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Design and Development of Competency-based Instructional Model for Instruction Delivery for Learning Disabled using Case Based Reasoning

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Abstract: ***Pedagogical policies are designed for organizing and sequencing the instruction plan provided to the learner, for supporting learning activities and deciding which learning environment will be suitable for what kind of learner. In this paper, a multi-level pedagogy model named competency-based instructional model (CBIM) is presented for LD learners. The pedagogy policies are recommended based on the CBIM model, it takes problematic skills of the learner as input and delivers a learner-centric instruction plan (IP) according to the problematic skill. For the implementation of CBIM model, case-based reasoning approach is used and CBRI and observation models are proposed.***

Index Terms**:** ***Intelligent Tutoring System, Learning Disability, Dyslexia, Dysgraphia, Dyscalculia.***

I. INTRODUCTION

Learning disability is a neurological processing problem that interferes with basic learning skills such as reading, writing, and calculation, as well as higher-level skills such as time planning, thought organization and short term attention. Learning disabilities affect one's academics and can have an impact on the daily social life of the learner. The symptoms of learning disability can be diagnosed in early student life if observed, but due to lack of knowledge of the teacher and school authorities, it is never identified and such learners are labeled as slow learners and failures. Receiving repeated failures can affect learner's self-esteem and they can stop trying to learn over time [1]. It is very difficult for a physical instructor to provide full attention to all learners and clear the topic for each learner. A digital learning environment can help provide learners one to one environment and delivering content according to the need of the learner.

ITS is a learning environment that keeps track of learner performance during the learning process, provides feedback and instructions whenever needed by the learner. ITS consists of four components: student model, domain model, pedagogy model and a user interface [2].

- Student Model: contains information about the learner such as previous knowledge level, physical limitations, requirements and learning style preferred by the learner, based on which instructions are provided to the learner.

- Domain model: contains the quiz, instruction plan and learning content to be taught to the learner.
- Pedagogy model: responsible for designing pedagogy policies according to the needs of the learner.
- User interface: displays the instruction plan suggested by the pedagogy model to the learner based on the learner profile stored in the domain model.

Out of these 4 components of ITS, the pedagogy model is the most important one as it implements different pedagogy policies that depend on the pedagogy knowledge and learner profile. Pedagogy policies are individual techniques that are employed to teach a particular topic. The pedagogy model includes decision making that suggests which instruction or content should be presented next. The pedagogy model takes input from the student model in the form of learner profile, checks for relevant instruction or content in the domain model and designs a differentiated instruction plan (IP) for the learner.

Pedagogy model provides differentiated instructions to the learner but by providing instructions, learning gain cannot be guaranteed, a learner may solve the question/ task at that moment but in long run, he may not be able to remember the concept. To ensure the learner can understand the concept, the learning environment or content should be delivered according to the preference of the learner. The main focus of the learning process should be developing competency in the learner, competency can be defined as individual skill representing a topic/ concept. Competency development in learners can be achieved by enforcing learners to practice the skill until mastery in skill is achieved. Achieving mastery at the present will help the learner in future academic performances. For this purpose, competency-based learning(CBL) is used. CBL is an outcome-based learning method that provides an outcome in the form of competency development.

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It provides a learner-centric environment to the learner that motivates the learner to spend more time in the learning process and understanding basic concepts. Mastery in competency can be achieved by enforcing learners to focus on one concept until he/she fully masters it and providing learners unlimited time to complete a task [3].

In this paper, a multi-level pedagogy model named as the competency-based instructional model is proposed for LD learners that incorporate multiple learning theories and provide a learner-centric environment to each learner.

II. LITERATURE SURVEY

The pedagogy model is responsible for generating pedagogy policies for the learner, how the learning content should be provided such that environment, learning style, and sequence. For implementing pedagogy policies, case-based reasoning is widely used for generating a learner-centric instruction plan.

Case-based reasoning (CBR) is a problem-solving approach that maintains a case base, case base contains information about the previous recommendations that were made by ITS in any particular situation. Whenever a new learner profile arrives for recommendation, CBR searches case base for any similar case and if found, then recommends the same or altered solution to the learner. After the learning process is complete, CBR registers the current case as a new case in the case base.

For content delivery, recommendation algorithms are also widely used in ITS. Recommendation algorithms are of two types: content-based, collaborative based. Content-based recommendation algorithms use similarity index to map previous actions of learners with the given options and recommend similar topics. Collaborative based algorithms find a similar user whose choices match with the current user and recommend liked topics by the similar user, to the current user.

This section presents a review of available literature on pedagogy model previously developed for personalization of ITS, use of case-based reasoning in delivering content, competency-based learning, and recommender systems.

A. Previously developed pedagogy model

In [4], the authors presented a multi-level pedagogy model to provide personalized pedagogy strategies in a web environment. For validating the pedagogy strategies authors developed an ITS named FUNPRO. The authors provided the learning content based on the previous knowledge level of the learner and learning style and provided the facility of changing learning theories, teaching methods and pedagogy tactics at each level. Results showed that as learner progress in the learning process, the number of required changes was minor and the performance of the learner was improved.

In [5], the authors designed and implemented an emotion-based intelligent tutoring system for providing instruction to teach English. Authors used Microsoft Agent as an interactive platform, and image and audio information as interactive methods. For designing pedagogy strategy, this ITS used features like real-time emotion of the learners, understanding state and interest of the learner. The authors used test scores and emotions as the factors to change the pedagogy of the learner.

In [6], the authors described a web-based ITS framework that constructs the learning environment for the learner based on the knowledge level of the learner, learning style and psychology characteristics. The authors proposed to add the fifth component in the traditional ITS architecture that is a curriculum model. ITS uses a domain model and pedagogy model to design the teaching process for the learner and send this information to the curriculum model. Curriculum model stores instruction plan for learners according to their knowledge level such as novice, beginner, intermediate and advanced.

In [7], the authors proposed a methodology for training engineering students in the maintenance and operations of mechanisms. The system takes information about a student like the previous knowledge level of the student, what learner should know to solve or repair a mechanism, and how the mechanism works. Based on this information, the tutor model provides a list of strategies for the learner to learn.

In [8], the authors introduced a multi-level ontology-based framework combining rule-based (cluster-based and user profile based) and content-based (domain ontology model) filtering and implemented it on Hypermedia platform. This approach recommended the next learning content that is similar to the previously viewed content. Whenever a learner searches for query q, the search engine provides him/her cluster of most similar documents. This research showed a 5-25% improvement in precision, in personalized semantic search.

B. ITS that used CBR for recommendation

In [9], the authors discussed the architecture of distributed ITS based on Multi-agent system and case-based reasoning. The system recommended content based on case-based reasoning. For executing tasks, after entry of the learner, the system uses multiple agents such as interface agent, teacher agent, student agent, Q & A agent, exchange agent, examination agent, CBR agent, and ware base agent. The authors also proposed a cognitive ability evaluation model in which after learning content or knowledge point, the learner is provided an exercise to strengthen the knowledge, then a test is presented to apply the knowledge of the learner.

In [10], the authors developed a prototype CITS based on case-based reasoning and implemented it in the biology domain. For providing a solution to the learner, the case adaption process was used. In this process, if the profile of the current learner matched fully with any previous case, the same solution was provided to the learner. And if the system could not find a similar case, it took a partially similar case, and provided a partial solution from the previous case and registered it as a new case in the case base.

In [11], the authors developed and ITS named Case-based reasoning ITS for algebra learning (CRISTAL). The information about the knowledge level and learning style of the learner is gathered from algebra pre-test and mathematic learning style inventory (MLSI). The authors used local similarity and global similarity to find similar cases for recommendation and found positive progress from the learners.

In [12], the authors proposed an ITS, in which analysing patterns and understanding are selected as a platform for implementing the proposed approach. In this paper, the BDI (Belief, desire, and intention) model is proposed for recommending learning content based on the problem and learning style of the learner. In the proposed system, content is recommended using the CBR technique and agents are used for the observation of the learning process of the learner, which allows the system to complete purpose-specific tutoring tasks.

C. ITS that used CBL

In [13], the authors presented an algorithm named as competency-based guided learning algorithm for generating an adaptive guided learning path to guide learners without the intervention of any physical tutor. The initial level of the learner was determined based on the pre-test. The pre-test contained questions related to N modules and bubble sort was applied for generating a learning path, on the score achieved by the learner in each module. The authors implemented this approach on the group of 24 students and concluded that students were satisfied with the learning path mechanism and learned effectively in the CBGL environment.

In [14], the authors discussed the importance of the tutors in the e-learning environment and divided tutors into groups based on their competency. The authors presented the K-complementarity technique for grouping tutors and assigned them to the learners, who face problems in a particular domain. This experiment was carried out at Algerian University and results showed that each group was able to solve 80 percent of the tasks assigned to them.

In [15], the authors studied the data of vocational education and training (VET), after using competency-based training (CBT) in Australia. The authors described the effect of CBT on teachers and the teaching process, based on 12 case studies and 24 telephone interviews. This study found that most teachers found the adaptation of CBT, a painful process, but later they accepted CBT to achieve the best result, after seeing the better performance of their students. CBT also changed the work environment and teachers were spending more time in the workplace.

D. Recommender systems

In [16], the authors proposed a content-based recommending system, named Multilanguage recommender system (MARS) that creates a cross-language user profile, it shifts traditional keywords based text representation to a more complex word-meanings based language-independent representation. This module used supervised learning to infer user interest from a different document, rated by the user in the training phase. The content analyser module identifies relevant concepts representing the content and selects the correct meaning of the word. This way document is represented using semantic instead of keywords.

In [17], the authors developed an e-learning system 'Comulang' to enhance the learning process in the e-learning environment using collaboration between workgroups and learners. This proposed system is used for learning multiple languages. In this work, based on the previous knowledge students were divided into k groups. If a student from 'group a' has any problem then he can take help from the student of 'group b' or 'group c', who can solve the problem. For this purpose, a collaborative based recommendation algorithm was used.

In [18], the authors presented a hybrid context-aware recommender system that recommends based on the preference of the user as well as similarity of items or user, for recommending books and movies. In the developed approach, cosine similarity was used to determine the similarity between items or users, and for calculating the unknown rating, mean squared error (MSE) is used in test and train datasets. This approach reduced the complexity of collaborative filtering and provided more accurate results and personalized recommendations.

III. THEORETICAL FRAMEWORK

The proposed ITS is being developed for learners who are facing learning disabilities aged between 4-10 years. In the proposed ITS, two grade levels are presented to the learner. Grade 1 is for the learners who feel a problem in basic concepts like spelling, alphabet sound, left-right recognition, counting, two-digit addition and subtraction, and simple series. Grade 2 is for learners who feel problems in advance topics of grade 1, like word sound, sentence structure, directions, multiplication, division, and time-telling. Each problem taken in grade 1 and grade 2 are associated with 3 learning disability- dyslexia, dysgraphia, and dyscalculia, and treated as an individual skill or competency. In this ITS, individual competencies of the grade level are focused and the learner is provided content according to the skill in which the learner faces a problem, which is termed as problematic skills. In the proposed ITS, the learner is presented a pre-test containing skills that are categorized into 3 categories: cognitive category, psychomotor category, and affective category. The cognitive category represents cognitive skills included in the proposed ITS and, includes competencies related to 3 learning disabilities: dyslexia, dysgraphia, and dyscalculia. From the above 3 learning disabilities, the problematic skills that are taken as target problems are: Dyslexia- literacy skill(LS) and phonological awareness(PA); Dysgraphia- sentence and word expression(SWE) and visual-spatial response(VSR); Dyscalculia- counting(CN), basic calculation(BC) and reasoning(RE). The psychomotor category includes competencies related to learner's handwriting that are: motor dysgraphia, spatial dysgraphia, and dyslexic dysgraphia. The affective category includes learner's problems related to social behaviour and self-management, these are Interpersonal and Intrapersonal competencies. For implementing the above competencies, a theoretical model termed as the competency-based instructional model (CBIM), based on competency-based learning is proposed. CBIM is introduced for providing a learner-centric environment and focuses on developing competencies in the LD learners. For developing competencies, the CBIM model works on the rules discussed below:

- Problematic skill of the learner is determined based on the result of three pre-tests presented under following categories: psychomotor category, and affective category.
- A detailed learner profile is developed based on the result of all three pre-tests that contain a set of problematic skills.

- IP related to only one problematic skill is presented at a time so that learners can concentrate on one competency at a time without being distracted.
- A learner can switch to the next competency only after achieving mastery in the current competency.

CBIM is a multilevel pedagogy model, in which each level represents a pedagogy policy for providing a learner-centric environment to the learner. The following five levels compose the pedagogy level:

1. Instruction level
2. Macro Designing level
3. Micro Designing level
4. Implementation level
5. Observation level

The instruction level represents the instruction techniques or theories that are used to develop an instruction plan for the learner. The macro designing level represents the learning course packages that contain a set of instruction plans based on a particular category such as dyslexia, dysgraphia, dyscalculia, motor skills, interpersonal competency or intrapersonal competency. The Micro designing level further divides the learning course package into a detailed differentiated instruction plan that is developed based on individual problematic skill. At the implementation level, a learner-centric plan is presented to the learner based on the detailed learner profile. In observation level, a learner is monitored while the instruction plan is presented to the learner, to determine if the learner is able to understand the topic or not. For representing the levels of the CBIM model and relationship between the five levels, ontologies are used. An ontology is a specification of concepts and relationship among the concepts, that is used for information sharing and reuse.

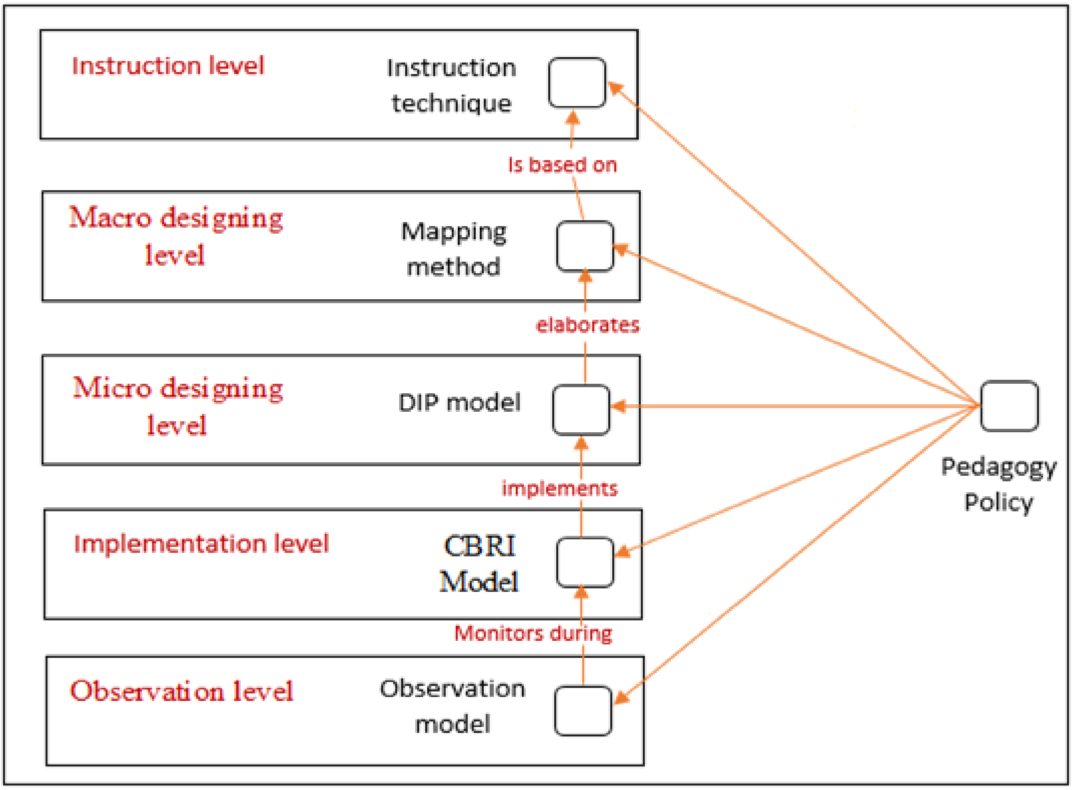

Fig 1. Competency-based instructional model(CBIM)

A. Instruction level:

The method of providing instructions to the learner plays an important role in the learning process. Instructions that are provided considering the initial level and problems of the learner, motivate the learner to spend more time in the learning process. In this paper, instructions are provided based on 3 learning theories: remedial instructions, guided discovery and Vygotsky's theory of social development. In remedial instruction method, learners are provided learning content and at regular intervals, a related quiz is presented for determining whether the learner is able to gain knowledge in the provided environment or not. Remedial instruction theory is used for learners who are falling behind in studies, to check if the learner needs any special assistance or change in learning style. Using remedial instructions may help in solving difficulties in learning, faced by the learner. In the guided discovery method, step by step statements or questions are provided to the learner, to achieve a pre-determined goal. Active participation of learners, makes the learning process interesting and motivates the learner to spend more time in the learning process and gain more knowledge [19]. In the social development method, a list of tasks is provided to the learner for cognition development, and some kind of help in the form of hints or instructions is provided to the learner for completing a task. The tasks provided are based on real-life situations related to social interaction (interaction between people) or individual level (inside the learner), for developing social behaviour in learners [20].

It is reviewed through survey work done previously in this research work that learners who face problem in the cognitive category, learn better in remedial instruction environment. In remedial instruction environment, learners are provided quiz in pre-determined intervals, during the learning process.

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This quiz helps in determining the learning gain of learner or if the learner needs any kind of help/ change in learning style. For learners, who have problems with motor skills, it is reviewed that they learn better in a guided discovery environment. Learners who feel problems related to social behaviour and self-management are provided a social development environment.

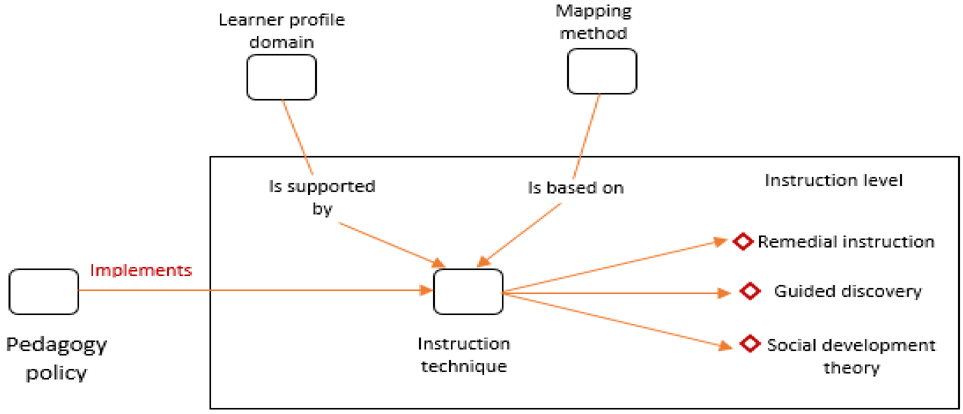

Fig 2. Ontology in Instruction level

B. Macro designing level:

A learning course package is comprised of the instruction plan that includes an orderly logical arrangement of the learning content pieces. The mapped learning course packages are based on pedagogical theories; each package may contain all or part of the pedagogical principles in the learning theories. The learning course package is based on an instruction technique and is supported by the Differentiated instruction plan(DIP) model. The proposed ITS offers an instruction plan for problematic skills related to dyslexia, dysgraphia, dyscalculia, motor skills, interpersonal competency and intrapersonal competency, so in micro designing level course packages related to these competencies are introduced.

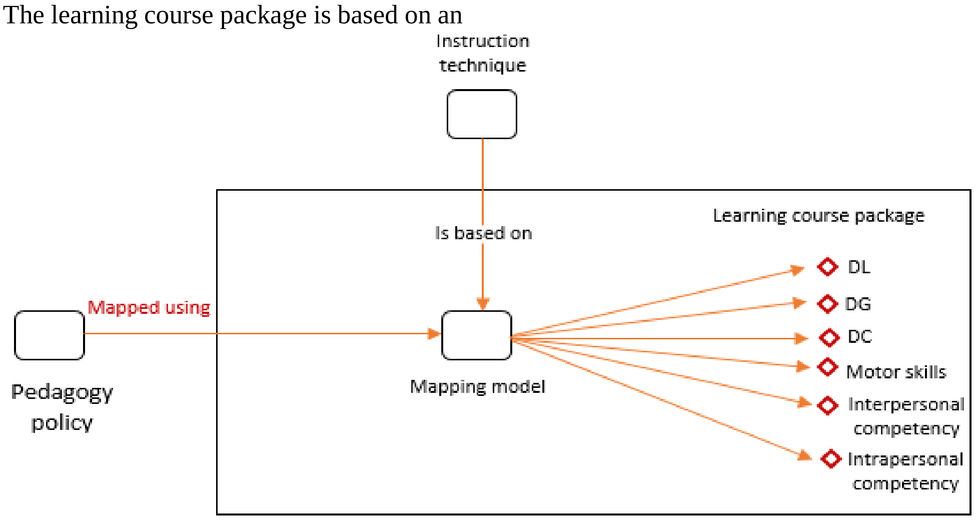

Fig 3. Ontology in Macro designing level

C. Micro designing level:

In the micro designing level, Differentiated Instruction Plan (DIP) model is introduced. DIP model further divides a learning course package into an instruction plan for each problematic skill. The learner is provided content based on his/her problematic skill and a set of problematic skills may differ for each learner, so each learner is provided a different instruction plan which is termed as differentiated instruction plan. DIP model represents an instruction plan for individual problematic skills and recommends it to the learner when needed. Each learning course package includes a set of instruction plans such as DL package is comprised of instruction plans related to literacy skill(LS) and phonological awareness(PA). DG package includes instruction plan related to sentence and word expression(SWE), and visual-spatial response(VSR); DC package includes instruction plan related to counting(CN), basic calculation(BC), and reasoning(RE); motor skills package includes instruction plan related to motor dysgraphia, spatial dysgraphia, and dyslexic dysgraphia; interpersonal competency package includes instruction plan related to school anxiety and social anxiety; intrapersonal competency package includes instruction plan related to self-confidence and self-management.

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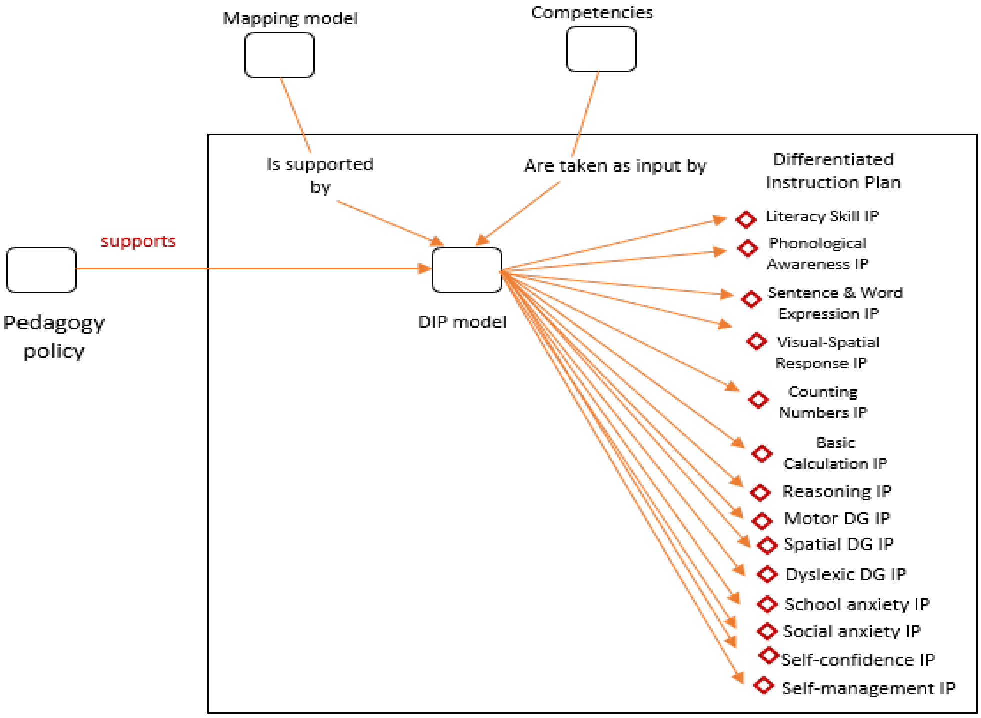

Fig 4. Ontology in Micro Designing level

D. Implementation level:

In the implementation level, a case-based reasoning implementation(CBRI) model is proposed. CBRI model provides learner-centric IP based on the learner characteristics i.e. competency and learning style. The instruction plans mentioned in the DIP model are developed in four learning styles: reflective, visual, active and kinaesthetic learning style. Learner-centric IP contains a set of differentiated IP based on the competencies of the learner. This ITS is based on competency development, so the learner is provided one content at a time to give learners time to understand one topic only and can switch to another content only when he/she fully understands the topic.

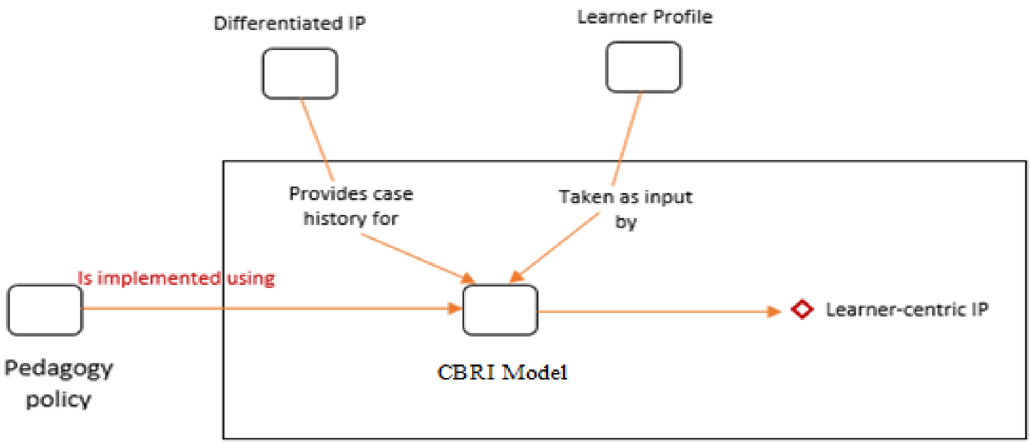

Fig 5. Ontology in Implementation level

E. Observation level:

In the observation level, a learner is monitored during the learning process. In the observation model, an interactive quiz is presented to the learner to determine the learner's status during the learning process. If the learner provides a positive response in the interactive quiz, IP is continued. If the learner provides a negative response, the pedagogy is changed accordingly.

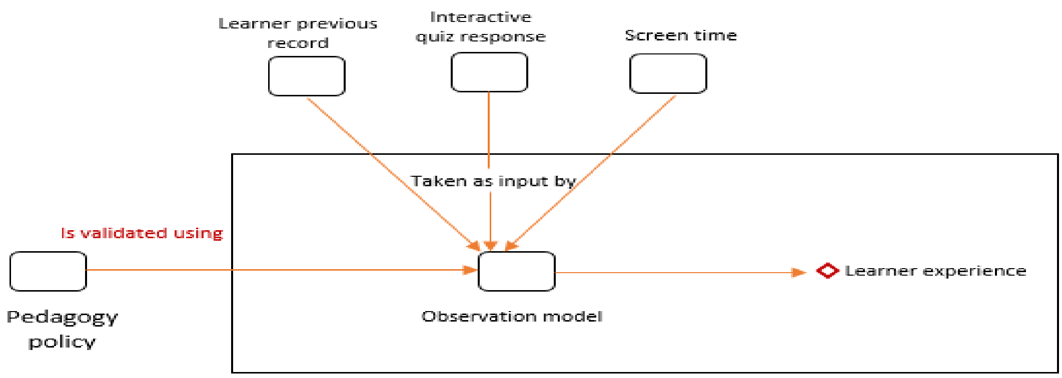

Fig 6. Ontology in Observation level

IV. IMPLEMENTATION OF CBIM

For recommendation instruction plan to the learner in ITS, multiple AI techniques i.e. reinforcement learning, content or collaborative filtering, and case-based reasoning, are used. For implementing the proposed multi-level pedagogy model, case-based reasoning method is used. Case-based reasoning (CBR) is a problem-solving approach that solves a new problem with the help of previous problems. In the proposed ITS, instruction plan is recommended to the new learner based on the recommendation history of the similar learner. CBR is a four-step process: retrieve, reuse, revise and retain. In the first step, it retrieves a similar case from the case base. In the second step, it adapts the solution from the previous case as needed to fit the new problem. In the third step, it tests the new solution and if necessary, revise. In the last step, after successfully implementing the solution, it stores the experience as a new case in the case base. For implementing the CBR approach in proposed ITS, the CBIM model is introduced. The CBIM model has internal representation consisting of three sections: case base development, recommendation and learner experience. In the first section, case base development is implemented using the DIP model. DIP model takes target competencies and set of instruction plan as input, and provide differentiated instruction plan as output. The second section and third section, recommendation, and learner experience are implemented using the CBRI model and observation model that is based on case-based reasoning. It takes learner profile as input, delivers learner-centric instruction plan and monitors learners during the learning process.

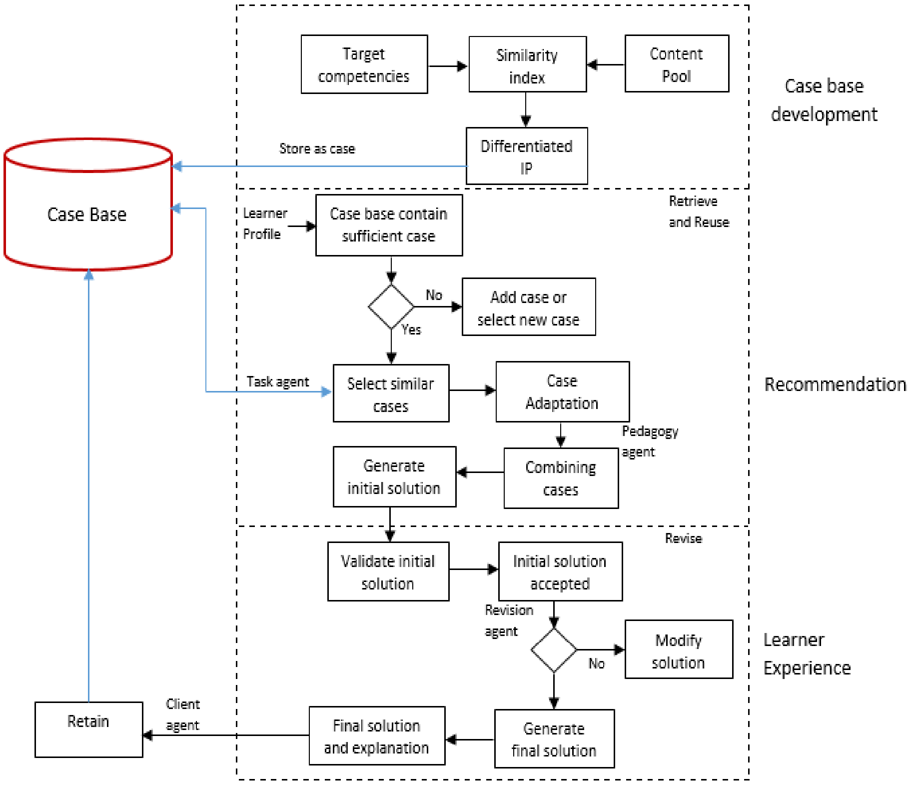

Fig 7. Implementation of CBIM model

A. Case base development:

In this section, the DIP model is implemented for developing a case base. In the DIP model, specific features i.e. grade, competency category, disability type, and keywords, are used as tags to define each problematic skill and instruction plan. The grade represents the level of problematic skill or instruction plan belongs to whether it is grade 1 or grade 2. The competency category represents whether a problematic skill or instruction plan belongs to the cognitive category, psychomotor category or affective category. Disability type represents whether problematic competency or instruction plan belongs to dyslexia, dysgraphia, dyscalculia, motor dysgraphia, spatial dysgraphia, dyslexic dysgraphia, interpersonal competency or intrapersonal competency. Keywords represent the cognitive strength and attributes related to problematic skill or instruction plan. DIP model takes problematic skills of a learner from the detailed learner profile and uses cosine similarity to match tags of problematic skill and instruction plan stored in its vectors. The features of problematic skills are stored in vector 'C' and features of each instruction plan are stored in vector 'I'. The similarity between vector C and I is calculated as follows:

cosine_sim = cosϴ = C.I/ (|C| . |I|) = ∑i=1n Ci.Ii/ (|∑i=1n Ci| ∑i=1nBi|)

where Ci and Bi are components of vector C and I respectively.

The top 2 matching instruction plan is stored as a future recommendation for the target competency, and stored in the case base.

B. Recommendation:

In this section, a learner-centric recommendation is provided in the form of IP to the learner and implemented using the CBRI model. CBRI model is based on case-based reasoning, consisting of 4 sections: retrieve, reuse, revise and retain. Out of these 4 sections, the first 2 sections retrieve and reuse are used in the CBRI model.

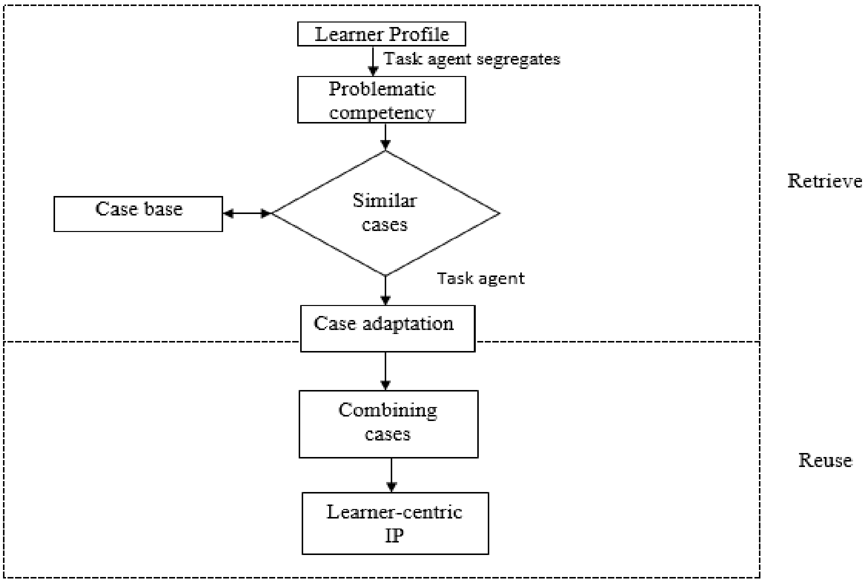

Fig 8. CBRI model for recommendation

Retrieve: Whenever a learner profile is received, the task agent looks into the case base for any similar case, if a similar case is found then similar case is fetched by the task agent from the case base otherwise task agent sends a request to the DIP model for a new case generation. For retrieving similar cases in the proposed ITS, k domain tree (kd-tree) is used. A kd-tree for case base(CB) is a binary tree T(CB) that has k ordered domains L1, L2, …., Lk for attributes A1, A2, …., Ak such that CB ⊆ T1, T2, …, Tk and the size of the case base is N.

1. if |CB| ≤ N: T(CB) is a leaf of the kd-tree, denoted as CB.
2. if |CB| > N: T(CB) is a tree whose
   a. root has an attribute Ai and a value Vi ∈ Ti and
   b. two sub-trees T≤(CB≤) where CB≤ := {(x1, x2, …., xk) ∈ CB| xi ≤ vi} and T>(CB>) where CB> := {(x1, x2, …, xk) ∈ CB| xi > vi} and a value vi ∈ Ti.

All the cases are stored as leaf nodes in the kd-tree. For the generation of kd-tree following algorithm is used.

CBTree Generation Algorithm:

PROCEDURE GenerateTree (CB): kd-tree
If |CB|<N
then
return marked leaf node from case base CB
else
Ai = select_attribute(CB)

vi = select_split_value (CB, Ai)
return tree with its subtrees
GenerateTree ({(x1, x2, …., xk) ∈ CB| xi ≤ vi})
GenerateTree ({(x1, x2, …, xk) ∈ CB| xi > vi})

After generating kd-tree for cases in the case base, similar cases are fetched from the case base for the given problematic skill, using cosine similarity. The algorithm used for retrieving cases is as follows:

CaseRetrieval Algorithm:

PROCEDURE Retrieval (k: kd-tree, Q: query)
If k is a leaf node
Then
for all a∈ CBk :
cosine_similarity (Q, a)
insert 'a' into stack
else
register new_case
return

- **Reuse:** In this section, the pedagogy agent adapts solution according to the learner's need either by selecting IP or combining two or more cases and generates a learner-centric IP for the learner and provides it to the learner.

C. Learner experience:

This section implements the observation model and uses revise and retain section of case-based reasoning to observe learner, flipping pedagogy and incorporating learner experience as given below:

- **Revise:** In this section, the revision agent presents an interaction quiz to the learner during the learning process at a regular interval. If the learner provides a positive response to the interactive quiz, then the revision agent assumes the learner has achieved mastery in the related competency and presents the next IP to the learner. If the learner provides a negative response to the learner, then the revision agent changes the presentation style of the IP and provides it to the learner until the learner provides a positive response. After the learning process is over, the learner is presented a post-test and based on the score achieved in the post-test and number of times presentation style of the instruction plan is changed, learner experience is calculated. The overall experience of the learner is calculated based on the given algorithm:

LExperience Algorithm:

Score_difference = Post-test score in problematic section – Pre-test score in problematic section
If Score difference is positive:
IPC := no of times presentation style of IP is changed
Learner_Experience = [(Score_difference/10) - (IPC/10)]
If Learner_Experience >= 0.2:
Overall_Experience = very good
Else-if Learner_Experience = 0.1:
Overall_Experience = good
Else-if Learner_Experience = 0:
Overall_Experience = satisfactory
Else:
Overall_Experience = Satisfactory after several attempts
Else:
Overall_Experience = not satisfactory

- **Retain:** After calculating overall experience, the client agent registers the final solution and explanation as a new case in the case base for future recommendation.

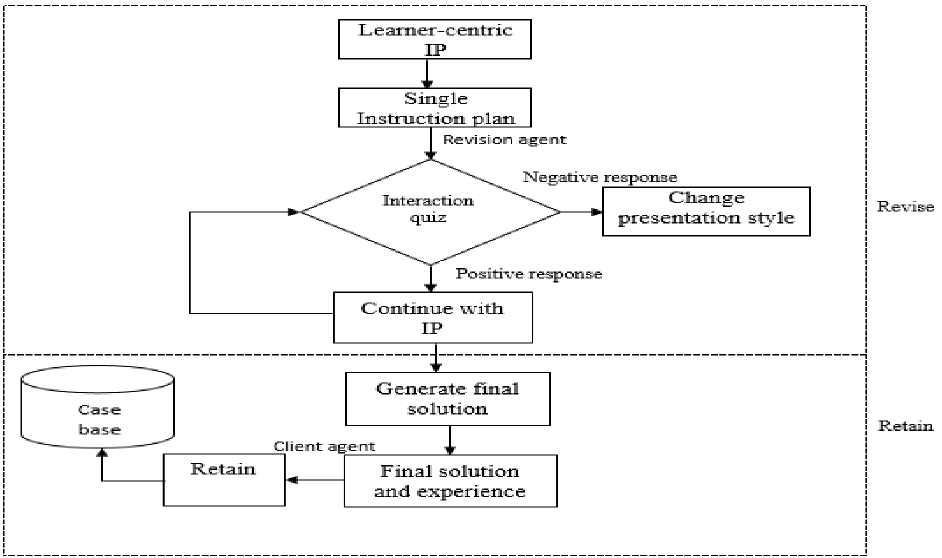

Fig 9. Observation model for monitoring learner

V. RESULT

This study was carried out in 20 learning disabled learners who have shown symptoms of dyslexia, dysgraphia and dyscalculia. Out of 20 learners, 9 learners were dyslexic, 5 learners were dysgraphic, 4 learners were dyscalculic and 2 learners has intrapersonal competency as problematic skill. The target group of this study is learners aged between 4 to 10 years who are learning disabled, so an instructor was provided to each learner who helped them in operating computer system. The score of pre-test and post-test are taken out of 3. When a new learner enters the system, he/she is redirected to grade 1 pre-test and only those learners who are assigned grade 2 by their physical instructor, are redirected to grade 2. Both pre-test contain questions related to cognitive category, psychomotor category and affective category. Firstly, learners are presented questions related to cognitive category, it contains 3 questions each related to dyslexia, dysgraphia and dyscalculia. After presenting questions related to cognitive category, if a learner is found to be dysgraphic, he/she is redirected to detailed dysgraphia test that contain 3 questions related to motor dysgraphia, spatial dysgraphia and dyslexic dysgraphia. Affective category test contain 3 questions related to interpersonal and intrapersonal competency. On the basis of detailed pre-test result, a learner profile is created that contain problematic skill of the learner and presentation style of the instruction plan. On the basis of problematic skill and presentation style, learner centric IP is recommended to the learner. During the learning process interaction quiz is presented to the learner to check the need of changing presentation style of the IP and ITS keeps track of the number of times presentation style is changed for the learner. After the learning process is over, learner is presented a post-test that contain 3 questions each related to the problematic skills of the learner. The details of the performance of the learners are provided in the table1:

Table 1. Performance of the learners during learning process

Learner	Problematic competency	Grade	Pre-test score	Post-test score	Score difference	No. of times presentation style changed	Learner experience	Overall experience
L001	DG	Grade 1	2	2	0	Not applicable	-	Not satisfactory
L002	DL	Grade 1	0	2	2	1	0.1	Good
L003	DL	Grade 1	0	1	1	0	0.1	Good
L004	DC	Grade 1	2	3	1	0	0.1	Good
L005	DC	Grade 1	1	2	1	2	-0.1	Satisfactory after two attempts
L006	DL	Grade 1	2	1	-1	Not applicable	-	Not satisfactory
L007	Intrapersonal competency	Grade 1	1	2	1	1	0	Satisfactory
L008	DG	Grade 1	1	2	1	1	0	Satisfactory
L009	DL	Grade 1	1	1	0	Not applicable	-	Not satisfactory
L010	DL	Grade 1	0	2	2	1	0.1	Good
L011	DC	Grade 1	2	3	1	0	0.1	Good
L012	DG	Grade 1	1	2	1	1	0	Satisfactory
L013	Intrapersonal competency	Grade 1	0	1	1	0	0.1	Good
L014	DL	Grade 2	1	1	0	Not applicable	-	Not satisfactory
L015	DL	Grade 2	1	3	2	1	0.1	Good
L016	DL	Grade 2	1	2	1	1	0	Satisfactory

L017	DG	Grade 2	0	2	2	0	0.2	Very good
L018	DG	Grade 2	2	3	1	1	0	Satisfactory
L019	DL	Grade 2	1	2	1	0	0.1	Good
L020	DC	Grade 2	1	2	1	1	0	Satisfactory

VI. DISSCUSSION

According to the performance of the learners in the pre-test, post-test and number of times learning style of the content is changed, experience of the learner during pedagogy process is determined. According to the experiment results showed in Fig 10, 40% of the learners had good experience, 30% of the learners had satisfactory experience, 5% of the learner had very good experience, 5% of the learners had satisfactory experience after changing learning style two times, and 20% of the learners had not satisfactory experience.

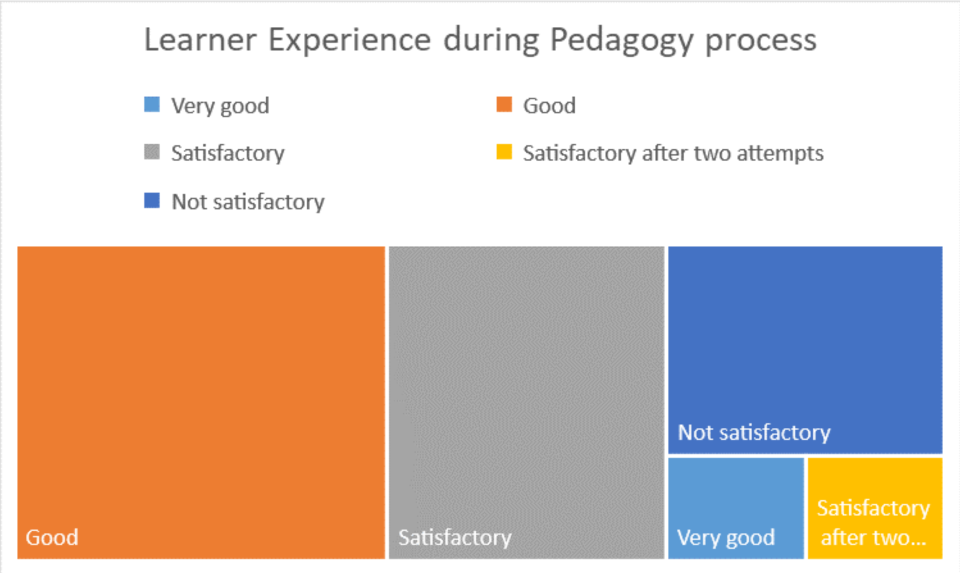

Fig 10. Learner Experience during pedagogy process

VII. CONCLUSION

In this paper, a multi-level pedagogy model based on ontologies for designing pedagogy policies for LD learners is presented. The results show that the presentation style of learning content plays an important role in the learning process of the learner. During the learning process, if a learner is not able to understand the learning content in the provided style, then changing the presentation style of the learning content helps the learner in understanding the concept and improve the performance of the learner.

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REFERENCES

1. Dr. Neena Sawhney, Dr. Sneh Bansal, "Study of awareness of learning disabilities among elementary school teachers", 2014.
2. Mohammad Alqahtani, An Overview: Intelligent Tutoring Systems, https://www.researchgate.net/publication, 2011.
3. Chang, C.C., Development of competency-based web learning material and effect evaluation of self-directed learning aptitudes on learning achievements. Interactive Learning Environments, 14, 2006, 265–286.
4. Manuel F. Caro, Darsana P. Josyula and Jovani A. Jiménez, "Multi-level pedagogical model for the personalization of pedagogical strategies in intelligent tutoring systems", Dyna rev.fac.nac. minas, vol.82, no.194, 2015.
5. Zhiliang Wang, Xuejing Gu, Jie He, Siyi Zheng and Wei Wang, "Design and implementation of an intelligent tutoring system for English instruction", IEEE conference proceedings, 2010.
6. Ahmed R. Salman, "The Use of Intelligent Tutoring System for Developing Web-based Learning Communities", International Journal of Computer Science Issues, Vol. 10, Issue 6, No 1, 2013, 156-161.
7. Enrique Sierra, Ramón García-Martínez, Zulma Cataldi, Paola Britos and A. Hossian, "Towards a Methodology for the Design of Intelligent Tutoring Systems", Research in Computing Science Journal, 181-189.
8. Leyla Zhuhadar, Olfa Nasraoui, Robert Wyatt and Elizabeth Romero, "Multi-model Ontology-based Hybrid Recommender System in E-learning Domain", International Conference on Web Intelligence and Intelligent Agent Technology, 2009.
9. Zhang Rongmei and Liu Lingling, "Research on Internet Intelligent Tutoring System Based on MAS and CBR", International Forum on Information Technology and Applications, 2009.
10. Abdel-Badeeh M. Salem, Hisham S. Katoua, "Case-Based Reasoning Approach for Intelligent Tutoring Systems", Recent Techniques in Educational Science.

11. Mona Masood and Nur Azlina Mohamed Mokmin, "Case-based Reasoning Intelligent Tutoring System: An Application of Big Data and IoT", ICBDR, 2017.
12. Mahmood Kharrat, Nima Reyhani and Kambiz Badie, "A Case-Based Reasoning Approach to Intelligent Tutoring System by Considering Learner Style Model", Proceedings of the 2003 Systems and Information Engineering Design Symposium, 2003, 41-46.
13. Wei-Chih Hsu & Cheng-Hsiu Li, "A competency-based guided-learning algorithm applied on adaptively guiding e-learning", Interactive Learning Environments, 23(1), 2015, 106–125.
14. Yacine Lafifi, Safia Bendjebar and Amina Zedadra, A K-complementarity Technique for Forming Groups of Tutors in Intelligent Learning Environments, Journal of Computing and Information Technology, 22, 2, 2014, 115–130.
15. Erica Smith, "How Competency-based Training Has Changed the Role of Teachers in the Vocational Education and Training Sector in Australia", Asia-Pacific Journal of Teacher Education, Vol. 27, No. 1, 1999, 61-75.
16. Pasquale Lops, Cataldo Musto, Fedelucio Narducci, Marco De Gemmis, Pierpaolo Basile and Giovanni Semeraro, "A Semantic Content-based Recommender System for Cross-Language Personalization", ACM, 2009.
17. Christos Troussas, Maria Virvou and Efthimios Alepis, "Comulang: towards a collaborative e-learning system that supports student group modeling", Springer Plus, 2013.
18. Rajshree Jain, Jaya Tyagi, Sandeep Kumar Singh, and Taj Alam, "Hybrid context aware recommender systems", AIP Conference Proceedings, 2017.
19. Neelu Jyothi Ahuja, "Developing an Intelligent Tutoring System for Individuals with Disabilities: Review and Recommendations", Journal of Web Engineering & Technology, Volume 4, Issue 3, 2017.
20. Rishabh Kumar Mishra, "Vygotskian Perspective of Teaching-Learning", Innovation: International Journal of Applied Research, Volume-1, Issue-1, 2013.

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