and Experiences.	1) Adapt, and 2) No adapt
Request	
Phase 1	
19. System.	1) Automatic adjusting, (AA) , 2) Manual adjusting (MA)
20. Learner.	1) Train, and 2) No train
Phase 2	
21. System.	1) Automatic adjusting, and 2) Manual adjusting
22. Learner.	1) Train, and 2) No train
Phase 3	
23. System.	1) Automatic adjusting, , 2) Manual adjusting
24. Learner.	1) Train, 2) No train
Phase 4	
25. System.	1) Automatic adjusting, and 2) Manual adjusting
26. Learner.	1) Train, and 2) No train

Second task consists of to build the qualitative part by identifying independences among variables; after that, we have to express these in DAG that encodes assertions of conditional independences. This graphic is named *BN structure* and is showed in Figure 1. In this figure, GAeLP is divided in four phases [27], [28]:

1. ***Previous knowledge phase***. In this stage, the level of the learner's knowledge is detected by mean of individual evaluation; then a procedure is tasted, and learning objects are elected according to learner previous knowledge identified. In our BM this phase is considered like a cause of the following objectives of personalization: *Learner's previous-knowledge*, *learner's cognitive-style* and *learner's communication-style.* Having these objective in mind, is possible to train learner (if necessary) to use the system optimally and to obtain learner's data. Thus, the system can be adapted to learner's needs, and ready to use during this and next phases.

2. ***Progress knowledge phase***. In this stage, learner learning progress is controlled by personal learning paths o personal itineraries, according to some learner's specific characteristics. This phase is considered as cause of objectives of personalization: *Learning style*, *learning techniques*, and *objects of personalization* such as individual preferences. Thus, is possible to train to the learner and to adapt to the system so that pupil obtains the knowledge desired during the learning stage, according to objectives and objects of personalization identified in this phase and in the first phase.

3. ***Teacher's aims and goals phase***. In this stage, learner is guided by special learning paths along with of learner/teacher objectives and goals. This phase is considered like a cause of objectives of personalization: *Curriculum* or *expertise area*, *personal needs*, *teaching style* preferred, and the *object* of personalization (*learning devices* preferred). With such objectives of personalization and the learning devices preferred is possible to prepare the pupil and the system according to learner/teacher's aims and goals, and to select the contents and its presentation.

4. ***Navigation preferences and experience phase***. In this step several navigation supports could be offered to the learner. Here, learner has total freedom for navigation; or learner could be guided to specific aims and goals by learning itineraries explicitly given. In the BM this phase is considered like a cause of the objects of personalization: usability of the system for the learner, input methods choice, learning objects choice, and learning objects presentation. Knowing these objects of personalization is possible to prepare the learner for the navigation and the system according to the pupil's preferences and experience. Results from all phases are used to determine the pupil's personalised learning model.

VI. EXPERIMENT RESULTS

Now, we are going to discuss the statistics obtained from our experiment (simulated on-line course), which it was described in Section 4. Here to forth, the shown probabilities are estimated from the relative frequencies obtained by simulation.

A. Joint and conditional probability distributions

Conditional independencies between objects and objectives of personalization define the BN structure in Figure 1.This structure is used to obtain joint probabilities of learners´ profiles, such like:

$$P(\text{High, IND, ASS, Adapt, Train, AA}). \quad (4)$$

in phase 1.

$$P(\text{Active, COLL, Visual, Adapt, Train, AA.}). \quad (5)$$

in phase 2. And so on.

In each phase, profiles are obtained by product of probabilities such as:

$$P(\text{High, IND, ASS, Adapt, Train})\times P(\text{High,IND,ASS,Adapt,AA}) \quad (6)$$

where the first factor corresponds to the learner's node probability and the second factor is the system's node probability. Profile with higher probability will be choosing as the learner's type of personalization in the correspondent phase. This profile represents credibility of the system

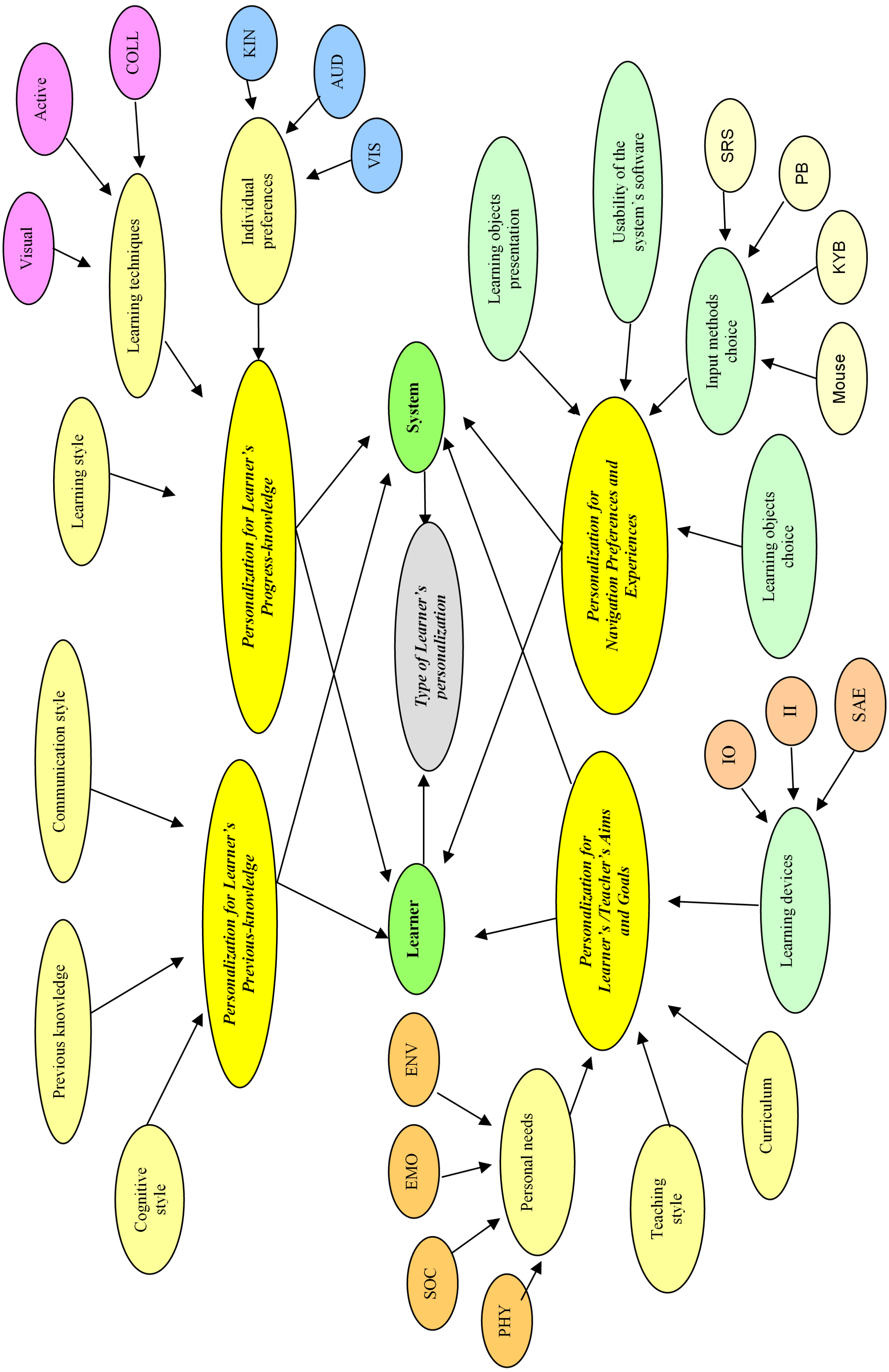

Figure 1. Bayesian Network Structure (see nomenclature in Table I)

regarding to learner's characteristic. In order to building a whole probabilistic Bayesian network, we have to assess a set of conditional probabilities, corresponding to local distributions $P(x_i|\Pi_i)$. Model is completed by establishing probability values associated to each node in the graph. That is, in each phase, one probability distribution function Π_i (*pdf*) is assigned for every state in the node. The pdfs associated with independent nodes have the multinomial distributions [44].

B. *Learner's profiles in phase 1*

Figure 2 shows the BN structure for personalization of previous knowledge phase 1. Tables II, III, and IV contain statistics for this phase, which represent probability distributions for the parent nodes *Previous knowledge-level*, *Cognitive style*, and *Communication style*, respectively.

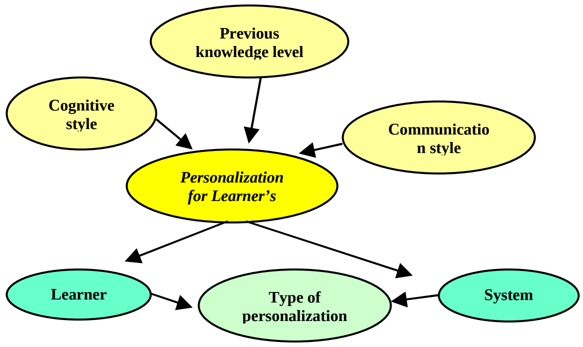

Figure 2. BN of phase 1: Personalization for Learner's Pre-knowledge

In Table II, note that 42.22 percent of the time the learner's previous knowledge level has been intermediate. These values are updated as the agent compile information about the level. Probabilities in Tables III and IV indicate something similar.

TABLE II.
PREVIOUS KNOWLEDGE LEVEL PROBABILITY FUNCTION

Previous knowledge level	Low	Intermediate	High
Probability	0.3111	0.4222	0.2667

TABLE III.
COMMUNICATION STYLE PROBABILITY FUNCTION

Communication style	Passive	Assertive	Aggressive
Probability	0.4444	0.2223	0.3333

TABLE IV.
COGNITIVE STYLE PROBABILITY FUNCTION

Cognitive style	Dependent	Independent
Probability	0.5556	0.4444

Proceeding in the same manner, Tables V, VI, and VII show conditional probabilities for children nodes "*Personalization for Previous knowledge*", "*Learner*" and "*System*", respectively.

TABLE V.
CONDITIONAL PROBABILITIES FOR THE NODE OF THE PHASE 1

Parent nodes			Adjusting of system in Previous knowledge phase	
Previous knowledge level	Communication style	Cognitive style	Adapt	No adapt
Low	Passive	Dependent	0.5	0.5
		Independent	1	0
	Assertive	Dependent	0	1
		Independent	1	0
	Aggressive	Dependent	0.6667	0.3333
		Independent	0.3333	0.6667
Intermediate	Passive	Dependent	0.25	0.75
		Independent	0.5	0.5
	Assertive	Dependent	0.6	0.4
		Independent	0	1
	Aggressive	Dependent	1	0
		Independent	0.6667	0.3333
High	Passive	Dependent	0.5	0.5
		Independent	1	0
	Assertive	Dependent	0.6667	0.3333
		Independent	1	0
	Aggressive	Dependent	0	1
		Independent	0.6667	0.3333

Fourth row and fourth column in Table IV, denotes the following conditional probability

$$P(\text{Adapt}|\text{Low, Aggressive, Dependent}). \qquad (7)$$

Conditional probabilities in Tables VI and VII indicate something similar.

TABLE VI.
CONDITIONAL PROBABILITIES FOR NODE "LEARNER" OF THE PHASE 1

Node	Learner	
Personalization in the Previous knowledge	Train	No Train
Adapt	0.5769	0.4230
No adapt	0.6316	0.3684

TABLE VII.
CONDITIONAL PROBABILITIES FOR NODE "SYSTEM" OF THE PHASE 1

Node	System	
Personalization in the Pre-knowledge	Adjusting automatic	Adjusting manual
Adapt	0.6484	0.3516
No adapt	0.5544	0.4456

C. *Learner's profiles in phase 2*

The BN structure of Personalization for Learner's Progress Knowledge phase can be seen in Figure 1. Tables VIII, IX, and X present results obtained in this phase. They represent respectively probability distributions for parent nodes *Learning style*, *Learning techniques*, and *Individual preferences*.

TABLE VIII.
LEARNING STYLE PROBABILITY FUNCTION

Learning style	Probability
Active	0.1778
Reflexive	0.2445
Theorist	0.3333
Pragmatic	0.2444

TABLE IX.
LEARNING STYLE PROBABILITY FUNCTION

Learning techniques	Probability
For visual learning	0.2444
For active learning	0.1556
For collaborative learning	0.2444

TABLE X.
LEARNING STYLE PROBABILITY FUNCTION

Individual preferences	Probability
Visual	0.3778
Auditive	0.3556
Kinestetic	0.2666

Tables XI, XII, and XIII, show conditional probabilities for nodes children "Personalization for Previous knowledge", "Learner" and "System"

TABLE XI.
CONDITIONAL PROBABILITIES FOR THE NODE OF THE PHASE 2

Parent nodes			**Adjusting of system in Progress knowledge phase**	
Learning style	Learning techniques	Individual preferences	Adapt	No Adapt
Active	Visual	Visual	1	0
		Auditive	0	1
		Kinestetic	0.5	0.5
	Active	Visual	0.5	0.5
		Auditive	0	1
		Kinestetic	1	0
	Collaborative	Visual	1	0
		Auditive	0	1
		Kinestetic	1	0
Reflexive	Visual	Visual	0	1
		Auditive	1	0
		Kinestetic	1	0
	Active	Visual	0	1
		Auditive	1	0
		Kinestetic	1	0
	Collaborative	Visual	1	0
		Auditive	1	0
		Kinestetic	1	0
Theorist	Visual	Visual	0.3333	0.6667
		Auditive	0.3333	0.6667
		Kinestetic	0.6	0.4
	Active	Visual	0.5	0.5
		Auditive	0	1
		Kinestetic	0.2	0.8
	Collaborative	Visual	0.5	0.5
		Auditive	1	0
		Kinestetic	0.5	0.5
Pragmatic	Visual	Visual	0.3333	0.6667
		Auditive	0.3333	0.6667
		Kinestetic	0.3333	0.6667
	Active	Visual	0.6667	0.3333
		Auditive	0.5	0.5
		Kinestetic	0.3333	0.6667
	Collaborative	Visual	0	1
		Auditive	0.6667	0.3333
		Kinestetic	0.3333	1

TABLE XII.
CONDITIONAL PROBABILITIES FOR NODE "LEARNER" OF THE PHASE 2.

Node	Learner	
Personalization for Learner's Progress Knowledge	Train	No Train
Adapt	0.5909	0.4090
No adapt	0.3043	0.6957

TABLE XIII.
CONDITIONAL PROBABILITIES FOR NODE "SYSTEM" OF THE PHASE 2.

Parent Node	System	
Personalization for Learner's	Adjusting	Adjusting
Progress Knowledge	automatic	manual
Adapt	0.4545	0.5455
No adapt	0.5217	0.4783

D. Learner's profiles in phase 3

From Figure 1, the BN structure of the Personalization for Learner's /Teacher's Aims and Goals corresponds to the phase 3. Tables XIV, XV, XVI, and XVII present results obtained in this phase. They represent respectively probability distributions for nodes parents "*Personal needs*", "*Teaching style*", "*Learning devices*", and "*Curriculum*" in our model.

TABLE XIV.
. PERSONAL-NEEDS PROBABILITY FUNCTION

Personal Needs	Probability
Environmental	0.4
Emotional	0.2889
Social	0.2
Physiological	0.1111

TABLE XV.
TEACHING-STYLE PROBABILITY FUNCTION

Teaching Style	Probability
Formal autority	0.2444
Demostrator	0.1556
Facilator	0.2444
Delegator	0.3556

TABLE XVI.
LEARNING-DEVICES PROBABILITY FUNCTION

Learning Devices	Probability
Inteligent Objects (IO)	0.3111
Inf. Infraestructure (II)	0.4
Shares Artif. Env. (SAE)	0.2889

TABLE XVII.
CURRICULUM PROBABILITY FUNCTION

Curriculum	Probability
Exact and Natural Sciences (ENS)	0.2
Engineering (ENG)	0.0889
Biology and Sciences of Health (BSH)	0.2444
Social Sciences (SSC)	0.1778
Economic and Administrative (ECA)	0.1556
Humanities and Beautiful arts (HBA)	0.1333

Tables XVIII, XIX, and XX, show conditional probabilities for children nodes "Personalization for Learner's /Teacher's Aims and Goals", "Learner", and "System". In Table XVIII some profile were truncated due to space.

TABLE XVIII.
CONDITIONAL PROBABILITIES FOR THE NODE OF THE PHASE 3

Parent nodes				**Adjusting of system in Personalization for Learner's /Teacher's Aims and Goals phase**	
Personal needs	Learning style	Learning devices	Curriculum	Adapt	No Adapt
Environmental	Formal authority	IO	ENS	0	1
			ENG	0	1
			BHS	0	1
			SSC	0	1
			ECA	0	1
			HBA	0	1

		II	ENS	1	0
			ENG	0	1
			BHS	0	1
			SSC	0	1
			ECA	0	1
			HBA	0	1
		SAE	ENS	0	1
			ENG	0	1
			BHS	0	1
			SSC	0	1
			ECA	1	0
			HBA	0	1
	TRUNQUED SECTION Demostrator or personal model				
Social AND Emotional					
Physiological	Delegator	IO	ENS	1	0
			ENG	0	1
			BHS	0	1
			SSC	1	0
			ECA	0	1
			HBA	0	1
		II	ENS	1	0
			ENG	0	1
			BHS	0.5	0.5
			SSC	1	0
			ECA	0	1
			HBA	0	1
		SAE	ENS	0.5	0.5
			ENG	0	1
			BHS	0	1
			SSC	0	0
			ECA	0	1
			HBA	0	1

TABLE XIX.
CONDITIONAL PROBABILITIES FOR THE NODE "LEARNER" OF THE PHASE 3

Node	**Learner**	
Personalization for Learner's /Teacher's Aims and Goals	Train	No Train
Adapt	0.2727	0.7273
No adapt	0.8696	0.1304

TABLE XX.
CONDITIONAL PROBABILITIES FOR THE NODE "SYSTEM" OF THE PHASE 3

Node	**System**	
Personalization for Learner's /Teacher's Aims and Goals	Adjusting automatic	Adjusting manual
Adapt	0.55	0.45
No adapt	0.2444	0.7556

From Figure 1, the BN structure of the Personalization for Learner's /Teacher's Aims and Goals represents the phase 4. Tables XXI, XII, XIII, and XIV present the results obtained in this phase. They represent respectively probability distributions for nodes parents "*Input methods choice*", "*Learning objects choice*" "*Learning objects presentation*", and "*Usability of the system's software*" in our model.

TABLE XXI.
INPUT METHODS CHOICE PROBABILITY FUNCTION

Input methods choice	**Probability** (Used)	(no used)
Mouse	0,9333	0,0667
Keyboard	0,9556	0,0444
Press button	0.0222	0,9778
Speech recognition system (SRS)	0.6667	0,3333

TABLE XXII.
LEARNING OBJECTS CHOICE PROBABILITY FUNCTION

Learning objects choice	**Probability**
Needs teaching programs (NTP)	0.6444
Facility to access to an particular learning object suggested. (FAO)	0.3556

TABLE XXIII.
LEARNING OBJECTS PRESENTATION PROBABILITY FUNCTION

Learning objects presentation	**Probability**
CD ROM	0.3111
On-line	0.2667
3. Combined	0.4222

TABLE XXIV.
USABILITY PRESENTATION PROBABILITY FUNCTION

Usability of the system's software	**Probability**
Deficient	0.4222
Regular	0.3556
Good	0.2222

Tables XV, XVI, and XVII, show conditional probabilities for nodes "Personalization for Navigation Preferences and Experiences", "Learner", and "System"

TABLE XXV.
CONDITIONAL PROBABILITIES FOR THE NODE OF THE PHASE 4

Nodes parent				**Adjusting of system in Personalization for Navigation Preferences and Experiences phase**	
Learning Objects presentation	Usability of the system's software	Input Methods choice	Learning objects choice	Adapt	No Adapt
CD ROM	Good	Mouse	NTP	0.6667	0.3333
			FAO	1	0
		Keyboard	NTP	0.6667	0.3333
			FAO	1	0
		Press button	NTP	0	1
			FAO	0	1
		SRS	NTP	0	1
			FAO	0	1
	Regular	Mouse	NTP	0.5	0.5
			FAO	0	1
		Keyboard	NTP	0.5	0.5
			FAO	0	1
		Press button	NTP	0	1
			FAO	0	1
		SRS	NTP	0	1
			FAO	0	1
	Deficient	Mouse	NTP	1	0
			FAO	0.5	0.5
		Keyboard	NTP	1	0
			FAO	0.5	0.5
		Press button	NTP	0	1
			FAO	0	1
		SRS	NTP	0	1
			FAO	0	1
On-line	Good	Mouse	NTP	0	1
			FAO	1	0
		Keyboard	NTP	1	0
			FAO	1	0
		Press button	NTP	1	0
			FAO	0	1
		SRS	NTP	0	1

			FAO	0	1
	Regular	Mouse	NTP	0	1
			FAO	1	0
		Keyboard	NTP	0.6667	0.3333
			FAO	1	0
		Press button	NTP	0.6667	0.3333
			FAO	0	1
		SRS	NTP	0	1
			FAO	0	1
	Deficient	Mouse	NTP	0	1
			FAO	0	1
		Keyboard	NTP	0	1
			FAO	0	1
		Press button	NTP	0	1
			FAO	0	1
		SRS	NTP	0	1
			FAO	0	1
Combined	Good	Mouse	NTP	0	1
			FAO	0	1
		Keyboard	NTP	0	1
			FAO	0.5	0.5
		Press button	NTP	0	1
			FAO	0.5	0.5
		SRS	NTP	0	1
			FAO	0	1
	Regular	Mouse	NTP	0	1
			FAO	0	1
		Keyboard	NTP	0.6	0.4
			FAO	1	0
		Press button	NTP	0.6	0.4
			FAO	1	0
		SRS	NTP	0	1
			FAO	0	1
	Deficient	Mouse	NTP	0	1
			FAO	0	1
		Keyboard	NTP	0.5	0.5
			FAO	0	1
		Press button	NTP	0.5	0.5
			FAO	0	1
		SRS	NTP	0	1
			FAO	0	1

TABLE XXVI.
CONDITIONAL PROBABILITIES FOR THE NODE "LEARNER" OF THE PHASE 4

Node	Learner	
Personalization for Navigation Preferences and Experiences	Train	No Train
Adapt	0.5	0.5
No adapt	0.4117	0.5882

TABLE XXVII.
CONDITIONAL PROBABILITIES FOR THE NODE "SYSTEM" OF THE PHASE 4

Node	System	
Personalization for Navigation Preferences and Experiences	Adjusting automatic	Adjusting manual
Adapt	0.3929	0.6071
No adapt	0.2353	0.7647

With conditional probabilities in Table XXVII the BM is complete. Probabilities associated to child nodes can be computed employing the Total Probability Theorem [44].

E. Previous and posterior probabilities of profiles

The purpose of this section is to calculate the probabilities of all possible profiles generated in each phase of personalization; for instance, in previous knowledge phase we obtain probabilities such as:

$$P(\text{High, IND, ASS, Adapt, Train, AA}) \tag{7}$$

This probability is calculated in two parts. First part provides the probability of learner's node, and the second parte includes the probability of the system's node. As consequence, the total probability is calculated as a direct multiplication, because both nodes are independent.

E.I Previous probabilities

As an example of evaluation of total previous probability values such as (7), we first have to calculate the probability associated to the learner's node

$$P(\text{High, IND, ASS, Adapt, Train,}) \tag{8}$$

Applying equation (1) twice, we have:

$$\begin{aligned} &P(\text{Train, Adapt, ASS, IND, High}) = \\ &P(\text{Train}|\text{Adapt, ASS, IND, High}) \times \\ &P(\text{Adapt, ASS, IND, High}) \\ &= P(\text{Train}|\text{Adapt, ASS, IND, High}) \\ &\times P(\text{Adapt}|\text{ASS, IND, High}) \times \\ &P(\text{ASS, IND, High}) \end{aligned} \tag{9}$$

Furthermore, since previous knowledge level, cognitive style and communication style are independent events among themselves, we have:

$$\begin{aligned} &P(\text{Train, Adapt, ASS, IND, High}) = \\ &= P(\text{Train}|\text{Adapt, ASS, IND, High}) \times \\ &\times P(\text{Adapt}|\text{ASS, IND, High}) \times \\ &P(\text{ASS}) \times P(\text{IND}) \times P(\text{High}) \end{aligned} \tag{10}$$

Using data from Tables VI, V, IV, III, and II, the probability of the learner's node (8) results

$$(0.5769)(1)(0.2223)(0.4444)(0.2667) = 0.0152 \tag{11}$$

On the other hand, previous probability for the system's node (7) can be derive as

$$\begin{aligned} &\text{P}(\text{AA}|\text{Adapt, ASS, IND, High}) \times \\ &\times P(\text{Adapt, ASS, IND, High}) \end{aligned} \tag{12}$$

Which in turn become,

$$\begin{aligned} &P(\text{AA}|\text{Adapt, ASS, IND, High}) \times \\ &\times P(\text{Adapt}|\text{ASS, IND, High}) \times \\ &P(\text{ASS}) \times P(\text{IND}) \times P(\text{High}) \end{aligned} \tag{13}$$

From Tables VII, V, IV, III, and II, the probability in (7) of the system's node results

$$\begin{aligned} &(0.6484)(1)(0.2223)(0.4444)(0.2667) \\ &= 0.0171 \end{aligned} \tag{14}$$

Thus, the total previous probability in (7) can be obtained as the following product

$$(0.0152)(0.0171) = 0.00026 \tag{15}$$

This indicates than 0.026 percent of the times, the learner's profile has been (High, IND, Adapt, Train, AA).

Likewise, we can recur to the Total Probability's Law [44] to calculate remaining previous probabilities. Thus, if we are in Previous knowledge (first) phase, the probability that an activity o module in the on-line curse requires adaptation before it be tough, namely $P(\text{Adapt})$, can be compute as follows:

$$
\begin{aligned}
&P(\text{Adapt})= \\
&P(\text{Adapt}|\text{High,PAS,DEP})\times P(\text{Low})\times P(\text{PAS})\times P(\text{DEP})+ \\
&P(\text{Adapt}|\text{Low,PAS,IND.})\times P(\text{Low})\times P(\text{PAS})\times P(\text{IND})+ \\
&P(\text{Adapt}|\text{Low,ASS,DEP})\times P(\text{Low})\times P(\text{ASS})\times P(\text{DEP})+ \\
&P(\text{Adapt}|\text{Low,ASS,IND.})\times P(\text{Low})\times P(\text{ASS})\times P(\text{IND})+ \\
&P(\text{Adapt}|\text{Low,AGG,DEP})\times P(\text{Low})\times P(\text{AGG})\times P(\text{DEP})+ \\
&P(\text{Adapt}|\text{Low,AGG,IND.})\times P(\text{Low})\times P(\text{AGG})\times P(\text{IND})+ \\
&P(\text{Adapt}|\text{INT,PAS,DEP})\times P(\text{INT.})\times P(\text{PAS})\times P(\text{DEP})+ \\
&P(\text{Adapt}|\text{INT,PAS,IND.})\times P(\text{INT.})\times P(\text{PAS})\times P(\text{IND})+ \\
&P(\text{Adapt}|\text{INT,ASS,DEP})\times P(\text{INT})\times P(\text{ASS})\times P(\text{DEP})+ \qquad (16) \\
&P(\text{Adapt}|\text{INT,ASS,IND})\times P(\text{INT.})\times P(\text{ASS})\times P(\text{IND})+ \\
&P(\text{Adapt}|\text{INT,AGG,DEP})\times P(\text{INT})\times P(\text{AGG})\times P(\text{DEP})+ \\
&P(\text{Adapt}|\text{INT,AGG,IND})\times P(\text{INT})\times P(\text{AGG})\times P(\text{IND})+ \\
&P(\text{Adapt}|\text{INT,AGG,DEP})\times P(\text{INT.})\times P(\text{AGG})\times P(\text{DEP})+ \\
&P(\text{Adapt}|\text{INT,AGG,IND})\times P(\text{INT})\times P(\text{AGG})\times P(\text{IND})+ \\
&P(\text{Adapt}|\text{High,PAS,DEP})\times P(\text{High})\times P(\text{PAS})\times P(\text{DEP})+ \\
&P(\text{Adapt}|\text{High,PAS,IND})\times P(\text{High})\times P(\text{PAS})\times P(\text{IND})+ \\
&P(\text{Adapt}|\text{High,ASS,DEP})\times P(\text{High})\times P(\text{ASS})\times P(\text{DEPt})+ \\
&P(\text{Adapt}|\text{High,ASS,IND})\times P(\text{High})\times P(\text{ASS})\times P(\text{IND})+ \\
&P(\text{Adapt}|\text{High,AGG,DEP})\times P(\text{High})\times P(\text{AGG})\times P(\text{DEP})+ \\
&P(\text{Adapt}|\text{High,AGG,IND.})\times P(\text{High})\times P(\text{AGG})\times P(\text{IND}).
\end{aligned}
$$

Expression (16) can be evaluated using the values from Tables II, III, IV, and V. We obtain $P(\text{Adapt}) = 0.5251$This result indicates 52.51 percent of the times some kind of the adaptation was needed before starting a activity o module during teaching process of the on-line course. Once this value is known, we can use it in the equation (16) for recover lost o doubtful data and using probabilities of the tables II-V.

E.II Posterior probabilities

When an activity or module is finished in the on-line course, we can do inferences on the following activity or module using previous probabilities and calculating posterior probabilities by means of Bayes' Theorem [55]. These probabilities could be used to infer learner's characteristics and needs, system's adjustments and other on-line course requirements. Too, these probabilities can be used in order to infer partial personalization profile such as $P(\text{High, Passive, Dependent}|\text{Adapt})$. In this section, we estimate the posterior probabilities for each nodes of our model. Next, we show how to accomplish inferences for partial personalization profiles.

In order to calculate posterior probabilities of all nodes of the previous knowledge phase, we use previous probabilities showed in tables II-VII, and MSBNX software [43]. Results are shown in Figure 3. Value in the first column and fourth row represents the probability $P(\text{Adapt})$, and means 56.19 percent of the times an activity or module in this on-line course needs some kind of adaptation before being begun.

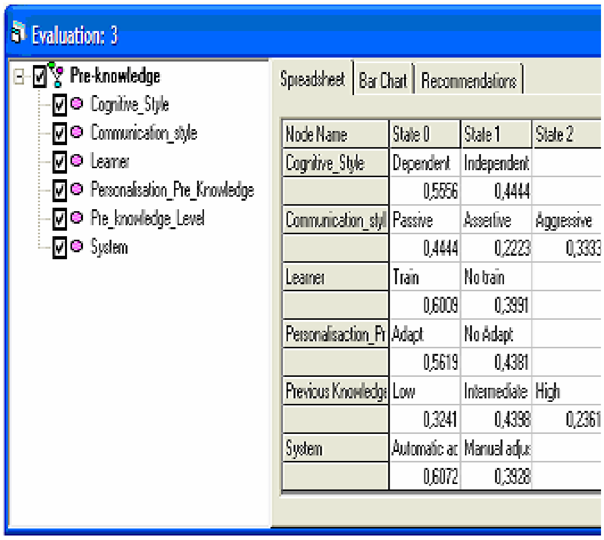

Figure 3 Posterior probabilities for the phase 1

According to our BM and the result of Figure 3 in first column and third row, there is 60.09% of probability a given learner require training before they realize any learning activity in the computer. Hence, system will take 60.09% of times decision to suggest learner training form. Similarly, according to first column and first row, there is 55.56% of possibility a particular learner has a cognitive dependent style. So, system will think 55.56% of times this learner has cognitive dependent style and so on.

On the other hand, using the values showed in figure 3 we can apply Bayes' Theorem [55] in order to calculate posterior probabilities and do inferences about learner's personalization partial profile regarding to his or her type of personalization. This calculus can do as follow:

$$P(\text{Adapt}|\text{High, Passive, Dependent}) = \frac{P(\text{High, Passive, Dependent}|\text{Adapt})\times P(\text{Adapt})}{P(\text{High, Passive, Dependent})} \qquad (17)$$

$$0.5 = \frac{P(\text{High, Passive, Dependent}|\text{Adapt})\times(0.5619)}{(0.2361)\times(0.4444)\times(0.5556)} \qquad (18)$$

Thus,

$$P(\text{High, Passive, Dependent}|\text{Adapt}) = 0.052 \qquad (19)$$

This indicates that when we know that on-line course needed adaptation, there is 5.2 percent that a specific learner will have a partial profile (High, Passive, Dependent).

In a similar way, we can to do deductions about a learner's partial personalization profile in on-line course calculating the previous probabilities using the value of table V (first column, and 13th row), and values in tables II-IV.

E.III Learner's profiles of personalization.

Using results in the Figure 3, we obtain Table XXVIII (see next page) by means of direct multiplications, because the events are independent. This Table contains all the possible profiles of personalization in the Personalization for previous knowledge phase and their probability.

According to our BM, the profile with higher probability will be the credibility of the expert system about learner's type of personalization. In this case, there are three possible profiles. They are profiles 49, 65 and 73 in Table XVIII. System will randomly choose one of them. In these three profiles we see three common things: 1) system require adaptation, 2) learner need training, and 3) adjusting of system must be manual.

F. Discussion of results.

We have designed a mathematical model usefully to infer the type of personalization of the learner using objects and objectives of personalization. Our model could optimize learner's global learning on-line process as long as contents, support, infrastructure and adequate orientation are given to learner. Therefore, it is necessary a multidisciplinary job among professional people of Education, Psychology and Computer Science, all of them supported by Knowledge Engineering whose application can respond, in general, to the requests and specific problems of learners and/or teachers.

Given complexity and cost that entail to implant our model, in this research we use learner's simulated data, using recommendations of recent publications and our personal propositions. From a technologic point of view, we think that our simulation initiatives are significant once its effectiveness is proven and confirmed, so they can be applied in the educational area to evaluate effects in real situations.

Main results obtained in this research are:

- Causal relations among objects and objectives of personalization, knowledge phases, learner and electronic system used to manage learner's teaching/learning process are major characteristics of the BM proposed here.

- A set of personalization profiles considering main learner's characteristics were obtained. These profiles could be used to propose a teaching/learning model to the learner, which can optimize the GAeLP according to his or her real needs.

- Using Table XXVIII we could diagnose type of personalization of a specific learner relative to the first phase.

- Furthermore, as learner data are compiled, other learning metrics and parameters of local pdfs will be obtained.

The designed BM yields the following outcomes

- A set of relations cause-effect among personalization objects, personalization objectives, learning phases, learner and system. These relations were used to manage learner's teaching/learning process.

- Tables with simulated results of BM variables, they can be used to initialize other similar models to realize inferences about characteristics´ learner.

- Previous and posterior probability tables to each node of BM, which were used to initialize our BM.

- We propose local pdfs to generate learning metrics to states variables in the model. Parameters of these pdfs will be determined gradually with real data compiled from the learner.

G. Conclusion

We have built a BM using objects and objectives of personalization. This model could be used to determine the learner's type of personalization with the aim to optimize his or her GAeLP. This was showed through simulation.

Also, this model can serve totally or partially, during the teaching/learning process, to realize diagnostics about the personalization type of the learner, in case of uncertainty or lost data relative to learner individual characteristics.

It worthwhile to be notice that the given model doesn't guarantee by itself learner's learning, because learner's knowledge depends (greatly) on the learner's attitude, effort, performance and interest to obtain knowledge. Effectiveness of BN in learner modelling has experimentally been proven. Prediction about learner's type of personalization is possible by means of BNs. To diminish the number of variables in the model is recommendable to detect statistical dependences or independences between objects and objectives of personalization in future works. Also, create probabilistic models combining BNs and fuzzy logic could be reduced learner's cognitive load.

TABLE XXVIII.
CONDITIONAL PROBABILITIES FOR THE NODE "SYSTEM" OF THE PHASE 4

Profile	Pre-knowledge	Cognitive style	Comm. style	Personalization for Pre-knowledge	Learner state	Adjusting of System	Prob.
1	Low	Dependent	Passive	Adapt	Train	Manual	0,0164
2						Automatic	0,0106
3					No train	Manual	0,0109
4						Automatic	0,0070
5				No adapt	Train	Manual	0,0128
6						Automatic	0,0083
7					No train	Manual	0,0085
8						Automatic	0,0055
9			Assertive	Adapt	Train	Manual	0,0205
10						Automatic	0,0133
11					No train	Manual	0,0136
12						Automatic	0,0088
13				No adapt	Train	Manual	0,0160
14						Automatic	0,0103
15					No train	Manual	0,0106
16						Automatic	0,0069
17			Aggressive	Adapt	Train	Manual	0,0164
18						Automatic	0,0106
19					No train	Manual	0,0109
20						Automatic	0,0070
21				No adapt	Train	Manual	0,0128
22						Automatic	0,0083
23					No train	Manual	0,0085
24						Automatic	0,0055
25		Independent	Passive	Adapt	Train	Manual	0,0164
26						Automatic	0,0106
27					No train	Manual	0,0109
28						Automatic	0,0070
29				No adapt	Train	Manual	0,0128
30						Automatic	0,0083
31					No train	Manual	0,0085
32						Automatic	0,0055
33			Assertive	Adapt	Train	Manual	0,0131
34						Automatic	0,0085
35					No train	Manual	0,0087
36						Automatic	0,0056
37				No adapt	Train	Manual	0,0102
38						Automatic	0,0066
39					No train	Manual	0,0068
40						Automatic	0,0044
41			Aggressive	Adapt	Train	Manual	0,0164
42						Automatic	0,0106
43					No train	Manual	0,0109
44						Automatic	0,0070
45				No adapt	Train	Manual	0,0128
46						Automatic	0,0083
47					No train	Manual	0,0085
48						Automatic	0,0055
49	Intermediate	Dependent	Passive	Adapt	Train	Manual	0,0223
50						Automatic	0,0144
51					No train	Manual	0,0148
52						Automatic	0,0096
53				No adapt	Train	Manual	0,0174
54						Automatic	0,0112
55					No train	Manual	0,0115
56						Automatic	0,0075
57			Assertive	Adapt	Train	Manual	0,0278
58						Automatic	0,0180
59					No train	Manual	0,0185
60						Automatic	0,0120
61				No adapt	Train	Manual	0,0217
62						Automatic	0,0140
63					No train	Manual	0,0144
64						Automatic	0,0093
65			Aggressive	Adapt	Train	Manual	0,0223
66						Automatic	0,0144
67					No train	Manual	0,0148
68						Automatic	0,0096
69				No adapt	Train	Manual	0,0174

70						Automatic	0,0112
71					No train	Manual	0,0115
72						Automatic	0,0075
73		Independent	Passive	Adapt	Train	Manual	0,0223
74						Automatic	0,0144
75					No train	Manual	0,0148
76						Automatic	0,0096
77				No adapt	Train	Manual	0,0174
78						Automatic	0,0112
79					No train	Manual	0,0115
80						Automatic	0,0075
81			Assertive	Adapt	Train	Manual	0,0178
82						Automatic	0,0115
83					No train	Manual	0,0118
84						Automatic	0,0077
85				No adapt	Train	Manual	0,0139
86						Automatic	0,0090
87					No train	Manual	0,0092
88						Automatic	0,0060
89			Aggressive	Adapt	Train	Manual	0,0223
90						Automatic	0,0144
91					No train	Manual	0,0148
92						Automatic	0,0096
93				No adapt	Train	Manual	0,0174
94						Automatic	0,0112
95					No train	Manual	0,0115
96						Automatic	0,0075
97	High	Dependent	Passive	Adapt	Train	Manual	0,0120
98						Automatic	0,0077
99					No train	Manual	0,0079
100						Automatic	0,0051
101				No adapt	Train	Manual	0,0093
102						Automatic	0,0060
103					No train	Manual	0,0062
104						Automatic	0,0040
105			Assertive	Adapt	Train	Manual	0,0149
106						Automatic	0,0097
107					No train	Manual	0,0099
108						Automatic	0,0064
109				No adapt	Train	Manual	0,0117
110						Automatic	0,0075
111					No train	Manual	0,0077
112						Automatic	0,0050
113			Aggressive	Adapt	Train	Manual	0,0120
114						Automatic	0,0077
115					No train	Manual	0,0079
116						Automatic	0,0051
117				No adapt	Train	Manual	0,0093
118						Automatic	0,0060
119					No train	Manual	0,0062
120						Automatic	0,0040
121		Independent	Passive	Adapt	Train	Manual	0,0120
122						Automatic	0,0077
123					No train	Manual	0,0079
124						Automatic	0,0051
125				No adapt	Train	Manual	0,0093
126						Automatic	0,0060
127					No train	Manual	0,0062
128						Automatic	0,0040
129			Assertive	Adapt	Train	Manual	0,0096
130						Automatic	0,0062
131					No train	Manual	0,0063
132						Automatic	0,0041
133				No adapt	Train	Manual	0,0075
134						Automatic	0,0048
135					No train	Manual	0,0050
136						Automatic	0,0032
137			Aggressive	Adapt	Train	Manual	0,0120
138						Automatic	0,0077
139					No train	Manual	0,0079
140						Automatic	0,0051
141				No adapt	Train	Manual	0,0093
142						Automatic	0,0060
143					No train	Manual	0,0062
144						Automatic	0,0040

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