Learning Style Deriving Approach to Personalize E-Learning Material Resources

Ibrahim F. Moawad

Information Systems Department, Faculty of Computer and Information Sciences, Ain shams University
Cairo, Egypt

Abstract

Personalized recommender systems in e-learning environment make the learning process more effective and efficient. In this paper, we present a detailed knowledge-based system design for personalizing the e-learning material resources. Initially, the approach rates the different learning styles according to the learner personal data and preferences, and then it personalizes the learning material resource type, the material abstraction level, and the learning session time. The learning material resources are recommended to the learner in two alternatives: the learning material resources of the most-ranked learning style to learner or an ordered list of material learning resources based on the learning styles ranking. To show how the approach is very beneficial in e-learning systems, we present a case study with different usage scenarios.

Keywords: *Recommender System, Personalization, E-learning, Learning Styles, Learning Profile, Domain Knowledge.*

1. Introduction

E-learning is defined as “learning where the Internet or intranet plays an important role in the delivery, support, administration and assessment of learning” [1]. E-learning puts the control where it’s needed, in the hands of learners, so that they can learn wherever and whenever it suits them best. It also gives new resources to instructors such as interactive multimedia, simulations and other emerging learning techniques [2]. Personalized E-learning System (PES) is suggested as the next generation of e-learning systems [3].

In the e-learning environment, the process of teaching involves a lot of sending messages between learners and tutors. Also, it involves access to information and electronic resources [4]. On the learner's side, it is difficult to find the learning materials that best suit learner's needs. On the educator's side, tutors need to find an automatic way for getting feedback from learners and monitoring their learning styles [5]. Therefore, finding a way to better guide learners for selecting their suitable learning materials is becoming a challenging factor [6]. The recommender systems can help to tackle this challenge. Recommender systems were implemented successfully in e-commerce [7, 8]. Using recommender systems in the e-learning environment can help in providing an automatic process to support learners in finding their suitable materials instead of relying on classmates, tutors, and other sources [9]. Previous research works proposed generic e-learning personalization frameworks [10, 11]. In this paper, a detailed knowledge-based system design is proposed to personalize the e-learning material resources. In our approach, the different learning styles are rating according to the learner personal data and preferences, and then the learning material resources are personalized and recommended to the learner in two alternative methods: the learning material resources of the most-ranked learning style to learner or an ordered list of material learning resources based on the learning styles ranking.

The remainder of the paper proceeds as follows. Section 2 presents the related work. While section 3 describes the system architecture, both section 4 and section 5 present the personalization knowledge conceptual view and the personalization knowledge base design respectively. Section 6 presents a case study with different learning scenarios. Finally, in section 7, we conclude the paper.

2. Related Work

Previous research work proposed a generic framework of an expert personalized e-learning recommendation system [10, 11]. The framework can help learners in finding learning materials that best suits their needs. It consists of six components: Gathering Learner Information (GLI), Materials Recommendation Creation (MRC), Learner Profile (LP), Expert System (ES), Domain Knowledge Management (DKM) and Domain Knowledge Tree (DKT). The learner initially registers to the system. During registration some personal settings are saved in the learner profile. The learner profile consists of learner’s style, background, type (part time, full time), etc. In addition, the learner profile contains all the information about learners,

like their preferences, interests and knowledge levels, which can be obtained during the registration process.
Based on the framework provided in [10, 11], in this paper, we propose a detailed knowledge-based system design to personalize the e-learning material resources for learner according to his learning style. The learning material resources are personalized and recommended to the learner in two alternative methods: the learning material resources of the most-matched learning style to learner or an ordered list of material learning resources based on the learning styles ranking. According to Neil Fleming's VAK/VARK model, we consider the following four learning styles [12, 13].

1. **Visual learners** who learn best by seeing. Graphic displays such as charts, diagrams, illustrations, handouts, and videos are all helpful learning tools for visual learners.
2. **Tactile learners** who learn best by touching and doing. Hands-on experience is important to tactile learners.
3. **Auditory learners** who learn best by hearing information. They tend to get a great deal out of lectures and are good at remembering things they are told.
4. **Reading learners** who prefer to take in information displayed as words. Learning materials that are primarily text-based are strongly preferred by these learners.

3. System Architecture

Figure 1 shows the system architecture, which has two actors: Learner and Instructor. The architecture enables the Instructor to either manage the course question bank using the Question Bank Management module or to manage the course Domain Knowledge Tree (DKT) using the Domain Knowledge Tree Management module. The Domain Knowledge Tree represents a hierarchal organization of the course topics. The tree root represents the main course topic, which is composed of sub-topics represented in the root child nodes. Each tree node contains four different media types (Text, Image/Video, Hands-on, and Audio) in two abstraction levels (Detailed and Summarized). Therefore, each tree node is attached with eight media resources.
On the other hand, the learner can manage his profile using the Learner Profile Management module. The learner profile consists of two parts: personal data and learning preference data. In addition to the next Topic the learner should start in during the next session, we consider the minimal personal data required in the learner profile: the learner full name, gender, birth date, father job, mother job, and order in family. Besides, the learning preference data is collected from the learner by asking him set of questions related to his learning preferences. The learning preference data is used to weight the learning styles, and hence to infer the most preferred leaning style to learner.

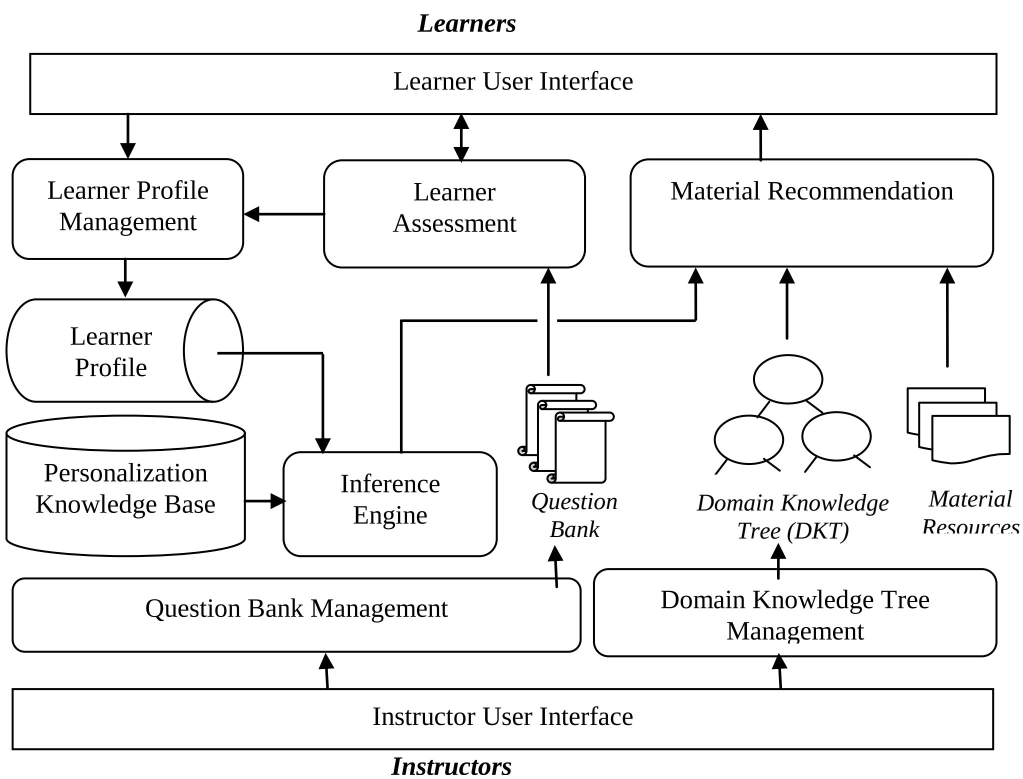

Fig. 1 System architecture.

As shown in the system architecture, the Inference Engine accesses the learner profile and reasons using the Personalization Knowledge Base to infer the most suitable learning conditions to learner: the preferred learning style (Visual, Reading, Auditory, or Tactile), the weight of each learning style, the material abstraction level (Summarized or Detailed), and the learning session time (Morning or Afternoon). Based on the next course topic the learner should start in during the next learning session and the suitable learning conditions passed from the Inference Engine, the Material Recommendation module retrieves the suitable media resources, and then displays them in two alternative methods: the media resources for the preferred learning style and an ordered list of media resources according to the learning style weights.

After studying the recommended material for some topic, the learner can assess his level using the Learner Assessment module, which accesses the question bank for the current course topic questions to evaluate the learner. According to the assessment results, the learner profile is updated with the next course topic the learner will start in during the next session.

4. Personalization Knowledge Conceptual View

Figure 2 shows a conceptual view for the domain ontology of the e-learning personalization knowledge. The ontology contains eight concepts, which can be grouped into three categories. Firstly, the learner profile category contains the *LearnerProfile* concept with three attributes (FullNamre, etc.) and the *FamilyCircumstances* concept with three attributes (FatherWork, etc.). Secondly, the preferred learning conditions category contains the *LearningConditions* concept that determines the preferred learning style, the material abstraction level, and the learning session time. Finally, the learning styles category contains a super concept called *LearningStyle* with the *Weight* common attribute and four sub-concepts for the different learning styles considered in this research: *AuditoryStyle*, *TactileStyle*, *ReadingStyle*, and *VisualStyle* concepts. Each concept of the learning style concepts contains equally-weighted four attributes that are used to determine how far the learning style is closed to the learner.

To infer the most suitable learning conditions to learner, as shown in figure 3, the Inference Engine executes three Inference steps. Firstly, the Preferred Learning Material Level and Session Time Inference Step accepts the learner gender, birth date, father job, mother job, and order in family, and then infers the preferred abstraction level of material and the learning session time. Secondly, the Learning Style Weight Inference Step accepts the four attributes of the different learning styles and determines the weight of each learning style (i.e. How far does some learning style close to the learner?). Finally, the Preferred Learning Style Inference Step accepts the weights of the different learning styles and derives the Preferred Learning Style.

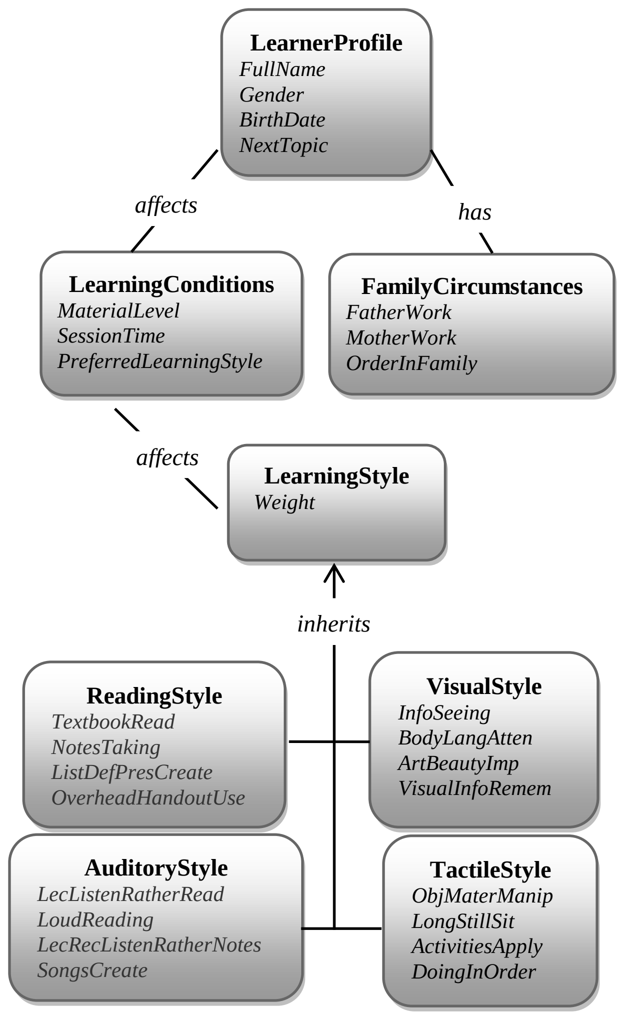

Fig. 2 Conceptual view of personalization domain ontology.

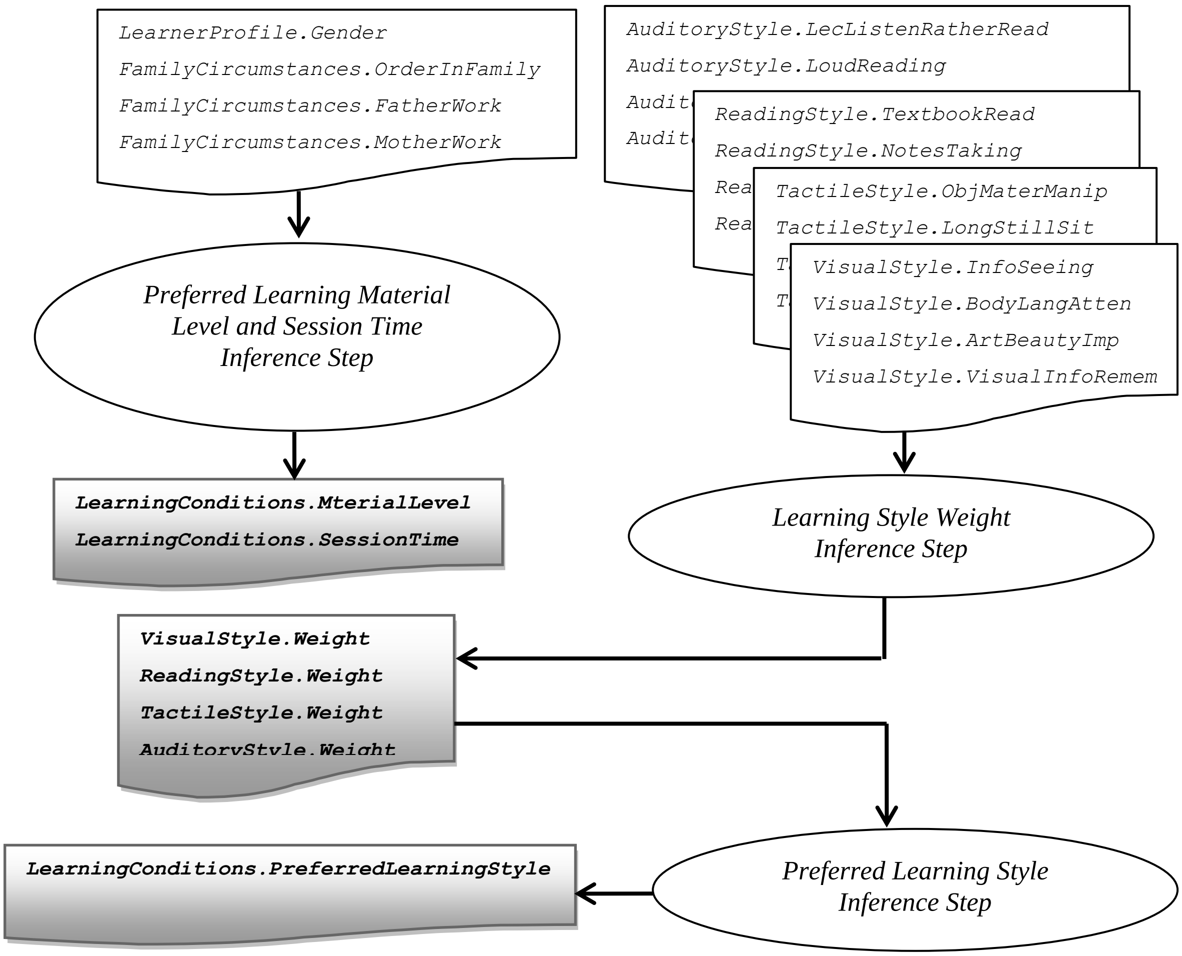

Fig. 3 Conceptual view of personalization inference steps.

5. Personalization Knowledge Base Design

The personalization knowledge base consists of two main components: the personalization domain ontology and the personalization heuristic rules. The personalization domain ontology defines the eight concepts presented in figure 2. The personalization heuristic rules are classified into three relations that are invoked by the three inference steps shown in figure 3. These relations are the Preferred Learning Material Level and Session Time Relation, the Learning Style Weight Relation, and the Preferred Learning Style Relation.

5.1 The Personalization Domain Ontology

The personalization domain ontology has three categories of concepts: the learner profile category, the preferred learning conditions category, and the learning styles category. Each concept attribute is specified using five facets: attribute name, description, source of value (user or derived), data type (string, number, etc.), and legal values (set of values).

Table 1 shows the ontology specifications of the learner profile category, which consists of the LearnerProfile and FamilyCircumstances concepts.

Table 1: The ontology of learner profile category

LearnerProfile Concept

Name	**FullName**
Description	The learner's name
Source of Value	User
Type	String
Name	**BirthDate**
Description	The learner's date of birth.
Source of Value	User
Type	Date
Name	**Gender**
Description	The learner's Gender
Source of Value	User
Type	String
Legal values	"Male ", "Female"
Name	**NextTopic**
Description	The topic in the domain knowledge tree the learner should learn next time.
Source of Value	Derived
Type	String

FamilyCircumstances Concept

Name	**OrderInFamily**
Description	The order of the learner among his brothers and sisters.
Source of Value	User
Type	String
Legal values	"Oldest", "Middle age", "Younger"
Name	**FatherWork**
Description	The learner father's work
Source of Value	User
Type	String
Legal values	"Working", "Jobless", "Passed away"
Name	**MotherWork**
Description	The learner mother's work
Source of Value	User
Type	String
Legal values	"Working", "Jobless", "Passed away"

Table 2 shows the ontology specifications of the preferred learning conditions category, which has the LearningConditions concept only. This concept defines the most suitable learning conditions such as the preferred learning style and the material abstraction level. The learning styles category contains the LearningStyle super concept with the *Weight* common attribute and four sub-concepts representing the different learning styles: AuditoryStyle, TactileStyle, ReadingStyle, and VisualStyle concepts. Table 3 shows the ontology specifications of the LearningStyle and the VisualStyle concept as an example of the different learning styles.

Table 2: The ontology of preferred learning conditions category

LearningConditions Concept

Name	**MaterialLevel**
Description	The abstraction material level.
Source of Value	Derived
Type	String
Legal values	"Detailed", "Summarized"
Name	**SessionTime**
Description	The learning session time.
Source of Value	Derived
Type	String
Legal values	"Morning", "Afternoon"
Name	**PreferredLearningStyle**
Description	The most preferred learning style to the learner.
Source of Value	Derived
Type	String
Legal values	"Visual", "Reading", "Tactile", "Auditory"

Table 3: The ontology of LearningStyle and VisualStyle concepts

LearningStyle Concept

Name	**Weight**
Description	The learning style weight.
Source of Value	Derived
Type	Number
Legal values	0 to 4

VisualStyle Concept

Name	**InfoSeeing**
Description	Does the learner have to see information in order to remember it?
Source of Value	User
Type	String
Legal values	"Yes", "No"
Name	**BodyLangAtten**
Description	Does the learner pay close attention to body language?
Source of Value	User
Type	String
Legal values	"Yes", "No"
Name	**ArtBeautyImp**
Description	Is art, beauty, and aesthetics important to learner?
Source of Value	User
Type	String
Legal values	"Yes", "No"
Name	**VisualInfoRemem**
Description	Does visualizing information in learner mind help him to remember it better?
Source of Value	User
Type	String
Legal values	"Yes", "No"

IJCSI International Journal of Computer Science Issues, Vol. 10, Issue 3, No 1, May 2013
ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org

5.2 The Personalization Heuristic Rules

The personalization heuristic rules are classified into three relations. Each relation consists of set of heuristic rules. These relations are as follow.

1. The Preferred Learning Material Level and Session Time Relation is invoked by the Preferred Learning Material Level and Session Time Inference Step to derive the preferred abstraction level of learning material and the learning session time. Table 4 presents the heuristic rules of the Preferred Learning Material Level and Session Time Relation.

Table 4: The preferred learning material level and session time relation

	Rule 1	
IF	LearnerProfile.Gender = "Male"	*And*
	FamilyCircumstances.OrderInFamily = "Oldest"	*And*
	FamilyCircumstances.FatherWork ≠ "Working"	*And*
	FamilyCircumstances.MotherWork ≠ "Working"	
THEN	LearningConditions.MterialLevel="Summarized"	*And*
	LearningConditions.SessionTime ="Afternoon"	
	Rule 2	
IF	LearnerProfile.Gender = "Male"	*And*
	FamilyCircumstances.FatherWork = "Working"	
THEN	LearningConditions.MterialLevel="Detailed"	*And*
	LearningConditions.SessionTime ="Morning"	
	Rule 3	
IF	LearnerProfile.Gender = "Male"	*And*
	FamilyCircumstances.FatherWork ≠ "Working"	*And*
	FamilyCircumstances.MotherWork = "Working"	
THEN	LearningConditions.MterialLevel="Detailed"	*And*
	LearningConditions.SessionTime ="Morning"	
	Rule 4	
IF	LearnerProfile.Gender = "Female"	*And*
	FamilyCircumstances.OrderInFamily = "Oldest"	*And*
	FamilyCircumstances.MotherWork ≠ "Jobless"	
THEN	LearningConditions.MterialLevel="Summarized"	*And*
	LearningConditions.SessionTime ="Afternoon"	
	Rule 5	
IF	LearnerProfile.Gender = "Female"	*And*
	FamilyCircumstances.OrderInFamily = "Oldest"	*And*
	FamilyCircumstances.FatherWork ≠ "Working"	*And*
	FamilyCircumstances.MotherWork ≠ "Working"	
THEN	LearningConditions.MterialLevel="Summarized"	*And*
	LearningConditions.SessionTime ="Afternoon"	
	Rule 6	
IF	LearnerProfile.Gender = "Female"	*And*
	FamilyCircumstances.FatherWork = "Working"	*And*
	FamilyCircumstances.MotherWork = "Jobless"	
THEN	LearningConditions.MterialLevel="Detailed"	*And*
	LearningConditions.SessionTime ="Morning"	

For example, in Rule number 1, if the learner is male, the learner is the oldest brother, the learner father is either jobless or passed away, and the learner mother is either jobless or passed away, then the learning material should be summarized and the learning time should be afternoon, because the learner should work to live.

2. The Learning Style Weight Relation is invoked by the Learning Style Weight Inference Step to derive the weight for each learning style. This relation accepts four equally-weighted attributes for each learning style, and then computes the total weight for each learning style. Table 5 lists the heuristic rules of the Learning Style Weight Relation. For example, from Rule 7 to Rule 10, the weight of Visual style is incremented by one if the answer of learner to one of VisualStyle concept attributes is "Yes".

Table 5: The learning style weight relation

	Rule 7
IF	VisualStyle.InfoSeeing = "Yes"
THEN	Increment(VisualStyle.Weight)
	Rule 8
IF	VisualStyle. BodyLangAtten = "Yes"
THEN	Increment(VisualStyle.Weight)
	Rule 9
IF	VisualStyle.ArtBeautyImp = "Yes"
THEN	Increment(VisualStyle.Weight)
	Rule 10
IF	VisualStyle.VisualInfoRemem = "Yes"
THEN	Increment(VisualStyle.Weight)
	Rule 11
IF	ReadingStyle. TextbookRead = "Yes"
THEN	Increment(ReadingStyle.Weight)
	Rule 12
IF	ReadingStyle.NotesTaking = "Yes"
THEN	Increment(ReadingStyle.Weight)
	Rule 13
IF	ReadingStyle. ListDefPresCreate = "Yes"
THEN	Increment(ReadingStyle.Weight)
	Rule 14
IF	ReadingStyle.OverheadHandoutUse = "Yes"
THEN	Increment(ReadingStyle.Weight)
	Rule 15
IF	TactileStyle. ObjMaterManip = "Yes"
THEN	Increment(TactileStyle.Weight)
	Rule 16
IF	TactileStyle.LongStillSit = "Yes"
THEN	Increment(TactileStyle.Weight)
	Rule 17
IF	TactileStyle.ActivitiesApply = "Yes"
THEN	Increment(TactileStyle.Weight)
	Rule 18
IF	TactileStyle.DoingInOrder = "Yes"
THEN	Increment(TactileStyle.Weight)
	Rule 19
IF	AuditoryStyle. LecListenRatherRead = "Yes"
THEN	Increment(AuditoryStyle.Weight)
	Rule 20
IF	AuditoryStyle. LoudReading = "Yes"
THEN	Increment(AuditoryStyle.Weight)
	Rule 21
IF	AuditoryStyle. LecRecListenRatherNotes = "Yes"
THEN	Increment(AuditoryStyle.Weight)
	Rule 22
IF	AuditoryStyle.SongsCreate = "Yes"
THEN	Increment(AuditoryStyle.Weight)

3. The Preferred Learning Style Relation is invoked by the Preferred Learning Style Inference Step to derive the Preferred Learning Style. This relation accepts the weights of the different learning styles derived by the Learning Style Weight Relation, and then considers the learning style with maximum weight as the Preferred Learning Style. Table 6 lists the heuristic rules of the Preferred Learning Style Relation.

Table 5: The preferred learning style relation

	Rule 23
IF	AuditoryStyle.Weight = Max(AuditoryStyle.Weight, TactileStyle.Weight, ReadingStyle.Weight, VisualStyle.Weight)
THEN	LearningConditions.PreferredLearningStyle="Auditory"
	Rule 24
IF	TactileStyle.Weight = Max(AuditoryStyle.Weight, TactileStyle.Weight, ReadingStyle.Weight, VisualStyle.Weight)
THEN	LearningConditions.PreferredLearningStyle = "Tactile"
	Rule 25
IF	ReadingStyle.Weight = Max(AuditoryStyle.Weight, TactileStyle.Weight, ReadingStyle.Weight, VisualStyle.Weight)
THEN	LearningConditions.PreferredLearningStyle="Reading"
	Rule 26
IF	VisualStyle.Weight = Max(AuditoryStyle.Weight, TactileStyle.Weight, ReadingStyle.Weight, VisualStyle.Weight)
THEN	LearningConditions.PreferredLearningStyle = "Visual"

6. Case Study with Different Learning Scenarios

To show how the presented approach can personalize the e-learning material resources according to the learner preferences, we present a case study with three scenarios for different learners. Figure 5 shows the Domain Knowledge Tree for the C++ Programming course [14]. In this tree, each tree node contains four different media types (Text, Image/Video, Hands-on, and Audio) in two abstraction levels (Detailed and Summarized). Therefore, each tree node is attached with eight media resources. The first topic that the learner should start to learn is "What is an object?" topic.

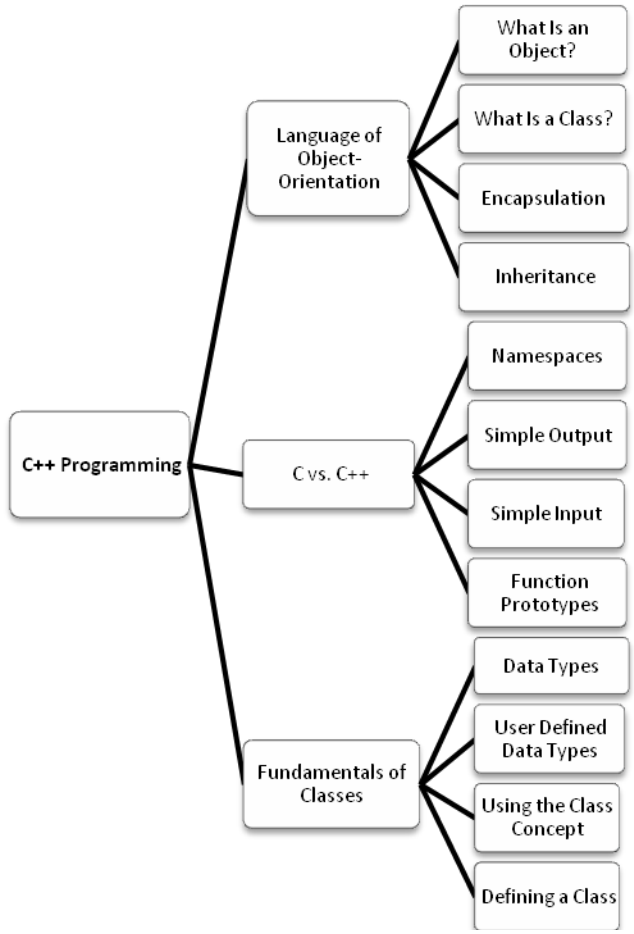

Fig. 4 Domain knowledge tree of C++ programming course.

Table 6 presents three scenarios (Sc1, Sc2, and Sc3) for different learners, where the table shows the input data in the form of concept and attribute. The inputs are grouped into four sections: the learner profile, the visual style, the tactile style, the reading style, the auditory style.
For example, the first scenario is for a male learner who is the oldest brother and has jobless parents. He wants to see information in order to remember. Art, beauty, and aesthetics are important to him. Visualized information helps him to remember. Also, he is enjoying performing tasks that involve directly manipulating objects. It is difficult to him to sit still for long periods of time. Finally, he is enjoying making lists, reading definitions, and creating presentations.

Table 6: The input data for three different scenarios

Concept	Attribute	Sc 1	Sc 2	Sc 3
Learner Profile	Gender	M	M	F
	Order In Family	Ol	Ol	Ol
	Father Work	Jo	Wo	Wo
	Mother Work	Jo	Jo	Wo
Visual Style	Seeing information in order to remember it?	Y	Y	Y
	Paying close attention to body language?	N	N	Y
	Are art, beauty, and aesthetics important to learner?	Y	N	N
	Visualizing information helping to remember?	Y	N	Y
Tactile Style	Enjoying performing tasks that involve directly manipulating objects?	Y	N	Y
	Is it difficult to sit still for long periods of time?	Y	N	Y
	Is it good to apply activities such as painting and cooking?	N	N	Y
	Important to practice doing something to learn it?	N	N	Y
Reading Style	Reading a textbook is a great way to learn new information?	N	Y	N
	Taking a lot of notes during class and reading a book?	N	Y	N
	Enjoying making lists, reading definitions, and creating presentations?	Y	Y	N
	Preferring teachers to make use of overheads and handouts?	N	Y	N
Auditory Style	Listening to class lectures rather than reading from the textbook?	N	N	Y
	Reading out loud helping in remembering information better?	N	Y	N
	Listening to a recording of class lectures rather than going over your class notes?	N	N	N
	Creating songs to help remembering information?	N	N	N

Ol: *"Oldest"* ***Jo:*** *"Jobless"* ***Wo:*** *"Working"* ***Y****: "Yes"* ***N****: "No"*

Scenario 1

Material Abstraction Level: "Summarized"
Learning Session Time: "Afternoon"
Visual Style Weight: 3
Tactile Style Weight: 2
Reading Style Weight: 1
Auditory Style Weight: 0
Preferred Learning Style: "Visual"
Material Alternative 1: *Image/Video*
Material Alternative 2: *Image/Video, Hands-on, then Text*

Scenario 2

Material Abstraction Level: "Detailed"
Learning Session Time: "Morning"
Visual Style Weight: 0
Tactile Style Weight: 0
Reading Style Weight: 4
Auditory Style Weight: 1
Preferred Learning Style: "Reading"
Material Alternative 1: *Text*
Material Alternative 2: *Text, then Audio*

Scenario 3

Material Abstraction Level: "Summarized"
Learning Session Time: "Afternoon"
Visual Style Weight: 3
Tactile Style Weight: 4
Reading Style Weight: 0
Auditory Style Weight: 1
Preferred Learning Style: "Tactile"
Material Alternative 1: *Hands-on*
Material Alternative 2: *Hands-on, Image/Video, then Audio*

Fig. 5 The personalized learning results of the three different scenarios.

Figure 5 shows the personalized learning results of the three different scenarios. The results contain both material abstraction level and learning session time. The learning style weights and the preferred learning style are also presented. Finally, the learning material recourses are recommended in two alternatives: the material for the most-ranked learning style to learner or an ordered list of material learning resources based on the learning styles ranking.

For example, in scenario 1, because the learner should work to live, the learning material is summarized and the learning time is at afternoon. Besides, according to the learner answers, the most-ranked learning style is visual style (weight is 3), and hence the first alternative of material resources recommended is Image/Video.

7. Conclusion

In this paper, a detailed knowledge-based system design for personalizing the e-learning material resources was presented. The different learning styles are weighted according to the learner personal data and preferences, and then the learning material resource type, material abstraction level, and the learning session time are derived. The learning material resources are recommended to the learner in two alternatives. The first alternative is the material resources of the most-ranked learning style to learner, where the second alternative is an ordered list of material learning resources based on the learning styles ranking. Finally, a case study with different usage scenarios was presented.

References

[1] K. Giotopoulos, C. Alexakos, G. Beligiannis, and S. Likothanassis, "Integrating Agents and Computational Intelligence Techniques in E-Learning Environments", in Proceedings of World Academy of Science, Engineering and Technology, August 2005, Vol. 7.

[2] K. Palanivel, and S. Kuppuswami, "Service-Oriented Reference Architecture for Personalized E-learning Systems (SORAPES)", International Journal of Computer Applications, Vol. 24, No. 5, 2011, pp. 35–44.

[3] A. Styliadis, I. Karamitsos, and D. Zachariou, "Personalized e-Learning Implementation", The GIS Case International Journal of Computers, Communications & Control, Vol.1, No. 1, 2006, pp. 59-67.

[4] T. H. Cho, J. K. Kin, and S. H. Kim, "A personalized recommender system based on web usage mining and decision tree induction", Expert Systems with Applications, Vol. 23, 2002, pp. 329-342.

[5] B. Bates, and J. Leary, "Supporting a range of learning styles using a taxonomy-based design framework approach", in Proceedings of the 18th annual conference of the Australasian Society for computers in learning in Tertiary education, December 2001, pp. 45-53.

[6] O.R. Zaiane "Web usage mining for better Web-based learning environment", in the Conference on Advanced Technology for Education, Banff, AB, 2001, pp. 60-64.

[7] J. B. Schafer, J. A. Konstan and J. Riedl, "Ecommerce recommendation applications", Data Mining and Knowledge Discovery, Vol. 5, 2001, pp. 115–153.

[8] J. K. Kim, Y. H. Cho, W. J. Kim, J. R. Kim, and J. H. Suh, "A personalized recommendation procedure for Internet shopping support", Electronic Commerce Research and Applications, Vol. 1, 2002, pp. 301-311.

[9] P. Resnick, and H. R. Varian, "Recommender systems" Communications of the ACM, Vol. 40, 1997, pp. 56-58.

[10] A. Al Hamad, N. Yaacob, and A. Y. Al-Zoubi, "Integrating 'Learning Style' Information into Personalized e-Learning System", IEEE Multidisciplinary Engineering Education Magazine, Vol. 3, No. 1, 2008, pp 2-6.

[11] M. A. Otair, "Expert personalized e-learning recommender system", in the first International Conference on E-Business and E-Learning (EBEL), Jordan,2005.

[12] F. Coffield, D. Moseley, E. Hall, and K. Ecclestone, "Learning styles and pedagogy in post-16 learning: A systematic and critical review", Learning and Skills Research Centre, London, www.lsda.org.uk/files/PDF/1543.pdf, 2004.

[13] H. Paschler, M. McDaniel, D. Rohrer, and R. Bjork, "Learning styles: Concepts and evidence", Psychological Science in the Public Interest, Vol. 9, pp. 105–119.

[14] C++ Programming Course Outline, http://www.trainingetc.com/courseCatalog/html/individual/TE2201.html, 2012.

Ibrahim Fathy Moawad is an Assistant Professor at the Faculty of Computer and Information Sciences, Ain Shams University, Egypt. He is interested in Artificial Intelligence and Software Engineering research areas. He has published more than 30 technical and academic articles in both international journals and conferences. He is the author of the "A Framework for Multi-agent Diagnosis System: Argumentation-based Negotiation Technique for Belief Conflict Resolution" book. He had the best paper award of the 2012 International Conference on Computer Engineering and Systems (ICCES'2012).