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Evaluating the Effect of Learner's Knowledge, Background, and Attention's on Trust Using Open Learner Model

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Abstract- **The learner model is a distinctive characteristic of any Adaptive Educational Systems (AES) and Intelligent Tutoring Systems (ITS). The learner model not only is the base of adaptation in AES and ITS systems, but also in some way is used for assessment of learners. Hence, the accuracy of learner model is an important issue. In Open Learner Model (OLM), the learner's belief can change the learner model. Regarding this problem, it should be determined that how much a system can trust in learner's belief about his/her model and which characteristics of a learner affect on correctness of learner belief.**

In this paper we investigate if learner knowledge, background and attention have effect on system trust in Open Learner Modeling. We choose these parameters according to their importance in the learning system.

To obtain learner's knowledge and background multiple choice questions are utilized. The value of attention is estimated by Toulouse-Pieron Test. To evaluate the effect of mentioned characteristics of learner the chi-square distribution is used. The obtained results indicate that the value of learner's knowledge, background and attention affect on trust value.

Keywords: learner model, Open learner Model, Learner Model Parameters, Trust value.

I. Introduction

General Description: **A**daptive **E**ducational **S**ystems (**AES**) and **I**ntelligent **T**utoring **S**ystems (**ITS**) are interesting research domains in e-learning. Utilization of learner model in these systems is the most important characteristic which makes them different from other types of learning environments. In fact, learner model provides necessary information which capable the learning system to adapt its services to learning needs according to his/her knowledge, background, or other characteristics during the learning process. A Learner model includes parameters related to the learner's knowledge, interests, goals, educational backgrounds, emotional behaviors, and individual traits. A learner model is called "open" if its parameters could be viewed, inspected, and even changed by the learner or other permitted users. The most significant motivation for such a viewing and modification is to reach to a perfect and accurate model. In other words, the term of "open" in this argument means having the interior part exposed to general views (Self, 1999).

So far several investigations in the **O**pen **L**earner **M**odels (**OLM**) domain have been reported. One of the main purposes of OLM modeling is to improve the accuracy of the learner model. For example, in the works reported by Collins (Bull et al, 1995), STyLE-OLM (Zapata-Rivera and Greer, 2002) and ChatBot (Kerly et al, 2007) a negotiation mechanism is used to achieve the mentioned accuracy. In these systems, each learner can discuss his/her sight with the learning system and verify his/her model. In fact, the learner belief can be used to update the learner model and consequently the accuracy of OLM is increased.

Promoting learner reflection on knowledge and understanding is another aim of OLM. The empirical results indicate that OLM mostly causes learner to show reflection. For example in the systems such as the one presented in the work of Collins (Bull et al, 1995), and also STyLE-OLM (Zapata-Rivera and Greer, 2002) and ChatBot (Kerly et al, 2007) promote learner's reflection by encouraging them to defend his views by discussing and arguing against the system's assessment of his/her level of knowledge and his/her beliefs. In the work presented in (Bull and Kay, 2007) an interactive open learner modeling (IOLM) approach where learner diagnosis is being considered. This is an interactive process that involves both the computer the learner in construction of the learner model. The results obtained in IOLM showed some computational and educational benefits of IOLM in terms of improving the quality of the obtained learner model and fostering reflective thinking. In (Brusilovsky and Millan, 2007) ViSMod provides a way for students and teachers to interact through the creation of different views of a Bayesian Student Model. Each view could have different nodes and different evidences. Students and teachers experiment with their own views in order to create a model that reflects their own perception in the learning process with a high fidelity, this mechanism engages learners and teachers in discussions that support knowledge reflection. In (Gambetta, 2000) a student model is represented which could be inspected by the student. This model helps learners to focus his/her reflection on the learning process.

Other purpose of OLM is discussed in (Bull and Kay, 2007) and shows that OLM helps learners to plan their learning progress, facilitating collaboration and/or competition, facilitating learner navigation in the learning system, and facilitating self-assessment.

Motivation: Many issues are coming up in the field of open learner modeling. For example, how the learner model is available to the learner, partially or completely? Who is allowed to view the learner model? How much the representation of open learner model is similar to the structure of underlying learner model? How the learner model could be accessed? In this work a new item is added to the mentioned ones: "How much a learning system can trust to learner's belief and his/her feedback about his/her model?"

Considering the importance of accuracy of the learner model, the present paper has focused on this issue:"How much can system trust in learner's belief and his/her feedback about his/her model?" This could be a reasonable motivator for solving the problems related to the trust in AES and ITS systems.

Contribution: In order to solve the mentioned problem regarding trusting the learner's feedback about his/her model, it is necessary to find a measurable value in this regard. The main contribution of this work is to define effective parameters in the learner's model which could be necessary and utilized to calculate a Trust Value.

In this paper the effect of three important characteristics of learner including knowledge, background and attention on system's trust to learner belief is examined. The learner's attention has not been mentioned as a basic parameter in learner model, but according to the importance of attention for decision making and especially in response and feedback generated by learner it is considered as another parameter. Finally to estimate the relation of the mentioned parameters with Trust Value the chi-square distribution is employed.

This paper is organized in five sections. The first section aimed on a short introduction, our motivation in this work, and the gained contributions. The second section will be dedicated to the trust in general, and trust in OLM in particular. In the third section our proposed approach will be described, and then the result of the proposed approach, will be discussed in the fourth section. Finally, section five presents our conclusions to this work and its future extensions.

II. BACKGROUND THEORIES

LEARNER MODELLING:

In (Brusilovsky, 2007) mentioned that a Learner model includes parameters like: knowledge, interests, goals, educational backgrounds, emotional behaviors, and learning style. Each of these characteristics is discussed as follow.

Learner's Knowledge: The most important feature to found a learner model is knowledge (Brusilovsky, 2007). The learner's knowledge is a dynamic feature that changes from session to session, or during the same session. Learner's knowledge will increase if the user learns something new, but also it may decrease if the learner forgets something. Preparing a model for a learner is the main stand for adaptation in AES and ITS. Because in an adaptive system, for any type of adaptations, in the first step it is necessary to recognize any changes in the learner's knowledge, and update the learner model accordingly.

Learner Knowledge can be gained and encoded explicitly or implicitly. A simple and explicit way to obtain the learner's knowledge is taking a quiz. The rate of the correct answers to the quiz determines the level of the learner knowledge in a specific domain. Another explicit way is to invite the learner to judge and state directly about his knowledge, even though it is not a precise way. By means of monitoring the learner behavior and the navigations being done by the learner's information about the learner's knowledge could be obtained implicitly. Initializing the learner knowledge is an important issue that can be made by asking some questions or taking a quiz.

Learner’s Background: The learner's background is a common name for a set of features related to the learner's previous experience outside the core domain of a specific educational system (Brusilovsky, 2007). For example, mathematical AES can distinguish two or three categories of learners according to their knowledge of mathematics terminology and adapt content presentation to the learner category by selecting either mathematical terms or everyday language to present the same content. Also these systems can distinguish learners by their educational level which implies the level of knowledge. Background information is used most frequently for content adaptation.

Learner background is not a changeable learner feature and does not change during work with the system. According to static nature of the learner background, implicit way like monitoring the learner work can’t be a proper way for achieving learner background. So, learner background is usually provided explicitly, either by the learner herself or by some kind of a superior (a teacher in a college or an administrator at an institution).

Learner’s Interests: Learner's interest is a criterion that shows to which type off content, learning material or educational services, the learner is interested (Brusilovsky, 2007). Interest is the most important feature for user modeling in information retrieval and filtering systems. In the early days it was used in the mentioned systems and was known as preferences. But nowadays according to the rapid growth of volume and variation of information in ITS, learner's interest becomes important in learner modeling too. Like learner's knowledge, information about learner's interest can be obtained explicitly, through direct learner intervention, or implicitly, by means of the agents that monitor learner's activities.

Learner’s Goals: The learner goal is what the learner really wants to achieve. Sometimes goal is defined as some states of affairs that learner wishes to achieve. However a plan is sequence of actions to be taken or events to be happened to take result in the realization of particular state of affairs. According to the first definition the most changeable feature of the learner model is the learner's goal. It can change from one session to another or even may change several times during one session. In comparison to the characteristics such as knowledge and interest, the learner's goal has been mentioned fewer in learner modeling.

Determining learner's goal ranges from being a simple task, to a very difficult one. The basic algorithm works in this way: system observes the user inputs and choices and tries to determine all possible learner plans to which the observed actions can be complemented. Two approaches that were used for the recognition of learner’s:

- Plan libraries: In this approach, all possible learner plans are pre-stored in a plan library. The plans in this library are compared to the observed learner action, if the beginnings of plans match the observed learner action, then these plans are selected as learner’s goals.
- Plan construction: In this approach, a library of all possible learner actions with the effects and preconditions of these actions are stored. The observed user action sequence is completed by all possible user action sequences. These actions fulfill the requirement that the effects of preceding actions meet the preconditions of subsequent actions.

The plan library approach in contrast to the plan construction approach is adequate for small domain with limited number of goals. The weakness of the plan construction approach is its complexity.

Learner’s Emotional Behavior: Learner's emotional behavior could have an important role in learning process. Therefore, in the process of modeling this feature should be considered (Sarrafzadeh et al., 2003). Recognizing the emotional behaviors and motivating it is an important issue. So far five computerized methods have been used that explicitly or implicitly can recognize the learner's emotional behaviors:

- Question asking,
- Deduction making based on learner’s behaviors.
- Learner’s voice processing.
- Learner’s image processing.
- Learner’s behaviors monitoring using sensors.

Learning Styles: Learning styles refer to the way in which the learner prefers to advance his/her new information. Each person learns and processes information in his/her own special ways. However he/she shares some learning patterns, preferences, and approaches. Knowing the learning style also can help every learner to realize that other peoples may approach the same situation in a different way.

By understanding the learning style, learner can develop his/her natural approach in a learning process, and also can develop his/her capacity to learn in a manner that may require more effort. On the other hand instructors can understand the differences in learning process for any individual learner, and he can develop a range of educational strategies to engage individuals' strengths.

The analysis of existing classifications of learning style leads us to say that they all try to distinguish the three elements of definitions, namely preferences (sensory or environment), the cognitive ability/personality, and the learning process (experiential, data processing, learning strategy, etc.). They are largely based on the Curry’s ‘onion’ model (Bousbia et al., 2008).

Some educational systems use tests to assess the students’ learning styles, which consist of a number of questions, and compute the sums and averages of all the questionnaire answers.

Learner Modeling Approaches: Approaches which can be used for modeling mentioned features of learner including: Stereotype, Scalar, and Overlay.

Stereotype modeling is one of the most elderly approaches which are used for individual user modeling. Stereotype modeling as a learner modeling approach is an attempt to cluster all possible learners of an adaptive learning system into several groups, called stereotypes. Therefore, the same adaptation mechanisms are used for all the learners in one stereotype. In stereotype learner modeling approach every learner is represented as his/her current stereotype. When some features in a learner have changed, learner model could be updated by simply re-assigning the learner, if necessary, to a different stereotype. For more recent utilization of stereotype modeling in adaptive systems, works such as (Micarelli & Sciarrone, 2004; Tsiriga & Virvou, 2003), could be considered.

Scalar model is a simple way of user modeling that is mostly used for modeling of user knowledge. Despite their simplicity, scalar models can be used effectively to support simple adaptation techniques in AHS (Brailsford et al, 2002). Scalar model estimates the level of user domain knowledge by a single value on some scale – quantitative (a number ranging from 0 to 5) or qualitative (good, average, poor, none). By its nature scalar modeling approach, especially qualitative, is very similar to stereotype modeling. As stereotype modeling in which users are divided to some stereotypes, in scalar modeling users are divided into two or three classes according to their knowledge level in a subject (expert, intermediate, and novice). In contrast to their similarity, there is a difference between them. The difference is that scalar knowledge models focus exclusively on user knowledge and are typically produced by user self-evaluation or objective testing, not by a stereotype-based modeling mechanism (Brusilovsky, 2007).

In Comparing to the other user modeling approaches, scalar modeling limitation is its lower precision. Since in this approach the overall knowledge of a user is modeled, it is possible to determine precisely the level of the user knowledge in every part of the subject domain. For example, in the subject domain of C programming, a user may be a professional expert in functions, but a novice could be a qualified learner in macros. Scalar user modeling is not a proper approach for advanced adaptation technique. For advanced adaptation, structural models such as overlay, which will be explained in the next subsection, is more satisfactory. The structural models assume that the body of domain knowledge can be divided into certain independent fragments.

Overlay user modeling approach is a dominant approach for learner modeling in ITS and AES. Overlay approach matches properly to the core function of AHS, and provides personalized access to information. Therefore, it has been accepted as de-facto standard by almost all educational and many non-educational adaptive hypermedia systems (Brusilovsky, 2007). The overlay model is constructed from two parts:

- Generalized Domain Model: A generalized domain model is a set of aspects representing any characteristics that a user may have. Such as knowledge, interest, domain concepts, domain tasks and goals, and possible stereotypes.
- Generalized Overlay Model: A generalized overlay model is a set of pairs in the form of "aspect-value". In each pair the value can be "true" to indicate that the user has the characteristic defined by aspect or can be "false" to point out that he does not have. Also this value could be qualitative or quantitative.

BDI model: Also in some learner model other characteristics are considered for learner, for instance in BDI model.

In (Bratman, 1990) proposed the BDI model that is based on belief, desire and intention mental states. Each of these parameters are disused in following.

The beliefs stand for the information about the state of the environment that is updated properly after each sensing action. The beliefs could be considered as the informative parts of the model state.

The desires are the motivational state of the model which includes information about the objectives to be achieved. The fact that a learner has a desire does not mean she/he will do it.

The intention is a desire that was chosen to be executed by a plan, as it can be done based on the agent’s beliefs. The desires could be contradictory to each other, but the intentions couldn’t. The intentions show the currently chosen course of action. The intentions are constant. A learner will not quit on his/her intentions, until successfully gained them.

TRUST :

Trust is a human reaction which is a mixture of both the emotional behavior and the logical reasoning. Trust is an emotional reaction when someone exposes his/her honesty to people, but believes that they will not take advantage of his/her openness. On the other hand trust is a logical reaction when the probability of gain or loss should be assessed, or expected utility based on hard performance data must be calculated and in our case when it is necessary to conclude that the learner in response to the questions will behave in a predictable manner.

Trust has plays a central role in human relationships, and so has been the subject of study in many fields including business, law, social science, philosophy, psychology, and information technology.

As Gambetta (Gambetta, 2000) defines: “...trust (or, symmetrically, distrust) is a particular level of the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action, both before he can monitor such action (or independently of his capacity ever to be able to monitor it) and in a context in which it affects his own action”. Another definition of trust was presented by Grandison and Solomon (Grandison and Sloman, 2009): “Trust is a complex topic relating to belief in the honesty, truthfulness, competence, reliability, etc., of the trusted person or service."

In educational systems, trust is an important reaction which is expected in the process of interaction between a learner and a learning system. In one hand, it is the questionable that wheatear the learner can trust to the provided services by the system? On the other hand, it is more important that if the system can trust to any given information given by the learner? Trust in AES and ITS systems which are constructed on the basis of OLM modeling will be described in more details in the next section.

TRUST IN OPEN LEARNER MODEL

In open learner modeling, the learner and the system are in mutual and different kinds of interactions. According to (Bull and Kay, 2007) in an OLM based on different kinds of access the interaction between the learner and the system can be divided into six categories:

Inspectable Access: The basic and significant level of access in open learner modeling is allowing the learner to examine the model.

Editable Access: In this sort of access the learner can edit his/her model. Of course, it is arguable whether to allow a learner to edit his/her model or not. Since the learners can purposely make the model inaccurate or they may not have adequate knowledge to edit their own models appropriately. However, some learners may be able to provide useful information for an appropriate modification.

Additional Access: learner may add evidence which could be considered alongside the system's own conclusions. The difference between additional and editable access is that in additional access in contrary to editable access the model is not changing nor correcting, but it is provision of further evidence provided by the learner.

Learner Persuaded Access: learner can persuade the system. A simple and natural way for doing this is where the learner can request a test to persuade the system of his/her knowledge.

Negotiated Access: System and the learner may negotiate about their cases, for reaching to an agreement over the learner model. For achieving such an agreement, the system should maintain different viewpoints on learner knowledge in order to facilitate discussion and negotiation. Therefore, this type of access is based upon the system's understanding and the student's beliefs about the learner knowledge.

System Encouraged Access: In such an access the system attempts for motivating the learner to take action in development of his/her model.

Therefore, based on the above mentioned access, according to learner's idea the system changes the learner model in learner-system interactions of type Additional, Student Persuade and Negotiated accesses. In this regard one important issue is that "how much can system trust to the information provided by learner about him/her learner model?" This means that we should think about an acceptable trustiness between these two parties.

Trust in any interaction between learner and system can be investigated from two view points. 1- How much the learner can trust the suggestions and the model presented by the system, 2- How much the system can trust the information provided by the learner.

Case 1: How much can the learner trust the system? From this viewpoint trust means what is the idea of learner about OLM services that are provided by the system. In this case trust is shaped on the basis of complexity in model presentation, level of the control over the model contents, and release of the model to the other users (Bull et al, 2009), (Ahmad and Bull, 2009), and (Ahmad and Bull, 2008).

Case 2: How much can system trust the learner's feedbacks? In an Open Learner Model (OLM), the learner's belief of his/her model can badly change the learner model. Therefore it is necessary to agree on a trust scale which could be used as a judgment criterion for stating how much the system can trust the learners' belief about his/her model.

For calculating Trust Value in the second case, a two-stage approach is proposed. In the first stage, effective parameters in a learner model for computing Trust Value should be defined. Then in the second stage the mathematical model for computing of Trust Value is implemented. In this work the effect of learner's knowledge, backgrounds, and attention as the most effective parameters on Trust Value was examined.

RELATED WORKS

In the works reported by Collin (Bull et al, 1995), STyLE-OLM (Zapata-Rivera and Greer2002), and ChatBot (Kerly et al, 2007) the trust is calculated for interactions supported with inspectable and negotiated accesses. In these systems only the learner's knowledge is used as an effective parameter on trust. In these systems, for specifying Trust Value, two separate belief or confidence measures are being considered. In the first one the learner's own confidence in his/her performance is reflected which is named learner confidence while in the second one the learner's performance is evaluated by the system that is named system confidence. Trust value is calculated with equation (1).

$$T = |L-S| \qquad (1)$$

In equation (1) Trust value is shown by T, L stands for learner confidence and S stands for system confidence, also Trust Value is computed with the measure of difference between the system confidence and the learner confidence. Learner and system confidence values are expressed in four levels: 1- very sure, 2- almost sure, 3- unsure and 4- completely unsure. If Trust value is less than or equal to one, the system trusts in learner's belief. But if trust value is more than one, the system negotiates with the learner for some correction or modification in learner model. For example in such a situation the system supplies another exam and the learner is requested to answer the questions. If the leaner correctly answers to the questions, the system will trust to his/her feedback in the process of interaction. Otherwise the system does not trust to learner's response and learner model is remained unchanged. For instance in table (1) three learner confidence, system confidence and trust value for learners a, b and c is shown, also according to trust vale is determined which user is trustworthy and which one isn't. Trust value of *a* is 1 and *b* is 0 as trust value of both a and b is less equal to 1 they are trustworthy. Trust value of c is more than 1 so c is not trustworthy.

Table 1. Examples of trust value

Learner Name	*learner confidence (L)*	*system confidenc e (S)*	*Trust value (T)*	*Is trustworthy? (Yes/No)*
a	3	4	1	Yes
b	1	3	2	No
c	2	2	0	Yes

In the mentioned systems (Bull et al, 1995), (Zapata-Rivera and Greer2002) and (Kerly et al, 2007), learner's knowledge is the only effective parameter being considered in trust calculation. In the next section other effective parameters which could be considered in learner model for calculation of the Trust Value will be investigated.

III. RESEARCH METHODOLOGY

Problem definition:

As mentioned, in OLM learner model could be updated by means of learner's belief about his/her model. Therefore an important challenging issue is: "How much a learning system can trust in learner's belief about his/her model?"

Scenario:

As shown in Figure (1), the research includes four main steps: One, learner modeling; Two, opening the learner model; Three calculating the Trust Value and Four, calculating the effect of learner parameter (knowledge, background and attention) on the Trust Value. All these steps are explained with more detail in the following subsections.

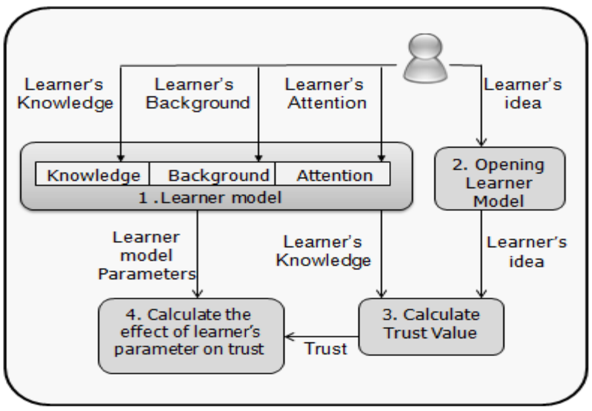

Figure 1. Steps of Research

Learner Modeling:

In this work the effect of three learner's parameter including knowledge, background and attention on trust value are studied.

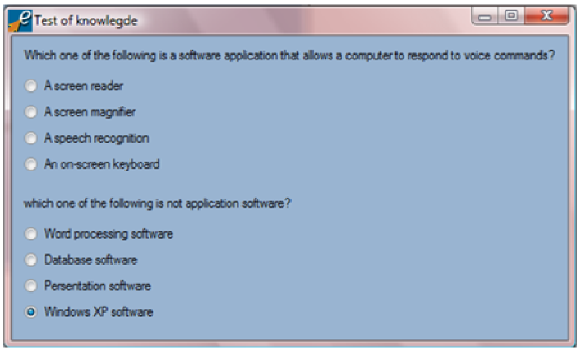

Figure 2. A sample of multiple questions

In learning environment the main factor which should be assessed and determined is knowledge. In Hence in this work on one of the parameter which is chosen to investigate its effect on trust value is the knowledge of learner. Another factor which is important in learning environment is learner background. In fact background is learner knowledge in related domains. As in this work learner declare his/her idea about knowledge value which is assessed by system, so his/her background in related domain will be effective on it. Also a learner may have enough knowledge to comment about his/her model but he/she may not have adequate attention when identifying his/her belief. Therefore another factor which its effect on trust value to learner's idea is studied is learner's attention.

Other learner characteristics like emotion, learning style, interest goal and so on could be effective on trust value which could investigated in future works.

Model of Learner's knowledge: In this work Overlay Knowledge Modeling has been utilized. The idea of overlay knowledge modeling is to represent the knowledge of each individual learner as a subset of a domain model that resembles the knowledge of an expert in related subject [5]. In this work learner's knowledge is assessed in "Principles of Computer Science" lesson which includes four concepts: 1- The Basic Concepts of Computer, 2- History of Computer, 3- Software and Hardware, 4- Binary Numbers and Their Applications. To gain learner's knowledge in each of mentioned concepts, 10 multiple choice question are applied that is equal to 40 questions for all of the 4 concepts. Questions are chosen from ICDL resources by two experts. Each correct answer has a one point and wrong answer has zero point for learners. Hence total grade in each concept is 10. Total learner's grade in each concept is normalized to a value between 0 and 1. For example a learner who got 8 from 10 in "History of Computer", his/her knowledge in this concept is equal to 0/8. An instance of multiple questions is shown in Figure (2).

Model of Learner's Background: In order to obtain background value, a multiple choice examination with 14 questions related to computer skills and familiarity with computer technology is used. These questions cover related subjects such as office software, multimedia software, and internet tools such as email and search engines.

Model of Learner's attention: The learner attention could be assessed by means of Toulouse-Piéron test (Toulouse and Pieron, 1986). Toulouse Piéron test which is a perceptual and attention test is a cancellation test and provides information about abilities such as concentration and monotony resistance, as well as perceptual speed and attention skills. Lower gained score reflects the general response slowing and inattentiveness.

The test sample contains 1600 dashed squares arranged in 40 rows of 40 items. As shown in Figure (3) each row includes squares with different dashed orientation. Three squares at the top of the questioner shape a pattern of squares which should be searched and specified by the one under examination. The learner is asked to carefully observe the pattern and then he/she should explore each row and search the squares for marking all the squares which are matched with the indicated pattern.

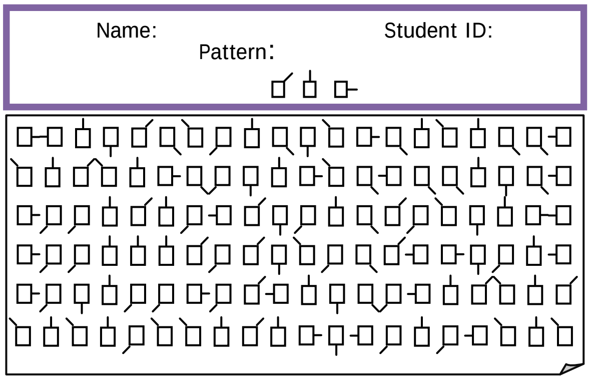

Figure 3. A Sample Page of Toulouse and Pieron Test

This test explains both a quantitative and a qualitative conclusion about the learner attention (Testul Toulouse-Pieron, 2010). Preliminary the following values should be calculated for each learner:

Tc: The total number of squares correctly crossed out

Tg: The total number of squares wrongly crossed out.

To: The total number of squares being missed.

The quantitative aspect of attention is the amount of squares correctly crossed out as defined by Equation 2. Hence;

$$\text{Quantitative value of attention} = Tc \qquad (2)$$

The qualitative aspect of attention is computed as below (Equation 3):

$$\text{Qualitative value of attention} = (Tc-Tg)/(Tc + To). \quad (3)$$

Qualitative value of attention is computed by first subtracting the total number of squares correctly crossed out from the total number of squares wrongly crossed out, i.e. (Tc-Tg). Then it is divided by the total number of squares which should be crossed out, i.e. (Tc + To).

In this paper the attention test has done in a limited time. A page containing 1600 shapes has shown to learner and the learner should select the shape that match with pattern (by clicking on shapes). In this research we use the Qualitative value of attention which computed as Equation (3).

Opening learner model:

Following the construction of learner model it is time to open the learner model to its possessor. For opening the learner model the following issues should be considered:

Which parts of the learner model are to be visible? This issue focuses on how much the learner model is available to the user, partially or completely? In this research learner model is constructed on the basis of three parameters: knowledge, background and attention, but learner's knowledge is the only part of the model which is presented to learner.

Who is allowed to view the learner model? In some systems in addition to learner, other users such as peers and/or instructors have access to the leaner model. In this research just learners are allowed to see their own model.

How open learner model is presented to learner? In this work the learner's knowledge in each concept of learning domain is presented to learner with skill meter. As reported in [4](Bull and Kay, 2007), skill meter is a part-shaded bar showing learner progress as a subset of knowledge defined by an expert. It is in fact the probability that a learner knows a concept.

How the learner model could be accessed? Different kinds of accesses have been explained carefully in section (2.2). In this work each learner has two levels of access: Inspectable Access and Additional Access.

Calculating the Trust Value:

As mentioned in pervious section in any interaction between learner and system Trust can be investigated from two points of view. 1- How much the learner can trust the suggestions and the model presented by the system, 2- How much the system can trust the information provided by the learner.

To compute Trust Value the similar way reported in (Bull et al, 1995), (Zapata-Rivera and Greer2002) and (Kerly et al, 2007) was used. (See section 2.3 for more details) and then the effect of learner's knowledge, backgrounds, and attention on trust value was investigated.

Calculating the effect of learner parameter on trust value:

In many domains of research two key questions are arisen whether two specific variables are correlated, and if so, what is the strength (or significance) of that correlation. For example, is there a significant correlation between gender or ethnicity and political affiliation? The Chi-Square test is a widely used method for measuring if a significant relationship exists between two nominal or categorical variables, such as gender and political affiliation. Responses to questions such as "What is your major?" or "Do you own a car?" are categorical because they yield data such as "Biology" or "No."

The Chi-Square test always makes use of null hypothesis, which states that there is no significant relationship between two variables. With specified significance level, if Chi-Square is greater than critical value then the null hypothesis (there isn't any relationship between two assumed variables) is rejected and the alternative hypothesis (there is a relationship between two assumed variables) is accepted (Freund, 1992).

The effect of knowledge, backgrounds, and attention on Trust Value is measured by Chi Square Distribution. We assume that there is no relation between each of the mentioned parameters of learner model and Trust Value as null hypothesis. The process and result of computing Chi-Square for our research is investigated fully in section 4.

Participant:

To establish a suitable test bed some parts of a B.Sc. course titled as Principles of Computer Science was selected. This course was presented during the fall semester 2009 in Elmi_Karbordi University. The selected parts of the mentioned course covers 4 concepts: 1- The Basic Concepts of Computer, 2- History of Computer, 3- Software and Hardware, 4- Binary Numbers and Their Applications. Then 64 learners (54 female and 10 male) with an average age of 22 were selected. These students studied in two different majors.

All concepts were taught in face to face sessions to learners. Then, a multiple choice examination was taken to estimate the learners' knowledge level in each concept. To obtain the learners' background some questions about appropriate computer skills and familiarity with computer technology were presented. These questions covered related subjects regarding office software, multimedia software, and internet tools such as email and search engines. Finally, the learner attention was estimated by means of Toulouse-Piéron test. Afterward the learners' knowledge levels related to each concept were presented to him/her by means of skill meter model as shown in the left side of Figure (4). Then, the learner is asked to specify his/her belief about the level of his/her knowledge in each concept in associated dialog boxes shown in the right side of Figure (4). The difference between the learner's knowledge level being examined by the system, and the level expressed by the learner as his/her belief about his/her knowledge, was used as a measure for system trust.

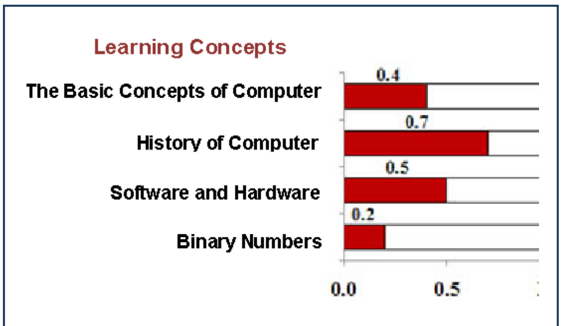

Figure4. The learner's knowledge level in each of the 4 concepts under examination in this work

IV. Results

As mentioned before, Chi Square Distribution is used to measure the effect of knowledge, backgrounds, and attention on Trust Value. The Chi-Square test is widely used to measure if there is a significant relationship between two nominal or categorical variables. In this work, Knowledge, Backgrounds, Attention and Trust Value assumed as categorical variables. The results of each examination regarding learner's Knowledge Level, Belief, Background and Attention were normalized to a number between 0 and 1.

As a sample, the value of these parameters for 6 learners is shown in Figure (5). The meanings of abbreviated terms which have been used to describe associated variables are explained as follows:

Cj: The knowledge of learner in concept j being obtained by the learning system.

K: The Numerical value for expressing an average for learner's Knowledge in a concept.

LBj: The Numerical value for expressing the learner's belief in concept j.

LB: The Numerical value associated to the learner's Belief about his/her average knowledge.

A: The Numerical value associated to the learner's Attention.

B: The Numerical value associated to the learner's Background.

Variables \ Learners	1	2	3	4	5	6
C_1	1	1	1	1	1	1
C_2	0.8	0.7	1	0.4	0.4	0.9
C_3	0.9	0.4	0.6	0.4	0.4	0.4
C_4	0.7	0.5	0.6	0.4	0.4	1
LB_1	1	0.9	0.5	1	1	0.5
LB_2	0.8	1	0.5	1	1	0.5
LB_3	0.6	0.8	0	0.5	0.5	0.4
LB_4	0.7	0.7	0	1	0.5	0.4
K	0.85	0.65	0.8	0.55	0.55	0.83
LB	0.78	0.85	0.25	0.88	0.68	0.45
B	0.35	0.38	0.13	0.33	0.35	0.38
A	0.62	0.61	0.64	0.56	0.69	0.66

Figure 5. A snapshot of learners' model parameters value

When the values associated to the above mentioned parameters are obtained, then Trust Value is computed as explained in section (2.3). Three levels are assumed for Trust Value, Knowledge Level, Background, and Attention: Good (0 to 0.3), Average (0.3 to 0.7) and Poor (0.7 to 1). To evaluate existence of relation between each of these pairs: (Knowledge and Trust Value), (Background and Trust Value) and (Attention and Trust Value) Chi-Square Distribution is used as reported in (Freund, 1992).

At first Null Hypothesis (H0) and Alternative Hypothesis (H1) should be defined:

For Knowledge and Trust Value:

H0 = There isn't a relation between Knowledge and Trust Value.

H1= There is a relation between Knowledge and Trust Value.

For Background and Trust Value:

H0 = There isn't a relation between Background and Trust Value.

H1= There is a relation between Background and Trust Value.

For Attention and Trust Value:

H0 = There isn't a relation between Attention and Trust Value.

H1= There is a relation between Attention and Trust Value.

Now the Contingency Table for all above null hypothesis should be constructed. By using Contingency Table the Chi-Square statistic and Degrees of Freedom is computed. The relationship between variable 1 and variable 2 could be shown as Contingency Table which is illustrated in Table (1). The amount of each table's cell shows the Observed Frequency of each category. For instance according to Table (1) if variable 1 is Poor and variable 2 is Poor too, then the Observed Frequency is equal to a. Also, to compute Chi-Square statistic the Expected Frequency of each Contingency Table's cell is necessary. The Expected Frequency (Ei) for each cell is determined by Equation (4).

Ei = (Total Row * Total Column)/Grand Total (4)

Now Chi-Square could be computed by Equation (5).

$$\text{Chi-Square Statistic} = \sum_i \frac{(O_i - E_i)^2}{E_i} \quad (5)$$

Where O_i is the Observed Frequency in a cell of Contingency Table and Ei is the Expected Frequency in a cell of Contingency Table.

Degree of Freedom (df) could be computed by Equation (6).

df =(Number of Columns -1) * (Number of Rows -1) (6)

So the Degree of Freedom of table (2) is computed as below.

df =(3 -1) * (3 -1) = 4

Table 2. contingency table of variable 1 and variable 2

Variable 1 / Variable 2	Poor	Average	Good	Row Total
Poor	a	b	c	a+b+c
Average	d	e	f	d+e+f
Good	g	h	i	g+h+i
Column Total	a+d +g	b+e+h	c+f+i	Grand Total a+b+c+d+e+f+g +h+i

The contingency between Knowledge and Trust Value, Background and Trust Value, and Attention and Trust Value is shown in the Contingency Table (Table 3-5). The results of Chi-Square statistic for these pairs of variables are computed by SPSS and are shown in Table (6). The Contingency Tables associated with these pairs of variables have 3 rows and 3 columns so the Degree of Freedom is 4.

Table 3: contingency table of Trust value and knowledge

Trust value / Knowledge	Poor	Average	Good	Row Total
Poor	10	5	7	22
Average	4	9	6	19
Good	3	5	15	23
Column Total	17	19	28	Grand Total 64

Table 4. contingency table of Trust value and background

Trust value / Background	Poor	Average	Good	Row Total
Poor	7	5	11	23
Average	4	9	6	19
Good	13	6	3	22
Column Total	24	20	20	Grand Total 64

Table 5. contingency table of Trust value and attention

Trust value / Attention	Poor	Average	Good	Row Total
Poor	5	12	8	25
Average	9	3	7	19
Good	3	5	12	20
Column Total	17	20	27	Grand Total 64

Chi-Square statistic values (in Table 6) are evaluated by using Chi-Square Distribution Table. In Chi-Square Distribution Table, values of Chi-Square statistic with different Degrees of Freedom for significant levels are shown. Significant levels define the probability level which probability level of null hypothesis should be less than it, in order to null Hypothesis be wrong and Alternative Hypothesis can be accepted. Significant levels usually are 0.01 or 0.05 (Freund, 1992). If for specified Degrees of Freedom the calculated value for Chi-Square is equal to or greater than critical value given in Chi-Square Distribution Table, the Null Hypothesis (there is not any relationship between two assumed variables) is rejected and the Alternative Hypothesis (there is a relationship between two assumed variables) is accepted.

As all contingency tables 2 to 4 have three columns and three rows according to Equation (6), Degrees of Freedom is equal to four. According to Chi-Square Distribution Table critical value with Degrees of Freedom four, for Significant level 0.01 is equal to 13.48 and for Significant level is equal to 9.49. According to Table (6) all obtained results for Chi-Square is greater than critical value with significant level 0.05. Therefore, the Null Hypothesis (there is not any relationship between two assumed variables) is rejected and the Alternative Hypothesis (there is a relationship between two assumed variables) is accepted.

Table 6. contingency table of Trust value and attention

The Relation Between	Degree of Freedom	Chi-Square
Trust Value and Knowledge	4	11.39
Trust Value and Background	4	10.98
Trust Value and Attention	4	10.7

Analysis the relation between system trust and learner trust

As mentioned before, trust in e-learning system is a two sided relation between learner and system. The aim of this work is to evaluate the effective parameters on system trust to learner in order to estimate this trust value more precisely. The amount of learner's knowledge which is assessed by system is changed based on learner's idea and system trust to learner. The accurate calculation of system trust would lead to better estimating learner's knowledge. This cases system provide learning services more properly that improve learner's satisfaction and learner's trust to system increases. While a learner has more trust to system his/her interaction and contribution will increase.

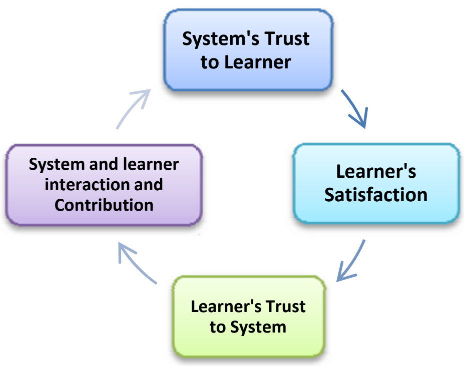

Figure 6. The relation between learner's trust and system's trust.

Also system trust to learner could be determined more accurately and this cycle will repeat when a learner has an interactive and positive interaction with system. Also if the trust value isn't adequately precise, the system's trust to learner will decrease and the estimation of learner's knowledge will not be proper. This causes learner's satisfaction decrease which leads to learner's trust to system reduce. When learner has a few trusts to system his/her willing to interact and contribute with system decrease and this cycle repeats. This cycle is shown in Figure (6).

V. Conclusions and Future Research

As discussed before, many issues are coming up in the field of Open Learner Modeling. For example, how the learner model is available to its owner, partially or completely? Who is allowed to access and view the learner model? How the learner model could be accessed? How much the representation of open learner model is similar to the structure of underlying learner model?

In this work focused on this issue: “How much a learning system can trust to learner’s belief and his/her feedback about his/her model?”

In this work the effect of learner’s knowledge, backgrounds and attention on the Trust Value was evaluated. To estimate the effect of these parameters the Chi-Square Distribution was used. The obtained results showed that Knowledge, Background and Attention have substantial effect on Trust Value.

In this works the relation between three learner's characteristics and system's trust are investigated. As shown in pervious section these characteristics have effect on system's trust to learner. Current system' trust computation model just applied learner's knowledge. According to achieved results, learner's background and attention are usable for this aim. Using more learner characteristics in trust computation provide this opportunity to determined trust vale more precisely. In open learner modeling learner and system have continuous interactions. Also, learner model which is the base of educational services is changed according to learner's idea and system's trust. Hence the increase of trust computation precise would lead to a more accurate learner model that cause more proper educational system. While learners achieve better educational services, his/her satisfaction will increase and his/her interaction will enhance. One of the most significant goals of educational systems is promotion of learner to have more interaction with system.

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