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Using DEMATEL for Contextual Learner Modeling in Personalized and Ubiquitous Learning

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Abstract: With the popularity of e-learning, personalization and ubiquity have become important aspects of online learning. To make learning more personalized and ubiquitous, we propose a learner model for a query-based personalized learning recommendation system. Several contextual attributes characterize a learner, but considering all of them is costly for a ubiquitous learning system. In this paper, a set of optimal intrinsic and extrinsic contexts of a learner are identified for learner modeling. A total of 208 students are surveyed. DEMATEL (Decision Making Trial and Evaluation Laboratory) technique is used to establish the validity and importance of the identified contexts and find the interdependency among them. The acquiring methods of these contexts are also defined. On the basis of these contexts, the learner model is designed. A layered architecture is presented for interfacing the learner model with a query-based personalized learning recommendation system. In a ubiquitous learning scenario, the necessary adaptive decisions are identified to make a personalized recommendation to a learner.

Keywords: Personalized e-learning; DEMATEL; learner model; ontology; learner context; personalized recommendation; adaptive decisions

1 Introduction

The availability of information over the Internet has made learning easier and unlocked different ways of learning [1]. However, recommendation of learning fitting to a learner's learning suitability and requirement remains lacking. Each Learner is different, in terms of various factors such as knowledge, demographics, environment, situation, difference in learning adeptness, requirements, etc. Accordingly, each learner's acceptability of the information available on the web is unique. Different situational conditions, educational backgrounds, and cognitive settings do not allow learners to uniformly accept the information or learning material available on the Internet [2]. Arbitrarily overloading learners with information often causes frustration and confusion that leads them to skip the learning process [3], which may lower learning efficiency. In this respect, exercising personalized learning recommendations allows necessary learning adaptation like selection and recommendation of learning information fitting to a learner's suitability [4]. Advancement in personalized recommendation systems is slow, but progress in formal and informal learning settings is evident. In a formal learning setting, personalization strongly focuses on recommending learning in a guided manner along the learning path set to meet the learning objectives [5]. By contrast, informal learning [6] settings involve an open and unstructured learning scenario where the learners interact with the learning recommendation systems mainly through unstructured queries. Demand for informal learning like self-directed learning [7] and situation-based learning [8] is high. Introducing the personalization aspect to the learning recommendation system can help elicit information overload problems in informal learning settings.

1.1 Personalized Learning Scenario

Personalized learning recommendation for informal learning settings has wide application usage. It is preferred in all learning scenarios where learners need impromptu information fitting to their learning situation and other requirements. Understanding how personalized learning-based recommendation is different from the conventional one is critical. The following scenarios demonstrate the need for personalized learning recommendations.

Case 1: *Yaman, a first-year student of a graduate program in biotechnology, wishes to have an understanding of HTML code for web programming classes. He is using his smartphone for learning while sitting in class and is connected to the Web through the institute's Wi-Fi*. Here, the student is unknowledgeable in the subject domain, which is an important consideration for his learning process. Other factors interfering with his learning are the background noise of the classroom, causing loss of concentration, and the Wi-Fi connection with limited bandwidth.

Case 2: *Mina, a computer instructor, possesses partial knowledge of data structure and good knowledge on C language. She wants to acquire some knowledge about B^+ tree while seated in a bus on her way to her institute. She is using her mobile phone for learning with 3G network connectivity*. In this scenario, the person does not know the B+ tree concept and has partial knowledge of data structure. Thus, overloading her with information on the topic will not help. That she has no prior topic knowledge and a beginner on the subject must be considered for appropriate learning delivery. Another factor that must be taken into account is that she uses a feature phone that may not support high-resolution images, high-quality video, and web pages in their standard form. As she is on a moving bus, she may also not have enough time to complete the learning. In addition, disturbances abound like people nearby, noise, and discomfort due to bus movement.

Case 3: *Riya, a working professional, is attending a seminar on nanotechnology. While the session is running, she wants to obtain fundamental idea on the technology discussed in the seminar. Here, the time is a constraint for learning, and she wants to learn things in between the running session. She is using an android mobile phone with a 4G connection*. In this scenario, the person needs to quickly grasp concepts or topics without many details. Further, the learning ambiance is not conducive due to the noisy background. Moreover, the learner cannot fully concentrate on learning from the mobile device because she has to be more attentive to the ongoing session.

From these scenarios, recommending learning material conventionally does not help. A personalized approach by considering the learners' situation and condition can help them learn efficiently. Overloading the learners with all possible information does not help. Tailoring information suitable to their present situation helps them understand things quickly.

1.2 Motivation

Personalization of learning requires a critical understanding of the learners and their learning context and suitability. For this, an appropriate learner model is required. The learner model is the computationally comprehensible description of a learner, which allows knowing the what, why, and how about the learner, thereby giving probabilistic reasoning on his/her learning situation, requirement, suitability, and intentions. One of the key success factors for the personalized recommendation system for informal learning settings is the learner model's right design.

The literature is lacking on learner modeling for personalized learning recommendation systems. Personalized learning applications vary, so do the supporting learning models. As a result, the learner model, which suits existing personalized learning applications, may not be useful for personalized learning based recommendations for informal learning settings in a ubiquitous learning environment. Although learning model standards exist (e.g., Learning Information Package [9]), they ask for learner information, which is generalized in nature. Moreover, they also lack the flexibility to meet the different personalized needs for personalized learning applications. The insufficient standard models and lack of work in fulfilling the typical requirements of personalized learning call for a learner model specific to a personalized learning recommendation system for informal learning.

1.3 Contribution

In this study, we propose a learner model for a query-based personalized recommendation system. The significant contributions of this study are as follows:

- Conducting a real survey on 122 undergraduate students and 86 experts for identifying learner attributes and applying Decision Making Trial and Evaluation Laboratory (DEMATEL).
- Building a learner model for personalized learning.
- Representing the proposed model with an ontological model.
- Presenting a layered architecture for interfacing the learner model with the query-based personalized learning recommendation system.
- Inferring information from the proposed learner model to decide on adapting resources for personalized learning.

1.4 Organization

The rest of the paper is organized as follows. The related work is reviewed in Section 2. The details of the survey that is carried to identify the most relevant dimensions of the learner in a personalized learning system are provided in Section 3. The proposed learner model is introduced in Section 4. The ontological representation of the proposed model is given in Section 5. The interfacing architecture of the model with the personalized learning recommendation system is presented in Section 6. The information inferred from the proposed model and the decision taken to recommend suitable learning resources are detailed in Section 7. The paper is concluded in Section 8 with a discussion on the further scope of this work.

2 Related Work

A learner model is an explicit representation of a learner that characterizes his/her learning requirements [10]. The models are purposefully designed for learning adaptation, learner behavior reasoning, prediction, and the necessary learning navigation. No simple or universal guidelines exist to build a learner model as personalized learning choices vary [11]. Characterizing a learner for his/her learning has many different facets, leading to various opinion assumptions for learner modeling. Although the assumption and design for all learner models differ, categorically, the information featured in the models is of two types—domain-specific and domain-independent. The domain-specific information specifies the learner's knowledge of learning domains.

By contrast, the domain-independent information specifies the learner's trait, activity, goal and objectives, demographics and situational information, background, and experience [12]. In [13], the domain-specific information is featured as the learner's performance in terms of completed course, whether test or assessment is taken, and achievement gain. The learner's domain-specific information is also depicted by prior knowledge on the domain, topic, and knowledge gain, as proposed in [14,15]. This information about the learner helps estimate the domain or topic learning suitability for the learner. The domain-independent information, which features the learner's learning characteristics (behavior, activity, psycho-cognitive skills, etc.) are varyingly selected and represented in the learner model depending on the application requirement. Noted works that showcase the learner features characterizing the domain-independent information for the learner model are listed below.

- Demographic information, current learning status, expectation, and context attribute [13].
- Personal information, ability, preference, learning style, and feedback [14].
- Learner activity, learner information, strategy, learning materials read by the learner, learning time to learn a learning material, and domain knowledge [15].
- Preference, goal, interest, personal information, address, department, organization, title, granularity performance, performance, portfolio, and certification [16].

The learner model's accuracy to reason and predict the learner depends on the information it contains and its authenticity and validity. Thus, updating the model with correct data input over time is essential. Depending on the learner model's attribute, different data acquisition and updating approaches are followed. The information about the learner's activity, situation, and other preferences are obtained by observing learning through sensors [17–21] and subsequently analyzing the captured data. Capturing all the implicit information of the learner is impossible, so the inputs on certain attributes are often collected by the learners. To increase the accuracy and learner–system confidence, models are made open to the learners, describing what the system thinks about them and subsequently calls for the necessary updating from the learners [22].

In online learning, learner models found in the literature differ as per application and learner's learning needs and characteristics. The learner model tends to be more realistic by including the learner's internal characteristics like learning behavior and cognitive, affective, and psychological characteristics, hence featuring the learner accurately. Ding et al. [23] proposed a learner model for learning adaptation to online learning. The model has four features, namely, basic information, learning style, knowledge state, and cognitive ability. These characteristics put forward the learner's suitability for learning and then the appropriate learning adaptation. Mejia et al. [24] proposed a learner model for adaptive recommendation through LMS virtual learning. The model encompasses learner demographics, competence, learning style, reading difficulties, a cognitive trait for adaptive learning analytics, and recommendation. Mobile-based learning demands an understanding of the learner in a dynamic situation. For mobile learning applications, Al-Hmouz et al. [25] put forward the learner model that focuses on four main components, namely, learner status, situation status, and educational activity status of the learner. In another work [26], along with specifying learner's characteristics, the current environmental and situational characteristics are observed to determine the learner's real-time learning context. A new model is thus proposed that takes into account the learner's learning style, knowledge, behavior, learning progress, satisfaction, preference, and environmental parameters (including location, noise, and motion).

Existing studies on learner modeling for online learning differ in terms of how they characterize and represent the learner. The learner models differ based on the learning application and the feasibility to describe a learner. Learner modeling for a recommendation-based learning for informal learning demands understanding the learner and his/her learning situation differently. The impromptu recommending learning demands comprehensive yet wide dimensions of knowledge of the learner. To our best effort, we cannot find any work on learner modeling for a personalized learning recommendation system for informal learning in a ubiquitous learning environment.

3 Identifying Learner's Attributes

Knowing the learner's different dimensions for personalized learning in an informal learning scenario is essential. The dimensions are the aspects of the learner that characterize him/her, and they reflect the learner's contexts in a temporal situation. Thus, identifying the dimensions of the learner is crucial in making an accurate learner model. For the modeling purpose, we adopt the learner's dimensions proposed by Economides [27]. The different dimensions selected are education, background knowledge, profession, performance, preferences, favorites, interests, health, current physiological needs, physical abilities, cognition, social abilities, cultural abilities, affective state, motivation and conation, learning styles, personality, people (related to), location, mobility, environmental condition, device, and network connectivity. These dimensions are not minimal in describing learners for an informal learning situation. An increase in the number of dimensions may cause integrity and consistency issues in the model.

To select the right set of dimensions, we surveyed learners and experts. We chose 208 candidates for the survey, among which 122 were students and 86 were experts. We considered these two categories of correspondents to have unbiased feedback. The candidates were queried for the impact or influence of the learner's dimension for learning a topic. The survey details are given in Tab. 1 that shows the accumulative feedback on the acceptance and rejection of each dimension. Based on learners' feedback, the observed influencing factors whose acceptance rate is greater than 50% are education, background knowledge, performance, preference, cognition, learning style, affective state, device, network, environmental condition, location, mobility, and activity. These dimensions are sufficient to specify the learner and describe him/her for the recommendation system for informal learning.

The selected dimensions of learner can be considered as the factors of the required learning model. These factors may have interdependency (relationship) and relative significance that may cause to influence other factors. Determining this helps design learner models for better data acquisition and probabilistic reasoning for a learner's informal learning setting. To determine the interdependency among the factors, DEMATEL technique is applied for analysis. This technique finds the interdependency among factors and maps the relationship among them. Further, it helps analyze the cause-and-effect group in the system.

The DEMATEL technique for the listed factors education, background knowledge, performance, cognitive ability, learning style, affective state, learning setting preference, infrastructure and connectivity, environment, location, mobility, and activity is carried out in the following formulating steps.

Table 1: Details of the survey conducted to assess the influence of learner's dimensions on learning

Dimension	Query	Feedback	
		Yes	No
Education	While learning a topic, does your education play a role in understanding new concepts?	182	26
Background knowledge	While learning a topic, does your background knowledge on the same topic or similar topics helps?	190	18
Profession	Does your present job or professional background impact your learning?	24	184
Performance	While learning a topic, does your past academic performance or other related performances play any role?	125	83
Preference	Do the font size, font style, font color, media type and format, and other presentation aspects influence your learning?	161	47
Favorites	Does your affinity for particular subjects, teachers, mentors, famous persons, educational resources, websites, or blogs impact your learning?	5	03
Interests	Does your interest in education, art, or profession have any impact on learning a topic?	20	188
Health	Does your health fitness level impact the new topic learning?	7	201
Current physiological needs	Does your body need impacts learning?	8	200
Physical abilities	Do your physical abilities and disabilities have any impact on learning?	5	203
Cognition	Does your cognition enable you to learn things quicker?	175	33
Social abilities	Do your different traits (e.g., social, loner, helpful, individualistic, dominating, dependent, tolerant, discriminating, adaptable, responsible, careless, friendly, and hostile) influence your learning?	8	200
Cultural abilities	Does being cultural impact your learning?	9	199
Learning style	While learning, does matching your learning style with the learning style supported by the learning material matter in the quick grasping of information?	167	41
Affective state	Do you think while learning, your mood plays a part in learning?	150	58
Personality	Does any of your personality traits (e.g., extraversion or introversion, confidence or sensitive, detail-conscious or unstructured, tough-minded or agreeable, conforming or creative) impact learning?	27	181
People (related to)	Does your being connected to other people over the Internet have any impact on learning?	7	201
Device	Do the features (hardware and software) and performance of the learning devices (e.g., smartphone or tablet) impact your learning?	183	25
Network	Are the network connectivity and its bandwidth important for learning through a mobile device?	176	32
Environmental condition	While you are involved in the learning process, does your surrounding environmental condition (humidity, noise, temperature, and illumination) impacts your learning suitability?	127	81
Location	While in a learning session, does the place where you are learning impact your learning suitability in terms of focus and learning time?	138	70
Mobility	While in a learning session, does your body posture and movement affect your learning and learning suitability in terms of concentration, fatigue, learning time, and choice of medium?	143	65
Activity	Does your current work activity performed along to learning affect your learning in terms of concentration, fatigue, time to learn, and medium choice?	154	54

1) Generating group direct-influence matrix

Seven experts assessed the relationship between all the factors for a direct influence of one factor over others. The experts assessed the influence of one factor on another in the integer scale, 0 = no influence, 1 = low influence, 2 = medium influence, 3 = high influence, and 4 = very high influence. By aggregating the individual expect opinion, the *group direct-influence matrix* can be obtained by Eq. (1).

$$Z_{ij} = \frac{1}{l}\sum_{k=1}^{l} Z_{ij}^{k}, \quad i, j = 1, 2, \ldots, 12 \tag{1}$$

where l is the number of direct influenced matrices aggregated. The generated group direct-influence matrix is given in Tab. 2.

Table 2: Group direct-influence matrix of expert opinions on contextual factors

		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
Education	F1	0	4	3.25	2.5	0.75	0	0	0	0	0	0	0
Background knowledge	F2	1	0	4	2	1.25	1	0.25	0	0	0	0	0
Performance	F3	1	0.75	0	0.25	0	0	0	0	0	0	0	0
Cognitive ability	F4	2.25	2.5	4	0	1	0	0.25	0	0	0	0	0
Learning style	F5	0.25	0	0	0	0	0	0	0	0	0	0	0
Affective state	F6	0	0	1	0	1.5	0	1.25	0	0	0	0	0
Learning setting preference	F7	0	0	0.25	0	0	0	0	0	0	0	0	0
Infrastructure & connectivity	F8	0	0	1.5	0	1.5	0.5	0.75	0	0	0	0	0
Environment	F9	0	0	2	0	3	2.75	2.25	0	0	0	0	0
Location	F10	0	0	0	0	3	2.5	1.75	2	0	0	1	2.75
Mobility	F11	0	0	0	0	3	1.75	1.5	1.5	0	0	0	0
Activity	F12	0	0	0	0	3	2.25	1.75	0	0	0	3	0

2) Generating normalized direct-influence matrix

The normalized direct-influence is obtained by Eq. (2), where s is defined by Eq. (3).

$$X = \frac{Z}{s} \tag{2}$$

$$s = max\left(\max_{1 \le i \le n}\sum_{j=1}^{n} Z_{ij}, \max_{1 \le i \le n}\sum_{i=1}^{n} Z_{ij}\right) \tag{3}$$

where n is the number of factors. The generated normalized direct-influence matrix is given in Tab. 3.

Table 3: Normalized direct-influence matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
F1	0	0.22222	0.180556	0.138889	0.041667	0	0	0	0	0	0	0
F2	0.055556	0	0.222222	0.111111	0.069444	0.055556	0.013889	0	0	0	0	0
F3	0.055556	0.04167	0	0.013889	0	0	0	0	0	0	0	0
F4	0.125	0.13889	0.222222	0	0.055556	0	0.013889	0	0	0	0	0
F5	0.013889	0	0	0	0	0	0	0	0	0	0	0
F6	0	0	0.055556	0	0.083333	0	0.069444	0	0	0	0	0
F7	0	0	0.013889	0	0	0	0	0	0	0	0	0
F8	0	0	0.083333	0	0.083333	0.027778	0.041667	0	0	0	0	0
F9	0	0	0.111111	0	0.166667	0.152778	0.125	0	0	0	0	0
F10	0	0	0	0	0.166667	0.138889	0.097222	0.111111	0	0	0.055556	0.152778
F11	0	0	0	0	0.166667	0.097222	0.083333	0.083333	0	0	0	0
F12	0	0	0	0	0.166667	0.125	0.097222	0	0	0	0.166667	0

3) Generating total influence matrix

The total influence matrix is generated using the normalized direct-influence matrix X using Eq. (4).

$$T = X\,(1 - X)^{-1} \tag{4}$$

The total influence matrix thus obtained is given in Tab. 4.

Table 4: Total influence matrix generated using the normalized direct-influence matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
F1	0.05494	0.271702	0.291964	0.180764	0.074124	0.015095	0.007332	0	0	0	0	0
F2	0.092039	0.050796	0.283317	0.133473	0.089087	0.058378	0.020502	0	0	0	0	0
F3	0.064663	0.06157	0.03227	0.030159	0.00893	0.003421	0.001512	0	0	0	0	0
F4	0.159847	0.19381	0.305663	0.047981	0.079238	0.010767	0.017995	0	0	0	0	0
F5	0.014652	0.003774	0.004055	0.002511	0.00103	0.00021	0.000102	0	0	0	0	0
F6	0.004876	0.003794	0.058682	0.001914	0.083924	0.000211	0.069538	0	0	0	0	0
F7	0.000898	0.000855	0.014337	0.000419	0.000124	0.00005	0.00002	0	0	0	0	0
F8	0.006782	0.005586	0.088588	0.002793	0.0865	0.028088	0.043734	0	0	0	0	0
F9	0.010484	0.008157	0.12613	0.004114	0.180668	0.153231	0.135811	0	0	0	0	0
F10	0.004728	0.002165	0.022712	0.001213	0.229974	0.169257	0.135539	0.117863	0	0	0.081019	0.1528
F11	0.003556	0.001535	0.014958	0.000872	0.182216	0.099622	0.093757	0.083333	0	0	0	0
F12	0.003731	0.001442	0.011898	0.000844	0.20771	0.14167	0.12156	0.013889	0	0	0.166667	0

4) Calculating prominence and relation vectors

The vectors R (sum of the rows) and C (sum of the columns) are calculated using Eq. (5).

$$R = [r_i]_{nx1} = \left[\sum_{j=1}^{n} T_{ij}\right]_{nx1}, \quad C = [c_j]_{1xn} = \left[\sum_{i=1}^{n} T_{ij}\right]_{1xn} \tag{5}$$

where i, j ∈ {1, 2 …, n} and n = 12, the number of factors.

The addition of vector (R + C) is termed as *prominence*. When $j = i$, the sum $(r_i + c_j)$ shows the total effect given and received by factor i on the system. In other words, it depicts the degree of significance the factor *i* has on the system. The subtraction of vectors (R − C) is termed as *relation*. For a subtraction ($r_i - c_j$) depicts the net effect the factor *i* contributes to the system. If ($r_j - c_j$) is positive, the factor F_i affects other factors, and if it is negative, the factor F_i is being influenced by other factors. The prominence and relation vector obtained from the total influence matrix T is given in Tab. 5.

The (R − C) shows that education (F1), background knowledge (F2), cognitive ability (F4), infrastructure & connectivity (F8), environment (F9), location (F10), mobility (F11), and activity (F12) influence other factors. The factors performance (F3), learning style (F5), affective state (F6), and learning style (F7) are highly influenced by other factors.

Table 5: Prominence and relation vector obtained from the total influence matrix

	Prominence (R + C)	Relation (R − C)
F1	1.31711596	0.474725222
F2	1.33277776	0.122405401
F3	1.45709813	−1.05204931
F4	1.2223561	0.40824452
F5	1.24985696	−1.1971925
F6	0.90293487	−0.4570571
F7	0.66410495	−0.6307015
F8	0.47715603	0.046986273
F9	0.6185948	0.618594796
F10	0.91724682	0.917246819
F11	0.72753513	0.232164762
F12	0.82218817	0.516632614

5) Generating influential relation map

The influential relation map (IRM) is obtained based on matrix T, which exhibits the relations among the system's factors. To build IRM, a simplified normalized total influence Ts is derived based on threshold value 'θ', calculated by Eq. (6).

$$\theta = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} T_{ij}}{n^2} \tag{6}$$

where T is the total influence matrix, and n = 12, the number of factors. The IRM is obtained by Eq. (7) and is given in Tab. 6. The T_{ij}^{s*} in the table (IRM) indicates that F_i influence F_j. Based on the prominence and relation vectors, the interrelationship between the factors is represented through an interrelationship map, as shown in Fig. 1.

$$T_{ij}^{s} = \begin{cases} T_{ij}^{*} & if\ \ T_{ij} > \theta \\ 0 & if\ \ T_{ij} \le \theta \end{cases} \tag{7}$$

The IRM demonstrates that education (F1), background knowledge (F2), cognitive ability (F4), location (F10), and activity (F12) are in quadrant I. These factors have high prominence and relation values and are the core factors that contribute significantly to comprehend the learner. Information and connectivity (F8), environment (F9), and mobility (F11) have low prominence and higher relation. They are autonomous and the driving factors in deciding about learner condition and situation. The learner's setting and preferences (F7) in quadrant III has low prominence and relation and is relatively disconnected. This factor does not influence other factors but is affected by other factors. The learner's performance (F3), learning style (F5), and affective state (F6) have a low relation but high prominence. These factors are highly influenced by other factors but do not influence other factors and are significant in comprehending the learner.

Table 6: Influential relation map

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
F1	0.0549*	0.2717*	0.2919*	0.1807*	0.0741*	0	0	0	0	0	0	0
F2	0.0920*	0.0507*	0.2833*	0.1334*	0.0890*	0.0583*	0	0	0	0	0	0
F3	0.0646*	0.0615*	0	0	0	0	0	0	0	0	0	0
F4	0.1598*	0.1938*	0.3056*	0.0479*	0.0792*	0	0	0	0	0	0	0
F5	0	0	0	0	0	0	0	0	0	0	0	0
F6	0	0	0.0586*	0	0.0839*	0	0.0695*	0	0	0	0	0
F7	0	0	0	0	0	0	0	0	0	0	0	0
F8	0	0	0.0885*	0	0.0865*	0	0.0437*	0	0	0	0	0
F9	0	0	0.1261*	0	0.1806*	0.1532*	0.1358*	0	0	0	0	0
F10	0	0	0	0	0.2299*	0.1692*	0.1355*	0.1178*	0	0	0.0810*	0.1528*
F11	0	0	0	0	0.1822*	0.0996*	0.0937*	0.0833*	0	0	0	0
F12	0	0	0	0	0.2077*	0.1416*	0.1215*	0	0	0	0.1666*	0

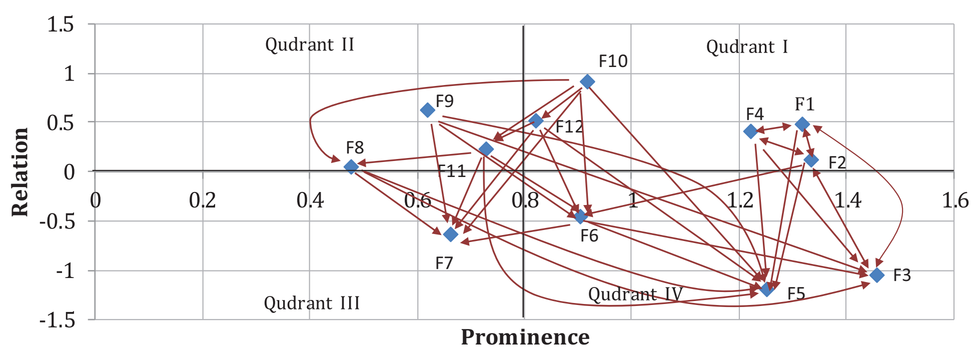

Figure 1: Interrelationship map showing the relations among the factors

4 Building the Learner Model

The learner model for a personalized and ubiquitous learning environment is proposed here. The model comprises four components, namely, Learner, Knowledge Background, Learning Fitment, and Learning Situation. Each component is an independent module of the model and describes the learner dimension for learning specified by concepts. The concepts describe the learner's intrinsic and extrinsic learning contexts.

4.1 Learner

This component describes the demographic dimensions of the learner. The demographic dimension is conceptualized by the concept *Personal Information* that incorporates the learner's necessary personal information. It is characterized by the attributes name, ID (learner identification code), and contact (phone number or email ID). These attributes allow recognizing the learner and making correspondence with him/her. *Personal Information* concept has the following functionalities:

- *getPersonalInfo*: Provides learner's personal information such as name, ID, and contact.
- *updatePersonalInfo*: Updates the attributes for any desired change.

4.2 Knowledge Background

This component represents the learner's dimensions like learning experience and knowledge gain, which he/she acquired in the past. The information is quite significant in staging the compatibility level of the learner for the recommended learning material. The learning experience and knowledge gain dimensions are conceptualized by the concepts *Education* and *Knowledge Acquired*, respectively.

i. *Education*: This concept specifies the learner's educational background and helps find her learning suitability while pursuing a new learning domain. It has a functionality getHigherEducation(stream) that determines the higher education attained by the learner in a field of study (stream). This concept is composed of a sub-concept *Course* that incorporates the specification of courses undergone by the learner. A learner may have completed multiple courses in different fields of study. *Course* is attributed by the followings:
   - Program: It specifies the learner's background education (e.g., grade school, high school, diploma, graduate, post-graduate, etc.). This attribute reflects the degree of matureness and efficacy the learner had gained in terms of education.
   - Stream: It specifies the attained educational program's domain (field of study), for example technical, science, literature, health, sociology, and so on. A learner may have undergone different programs and have specialization in more than one stream.

     The concept *Course* has the following functionalities:
   - *getCourseInfo*: Provides the course information in terms of program and stream.
   - *updateCourseInfo*: Updates the attributes for any desired change.

ii. *Knowledge Acquired*: This concept specifies the learning mastery the learner achieved on subject topics in the past, thus ensuring her learning suitability for learning the related topics. It has a functionality *getTopicKnowledgeLevel(topic, subject)*, which captures the learner's knowledge level and depth of a topic for a subject. This concept is composed of two sub-concepts, namely, *Topic Knowledge and Performance*.
   - *Topic Knowledge*: It specifies the topic of a subject the learner learned and the level of knowledge he/she acquired on the topic in the past. *Topic Knowledge* is characterized by attributes such as topic, subject, and level. The level specifies the extent to which the learner had learned the topic. The knowledge level of a learner on a topic is specified by Bloom's knowledge levels [28]. The *Topic Knowledge* concept has two functionalities:
     - *getTopicKnowledge(topic, subject)*: Returns the learner's knowledge level for a given topic and the subject.
     - *updateTopicKnowledge*: Updates the attributes for any change.
   - *Performance*: The *Performance* concept specifies how well a learner performed and gained knowledge on subject domains in the past. This concept has *updateTopicsKnowledge* functionality, which updates the learner's topics knowledge information based on her performance. *Performance* is composed of a sub-concept *Subject* that specifies learner performance on a subject. *Subject* has an attribute subject name that specifies a particular

subject. The concept has *aggregateTopicsKnowledge* functionality, which aggregates a learner's performance on the various topic assessments on the subject. *Subject* is composed of another sub-concept *Performance Assessment* that captures the learner's learning performance along the time for different topics of a subject. This concept is attributed by topic, level, and date. The topic specifies the topic on which the learner took the test or assessment, and the level specifies the assessment result. The date specifies the assessment date. This date feature is very useful as it tells how long back the learner had learned the topic, and as a result, whether the learner's knowledge level for the topic should be considered the same or not. *Performance Assessment* has functionality *updateTopicPerformance* that updates the attributes as per the learner's progress.

4.3 Learning Fitment

This component describes the learner's learning suitability dimension in the present situation, which is conceptualized by *Learning Suitability*. This concept exhibits the learner's intrinsic cognitive and psychological suitability for learning, learning mode, and other learning preferences. It typically specifies the learner's implicit fitment for learning, thereby rationalizing whether a learning material is suitable for his/her interpretation and comprehension. This concept is featured by the following two attributes:

- Cognitive ability: It specifies the learner's cognitive abilities or skills like mental mapping, relation making, inferring logic, mathematical skills, abstraction, reasoning, and so on. This attribute helps comprehend the learner's suitability in decoding and interpreting the information encoded in the learning material.
- Affective state: It specifies the learner's state of mind like confusion, satisfaction, disappointment, frustration, and delight in a present learning context [29]. The affective state helps to understand learners' attention and comprehension for learning material in an ongoing learning session.

Learning Suitability has the following two functionalities:

- *getLearningStyle*: Identifies the current learning style of the learner.
- *getLearnerPreference*: Determines the current learning setting preferences of the learner.

Learning Suitability is composed of the following two sub-concepts:

i. *Learning Style*: It specifies the learning strategy, approach, and mode that are preferred by a learner for learning. For learner modeling, we adopted VARK learning style, which specifies a learner's sensory-based affinity to different modalities of learning like visual, aural, read and write, and kinesthetic. Correspondingly, the concept is attributed by four attributes, namely, visual, aural, read and write, kinesthetic. The *Learning Style* concept has a functionality *updateLS* that assesses and updates the attributes with changing learning style of learner.
ii. *Learning Setting Preference*: It specifies the learner choice for interface setting for learning. The attributes include language, font style, font color, font size, display ratio, and media type. The display ratio is the learner's preferred display dimension, and media type is the learner's preference for media like text, image, audio, video, and their types. The concept has functionality *updateLearnerPreference* that assesses the change in learner preferences and updates the attributes accordingly.

4.4 Learner Situation

This component describes the learner's situational dimension, which is conceptualized by *Situational Information* that exhibits the learner's external situational information like the device used for learning, surrounding environment, location, activity, and so on. The following two attributes feature this concept.

- *Location*: It specifies the location of the learner where he/she is presently situated. This attribute helps in predicting the learner's location-wise suitability for learning.
- *Activity*: It specifies the learner's current activity in which he/she is involved while learning, like working, cooking, gardening, traveling, and so on. Determining the learner's activity directly helps assess the extent to which the learner is psychologically and physically ready for learning. It enables to predict learner engagement level and the probable learning time availability.

The *Situational Information* concept has the following functionalities:

- *getLocation*: Returns the present location of the learner.
- *updateLocation*: Updates the location attribute according to the changing learner's location.
- *upateActivity*: Assesses and updates the activity attribute according to the learner's present activity.
- *getActivity*: Returns the type of activity (e.g., physical or cognitive) the learner involved in the present context.
- *getEnvironmentalCondition*: Returns the learner's present surrounding environmental condition like light, noise, and so on.
- *getMobility*: Provides the learner's present body movement and posture.
- *getDeviceInfo*: Provides the learner's present learning device specifications information.
- *getNetworkingInfo*: Provides the present network suitability (bandwidth) to carry out the current learning activity.

Situational Information is composed of the following three sub-concepts:

i. *Environment*: It conceptualizes the learner's surrounding environment. This helps in determining whether the learner environment is suitable for learning. This concept has two sub-attributes, namely, the surrounding light and surrounding noise. The concept has the following functionalities:
   - *updateSurroundLightInfo*: Updates the surrounding light attribute according to the current illumination around the learner.
   - *updateSurroundSoundInfo*: Updates the surrounding noise attribute according to the current sound level around the learner.

ii. *Mobility:* It is featured by two attributes, namely, movement, and posture. The movement specifies the learner's current movement type like walking, running, traveling, and so on. The posture specifies the learner's body posture like lying, sitting, and standing. The concept has the following functionalities:
   - *updateMovement*: Assesses and updates the movement attribute according to the learner's current movement.
   - *updatePosture*: Assesses and updates the posture attribute according to the learner's current body posture.

iii. *Infrastructure and Connectivity*: It specifies the device(s) available to the learner for learning and their network connection. Comprehending these is critical in recognizing whether the learner's device can support the recommended learning material and the network connectivity is good enough to carry out the information delivery task seamlessly [30]. The concept has two functions, which are *assessDeviceSuitability* and *assessNetworkSuitability*, to determine whether the present learner device and the network connection are suitable for carrying out the learning activity. This concept is further composed of the following two sub-concepts:

- *Device*: It specifies the ubiquitous devices used by the learner for learning. A learner may have more than one learning device. *Device* is featured by the attributes ID, type, and hardware and software. The ID specifies the device's identification code, while the type specifies the kind of device it is. The hardware and software specify the respective information of the device. The concept has the functionalities *updateHardwareInfo, updateSoftwareInfo, getDeviceId, getDeviceHardwareInfo* and *getDeviceSoftwareInfo*.
- *Network*: It has an attribute bandwidth that specifies the current learning device's data exchange capacity. The concept has the following functionalities:
  - *updateBandwidth*: Updates the attribute as per the device's current network bandwidth.
  - *getBandwidthInfo*: Obtains the current network bandwidth of the device presently in use.

5 Learner Ontology Model

For better illustration, we represent the proposed learner model using ontology. An ontology-based model represents the conceptual model of a learner by relating his/her different dimensions at higher-level abstraction. The learner ontology model, shown in Fig. 2, is represented by UML, which presents the concepts discussed in Section 4.

The top class of the learner model is represented by *Learner* class. This class is an aggregation of *PersonalInformation*, *Education, KnowledgeAcquired*, *LearningSuitability*, and *SituationalInformation* classes representing the personal information, education, knowledge acquired, learning suitability, and situational information concepts, respectively, of the learner model. The *Learner* class is associated with the *PersonalInformation*, *Education*, *KnowledgeAcquired*, *LearningSuitability*, and *SituationalInformation* classes through the *hasPersonalInfo*, *hasEducation*, *hasKnowledge*, *hasSituation*, and *hasSuitability* properties, respectively.

6 Interfacing Learner Model

For necessary learning adaptation, the learner model is interfaced with the personalized learning recommendation system for proper adaptive decision making. Similarly, for necessary updating, the learner model is interfaced with the learner. The layered interface architecture is shown in Fig. 3. The architecture consists of four layers, as described below.

Layer 1: This is the lowest layer of the architecture and is responsible for data exchange. This layer contains interfaces to the database and sensors. The database interface allows moving learner data between the learner model and the database. The database acts as a repository for storing learners' contextual data. The sensor interface allows the sensors in the learner's device or other external sensors to receive the learner's contextual data. In contrast with extrinsic contexts, the intrinsic contexts are very internal to the learner and very difficult to procure. On the basis of changing values, they are also characterized as static and dynamic. The static context is relatively stable and does not often change, whereas the dynamic context values change frequently. The data are acquired through the sensor and user input. Tab. 7 shows the mechanisms to capture the contextual information for the different attributes of the model.

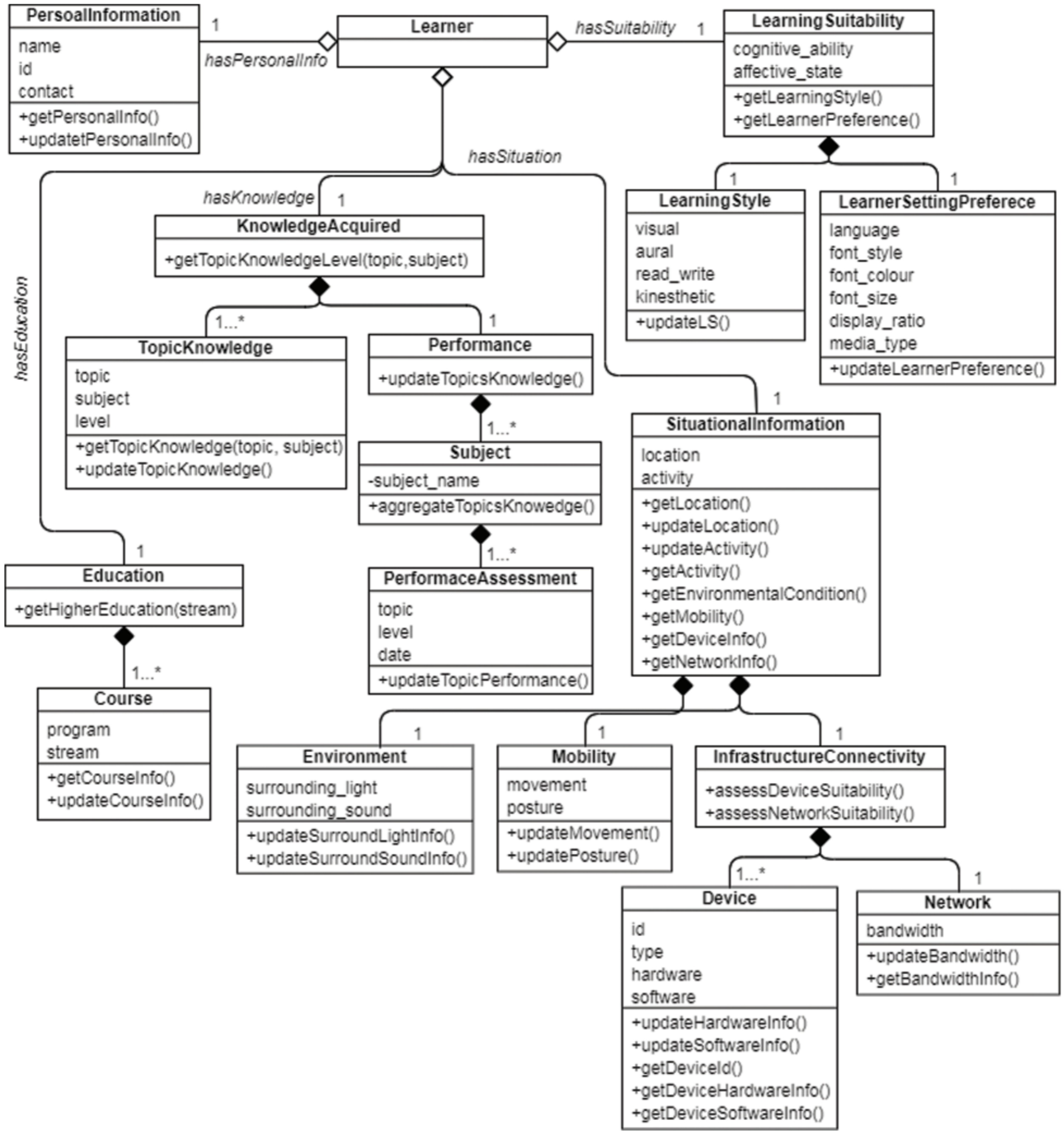

Figure 2: Ontological representation of the learner model

Layer 2: This layer represents the learner model. The learner model acts as an expert system that assesses the learner's contextual data and takes appropriate reasoning and thereby reflecting the learner's current state.

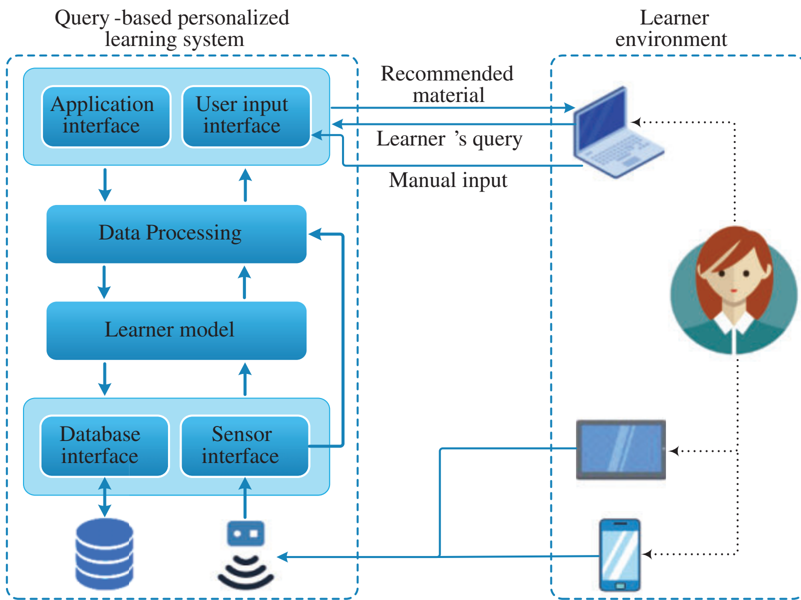

Figure 3: Layered architecture for interfacing learner model with query-based personalized learning recommendation

Table 7: Contextual information acquisition for the learner model

Concept	Attribute	Context	Data acquisition type	Data acquisition means
Personal Information	Name, ID, contact	Intrinsic, static	Learner input	Form input
Course	Program, stream	Intrinsic, static	Learner input	Form input
Topic knowledge	Topic, subject, level	Intrinsic, static	Learner input	Computationally analyzing learner performance
Performance assessment	Topic, level, date	Intrinsic, static	Learner input	Form input, assessing and analyzing test results
Learner suitability	Cognitive ability Affective state	Intrinsic, static Extrinsic, dynamic	Learner assessment input Sensor input	Assessing and analyzing test results Emotional state or state of mind detection through a camera
Learning style	Visual, aural, read and write, kinesthetic	Intrinsic, static	Learner assessment input	Assessing and analyzing test results and analyzing learner activity
Learning setting preference	Language, font style, font color font size, display ratio, media type	Intrinsic, static	Learner input	Form input

(Continued)

Table 7: Continued

Concept	Attribute	Context	Data acquisition type	Data acquisition means
Situational information	Location	Extrinsic, dynamic	Sensor input	GPS, internet-based geo location
	Activity	Extrinsic, dynamic	Sensor input	Motion sensor, location sensor, microphone
Device	ID, type, software, hardware	Extrinsic, static	Device input	Mobile device input
Network	Bandwidth	Extrinsic, dynamic	Device input	Mobile device input
Environment	Surrounding light	Extrinsic, dynamic	Sensor input	Device camera
	Surrounding noise			Device microphone
Mobility	Movement	Extrinsic, Dynamic	Sensor input	Accelerometer
	Posture			Gyroscope

Layer 3: The data acquired by the sensor interface are heterogeneous in scale and type. This layer processes the raw data obtained from the data acquisition layer and standardized them to fit into the model.

Layer 4: The interface layer is the top layer of the architecture. The layer consists of the application interface and user input interface. The application interface allows an application program to interface and accesses the learner model. Different applications have varying requirements and accession mechanisms. The application interface gives a standard way to interact with the model. In addition, the user input interface provides an abstraction for query input for a query-based personalized recommendation as well as an interface to take learner context as manual user input.

The layered architecture for the learner model interfacing with the other components in a query-based personalized learning recommendation system is shown through a schematic in Fig. 4. The figure shows the structural layout of different interfacing of learner model and data flow.

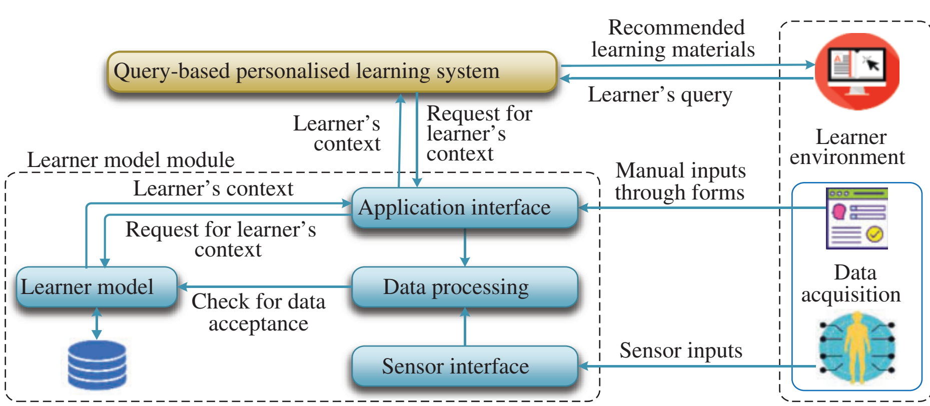

Figure 4: Sequentially structured architecture interfacing the model to system and learner

Table 8: Learning adaptation decision based on learner model's attributes

Concept	Attribute	Information inference/determines	Adaptation decision
Personal information	Name, ID, contact	Learner identification, communication information.	NA
Course	Program, stream	Learning suitability level (beginner, intermediate, advance) of the learner for a given subject domain.	Selecting learning material with appropriate suitability level (beginner, intermediate, and advance).
Topic knowledge	Topic, subject, level	Knowledge gained by the learner for given topics on a subject domain.	Selecting learning material with the topic as per the suitability of learner's learning level (remembering, understanding, applying, evaluating, and creating).
Performance assessment	Topic, level, date	Knowledge gained by the learner for given topic/s on a subject domain.	The Topic Knowledge is further improved.
Learner suitability	Cognitive ability	Learner capability to decode difficult information.	Selecting learning material with an appropriate difficulty level.
	Affective state	Determines learner's concentration, learning mood, and readiness for learning. This also acts as feedback on whether the learner comprehended the given learning material and is satisfied with it.	Reselecting learning material suitable for learner's comprehension.
Learning style	Visual, aural, read and write, kinesthetic	The learner affinity toward different media types like text, audio, video, image, and web for learning.	Choosing learning material with the right media type (text, audio, video, images, slide shows, and programs) matched the learner's learning style.
Learning setting preference	Language, font style, font color, font size, display ratio, media type	The language and the visual aspect preferences for learning.	Changing the layout format of learning material to make it suitable as per learner's preferences.
Situational information	Location, activity	The learner's comfort level for learning and thus determine the probable learning time, acceptable learning mode (learning style), and the possibility to ingest high magnitude information.	Selecting learning material with appropriate difficulty level, information richness (semantic density), media type, and time to complete.
Mobility	Movement, posture		
Device	ID, type, software, hardware	The suitability of the learner's current learning device and its network connectivity for delivering the learning material.	Selecting learning material suitable for the learner's current device and network connectivity.
Network	Bandwidth		
Environment	Surrounding light, surrounding noise	The environmental discomfort and disturbance and prediction of the concentration of learner in the current learning situation.	Selecting learning material with suitable difficulty level, layout format, and the media type to make comprehension easy with less distraction due to environmental noise. Changing the screen brightness as per reading suitability.

The proposed learner model is advocated to be open to the learner, allowing the learner to visualize the knowledge estimated about him/her through different modes (e.g., visual, graph, and text). An open learner model helps the learner in self-monitoring and reflection. Acquiring the learner's context and analyzing them is a complex process, which may often lead to incorrect information about the learner. A model open to the learner allows correcting the information and other necessary updating. This enhances model accuracy and increases the learner's trust in the system.

7 Information Inference and Learning Adaptation

The learner's different features as defined by the attributes in the model rightly specifies the different academic, behavioral, knowledge, cognition, affective state, preferences, and situational parameters of the learner. These attributes can infer appropriate information and knowledge about the learner, which can estimate the learner's suitability and preference for learning and relevantly map them for appropriate personalized adaptation. Tab. 8 provides the information obtained from the model's attributes and the personalized adaptation that can be applied for the query-based personalized learning system.

8 Conclusion and Further Scope

In this study, we designed a learner model for a personalized and ubiquitous learning environment. The model can help the educational recommendation systems to recommend the learning materials that are truly personalized to the learner. A learner can be described by several contextual attributes, but considering all of them is costly for a ubiquitous learning system. To minimize the number of contexts, we surveyed graduate students. We used the DEMATEL technique to establish the importance of the selected contexts. The results show that the selected contexts are sufficient to understand and describe a learner. In addition, the different adaptive decisions can be generated on the basis of the learner context. The deliberation of the learner's preferences and suitability enables this model to assess learner's requirement more precisely compared with other existing learner models for ubiquitous learning scenarios. Furthermore, consideration of intrinsic (e.g., knowledge, affective state, cognitive ability, etc.) and extrinsic contexts (e.g., activity, movements, posture, etc.) gives an exact reflection of a learner that facilitates better decision making for learning material recommendation.

This work can further be extended by implementing the proposed model in a personalized recommendation system. This model can also be tried with a formal learning scenario where the range of attribute selection is wider. Moreover, as the intrinsic contexts are difficult to acquire, this opens up an important future research scope.

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