Chapter 4 Experimental system analysis

Chapter Outline:

4.1 Introduction

4.2 Learner module components

4.3 Tutor module components
This chapter discusses an analysis part of an experimental model for virtual collaborative learning environment (VCLE) which is being proposed in the chapter 3. This chapter also highlights the stakeholders of the model, components of the system, and the algorithmic approach being applied to impart intelligence to the model.

4.1 Introduction:

The VCLE model is a web enabled application that seek to simulate the methods and pedagogy of natural teaching learning cycle. Implementation of this model incorporates computational mechanism and knowledge representation in the domain of education.

Broadly this VCLE helps learner and tutor to improve the competency level of an individual and learning outcome of a group. The application tracks learner’s activities, tailoring feedback and reasoning along the journey. By continuously collecting information of individual learner’s performance, the agent can make inference about the learning pedagogy, strength, weakness and can suggest additional tasks and produces the personalize content to the learner.

In particular, VCLE attempt to adapt to the need of learners and so it provides more learner centric approach in the context of teaching-learning life cycle.

Two stakeholders are identified in the VCLE (a) Learner (b) Tutor. The agent applies two different approaches with these stakeholders to infer new knowledge from the available knowledge as well the knowledge being captured. The correlation between the tutors, learners, learner behaviour, content pool and question pool will greatly influence the standard of the
learning system. This is being applied by acquiring the knowledge of the domain, knowledge of the learner, pedagogical knowledge and the methodology to apply and correlated these different types knowledge to serve the needs of learner. The teaching learner agent mostly works on the following criteria:

(1) Learner background,
(2) Learner activity log,
(3) Learner preference(s),
(4) Learner learning pedagogy,
(5) Tutor strategy and
(6) Tutor administration.

Learner along with different parameter attached with assigned weights, calculates and identifies the competency skill of his/her in the system. The approach uses the forward chaining approach which is popularly known as deductive reasoning or deductive inference rule. To have an optimize outcome every parameter is being assigned equal probabilistic value such that combination of all the parameters help in efficient identification of the optimized competency level of the learner.

Tutor, when generates the evaluation parameter, takes into consideration the overall competency skill of the learners in the group. The calibration process that then tries to match and calibre the actual outcome against the expected outcome which helps in deciding the overall working of an agent and helps defining new learning rules. This backward chaining inference which is commonly known as inductive inference rule or inductive reasoning helps agent and in general the tutor to generate an appropriate evaluation pattern that effectively evaluates the learner in the system.
The expectation from the VCLE model is to provide basic functionalities like:

- Build an erudite model of cognitive process,
- Adapt processes successively,
- Control learning simulation, and
- Control evaluation simulation.

To provide these above mentioned functionalities following are the major models which to be looked upon:

- **Domain module:**
  
  This module contains the set of skills, knowledge and approaches towards the content being offered. This usually contains the knowledge of the expert with the activities being performed by the learner in the domain. This model is responsible in connecting content, general psychological states of the learner in such a way that it helps in understanding the possible pedagogy if the learner in the environment.

- **Learner module:**
  
  This module consists of the mental, emotional, motivational and other psychological states that are inferred from the behavior of the learner during the course of learning action. For identifying the pedagogy and to infer the state summary information, this model helps in providing the inputs to it. Learner tracing is the major activity being carried out that tracks the learner’s progress from time to time and builds a strong contour of competency skills relative to the domain model. This model is being considered as a subset of the domain model.
• Tutor module:

This model interprets the learner’s contributions through various input media and generates an output. In addition to the conventional human-computer interface, the system had the interface through tutor feeds the relevant resource pool as well as question pool in the initial phase and then it is the system that reads and observes the activities of the learner and accordingly the bifurcation of the content as well as the questions takes place. The system helps this model user to read the outcomes being generated from the previous two models (domain model and learner model) and accordingly helps in generating the evaluation parameters by reading and calibrating the learner competency skills and the evaluation pattern.

• Tutor-Learner interface module:

An interactive background interface helps the stakeholders of the system to use and generate the appropriate content. The content is depending upon the need and choice of the tutor or learner. It continuously interprets the learner's contribution through various mode of input and produces the output accordingly.

This chapter focuses specifically on the leaner and tutor models. In order to generate the clear perspective on models, it essential to show the interconnection of domain, and interface model as models cannot function in isolation. The structure of the domain model necessary is being considered as the outer layer context of the learner model.
4.2 Learner module components:

When the assessment of the model is done, it is more suitable to stress the reliability of representation. The outcome of the model is expected to generate the result which tries to observe different parameters of the learner and based on the input the model generates the output. Depending on the usefulness of the working model, several criteria are being considered that evaluates the working of the model. The criteria which are considered are:

(1) Appropriateness to data:

This is simply a validity criterion that refers to how well the learner model can be used to simulate the quantitative and/or qualitative pattern of learning in the real environment.

(2) Comfort of understanding:

The main objective if the VCLE design is that learner modeling methods need to be wide-ranging to the tutor as well as learners. So learner modeling methods that require simulation strengthening may have partial applicability unless the difficulties are being easily being inculcated.

(3) Elasticity and content creation:

Many of the learner models reviewed have one or two contexts being focused and implemented, many have limited expansibility. Research often mentions the high cost in creating new content and such costs also affects to the overall design of the model. Model should be constructive in terms of shuffling content, ranking the content, managing the discriminate index to the content being produced to the learner.
(4) Time measure:

This refers to the overall access of the learner model by an individual. A model must be capable enough to measure the overall time factor of the learner’s use of the system. It also should capture the individual activity to identify the learner’s effectiveness, sincerity and concern towards the learning. This helps in inferring the effectiveness of the content towards the improvement in the learner skill in the system environment. The individual time factor is being measured in identifying the activeness of the learner while evaluating the learning pattern. The time to answer the question being taken into consideration and accordingly the weightage as well as the correctness is considered.

(5) Learning increases in workout:

Increasing the learning is directly being a cause of pedagogical inference being offered by the learner module. Learning purely depends upon the learner’s pedagogy, learner-learner interaction as well as tutor-learner interaction with proper feedback mechanism.

To make use of these criteria, the learner module uses manageable number of categories with appropriate algorithms attached that helps inferring the learner behaviour to offer more learn-centric content.

Based on the proposed model architecture, we observe the learner module components in the model which is built for different purposed, such as recognizing the need of the learner, evaluating problem solving abilities, evaluating the understanding level of the learner by testing and calibrating the content produced versus learning.

Content in the model is categorized into different categories: easy, moderate and difficult. The questions in the model also are categorized into two major categories: type and difficulty level. The type is again
categorized into: understanding, analysis and remembering. The difficulty level is categorized into: easy, normal and difficult. Both, the content as well questions in the pool are calibrated as and when the use of it is over.

The major processes involved in the learner model that makes the learner model more user friendly, as well as personalized are:

(1) Initial competency skill check:

To handle this complex problem, a modeling and methodology tool, Multiple Criteria Decision Making (MCDM) [35] is used. To evaluate human and model human knowledge, fuzzy set approaches are suitable. Grey situation decision is a method to choose the decision with optimum effect from multiple decision and objectives, with the prerequisite that decision information should have grey elements. In the light of this development and to forecast the initial competency skill of the learner, Grey theory and Multi Objective Programming are used. This inspired us to use Multi-objective Grey Situation Decision-making theory (MGSD).

The MGSD uses three types of effect measures: upper, lower, central limit. The upper limit is used to find the maximum deviation data i.e. higher the better mechanism.

\[ r_{ij} = \frac{u_{ij}}{u_{max}} \]

Where \( u_{ij} \) is the actual effect measure for \( S_{ij} \), \( u_{max} \) is the maximum data in

\[ S_{ij}. \quad u_{ij} \leq u_{max}; r_{ij} \leq 1 \]

The lower limit is used to find the minimum deviation data i.e. lower the better mechanism.

\[ r_{ij} = \frac{u_{min}}{u_{ij}} \]
Where $u_{ij}$ is the actual effect measure for $S_{ij}$ and $u_{\min}$ is minimum data in $S_{ij}$.

\[ u_{ij} \geq u_{\min}; r_{ij} \geq 1. \]

The central effect measure takes the value near by the specific goal as consideration scope [33] and [34].

\[ r_{ij} = \frac{\min(u_{ij}, u_0)}{\max(u_{ij}, u_0)} \]

Where $u_{ij}$ is the actual effect measure for $S_{ij}$, $u_0$ is the reference point and $r \leq 1$.

For above mentioned equations, the value for $i, j$ remains 1 as this calculation is performed at the time of registration of individual learner.

This decision making using MGSD in VCLE uses following elements with their effect manner and their weight:

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Effect manner</th>
<th>Minimum (Weight)</th>
<th>Maximum (Weight)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Lower</td>
<td>16</td>
<td>23</td>
</tr>
<tr>
<td>Demographic location</td>
<td>Lower</td>
<td>1 (Urban)</td>
<td>3 (Rural)</td>
</tr>
<tr>
<td>Qualification</td>
<td>Upper</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Father Qualification</td>
<td>Upper</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Mother Qualification</td>
<td>Upper</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Basic Skills</td>
<td>Upper</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Experience</td>
<td>Upper</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Employment Type</td>
<td>Upper</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>
With above mentioned criteria, the comprehensive effect measure is being calculated that always generates a value which ranges between 0 and 1. The comprehensive effect measure value range with its outcomes:

<table>
<thead>
<tr>
<th>Range</th>
<th>Learning capability</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 0.28</td>
<td>Poor</td>
</tr>
<tr>
<td>0.26 – 0.55</td>
<td>Average</td>
</tr>
<tr>
<td>0.51 – 0.80</td>
<td>Good</td>
</tr>
<tr>
<td>0.76 – 1.0</td>
<td>Excellent</td>
</tr>
</tbody>
</table>

The fuzzy membership functions for the above situation is demonstrated in the following figure 4.1

**Figure 4.1 Fuzzy membership function**

The value of effect measure gives the effectiveness of the learner in the environment. More it nearer to 1 betters the competency skill, otherwise if it is nearer to 0 poor the competency skill [22].
(2) Continuous measurement based on time scale parameters:

Various parameters are considered for the learner that continuously measures the learner activities based on the time span scale. The time span is considered as a major factor for the following activities as it decides the activeness, involvement, sincerity, and also allows the agent to bifurcate the content as well as question based on access time parameter for various aspects of the learner.

(a) Overall system access time of the learner;

(b) Overall material access time of the learner;

(c) Time taken to answer the question (online evaluation to test basic competency using Multiple Choice Questions);

(d) Effect of correct attempt of a question on the question parameters;

(e) Frequency and time span for the access to the material, discussion forum, blog, and with evaluation parameter; and

(f) Time taken to give rating to the content or any material being produced.

Above mentioned parameters (a), (b), and (e) are assigned the fixed weights and have fixed role in the working environment as there is no evaluation takes place. These parameters help in measuring interest, choice, and pedagogy of the learner.

Parameter (c) and (d) identifies the direct competency skills by measuring the answer time against the type of the question.

The questions are mainly categorized into three major categories:

(i) Remembering (ii) Analysis and (iii) Understanding; each category is having three levels as (i) Easy (ii) Normal and (iii) Difficult
Based on the type and level of the question with their time to answer, the weightage of the question is determined. This helps in evaluating the learning capability of the learner.

The parameter (f) gives control over rating being given by the learner to the content or any other material/content being produced by the system. The parameter identifies the fake or irrelevant ratings by applying the regression analysis on the current as well as the past ratings given by the learner and also takes into consideration the time taken by the learner to respond. This regression analysis is used to predict and forecast the relevance of the content and question in the environment. It also helps in prioritizing the content as well as question and helps in deciding the frequency of it in the system environment.

(3) Measurement of learner in different preferences and usage of preferences

The parameters which are being taken into account to track the learner and learner behavior in the system are:

(a) Frequency of editing blog:

As we know blog tries to replicate the implicit knowledge to explicit which helps the other group members to make use of it to have a better and optimum group result.

(b) Frequency of reading blogs (reading time is taken into account to have an exact idea whether the content is read or not)

Normally the blog contains the implicit knowledge of oneself. Reading helps understanding the implicit thoughts of creators and that lead towards more bonding within the group and the outcome can be more productive.
(c) Frequency of accessing the discussion forum (access time is taken into account to have an exact idea whether the forum is utilized or not)

(d) Number of questions posed in the discussion forum

(e) Number of answers given in the discussion forum

(f) Number of questions and answers liked or ranked by other learners

These above mentioned criteria are used to measure the learner’s active involvement in the system. This also helps VCLE in identifying the learner’s competency skill as well as acceptance in the environment.

Every criterion has the weight assigned and has equal weightage in the system to have an effective measure of the learner in the working environment.

4.3 Tutor module components:

Tutor model allows tutor to perform input necessary content that feeds the domain pool. Domain pool consists of content for the learner, different courses, blueprint related to the courses, question pool and other necessary details.

The main activity that gives a great contribution to the tutor is generation of the evaluation parameters for them. There are two major types of evaluation parameters: (i) Multiple Choice Questions (MCQ) (ii) Full length paper.
Both types of parameters offered are generated by the system and to do that, system uses different parameters based on the competency level of the learners in the system.

(i) Multiple Choice Question (MCQ) paper generation:

Tutor needs to configure the date, time, number of questions to be asked with necessary learner related parameters like course, and class.

The questions are divided into three types (a) Understanding (b) Analysis (c) Remembering. Further, each category of questions are divided into three levels (a) Easy (b) Normal (c) Difficult

The process of conflict management is implemented to limit the negative aspect of conflict and that increases the positive aspect of the conflict. The aim of the conflict handling here is to increase the learning and group outcomes, including the effectiveness and performance of the group. To apply this, weightage of each chapter are mapped with the types of the questions and category of the questions.

Tutor must configure the test, in which tutor decides number of questions, date, time and class (cluster). Each paper generation is on the random basis. As per the understanding level identified by the agent, through the conflict handling matrix, the questions are being fetched from the question pool.

In case of abnormal result, calibration is done by the agent that re-assigned the weightage to the questions and may change the category and/or the type of the question. The calibration process is carried out with the time to answer and question parameters
(category and type). This may change the learner behavior and/or the question parameters.

(ii) Full length paper generation

Tutor can generate the full length paper for the selected subject. This automated paper generation takes care of the overall understanding of the target group. Following criteria are taken into consideration for generating the balanced paper:

(a) Existing level of understanding: *(Effect manner: Upper)*

The value here ranges from 0 to 1. This value continuously updated by the service tier as discussed in the previous chapter.

(b) Score in full length evaluation: *(Effect manner: Upper)*

Three major considerations are highlighted with range 0-20:
1. Score in analysis type of questions
2. Score in understanding type of questions
3. Score in remembering type of questions

(c) Score in subjective Multiple Choice Questions evaluation: *(Effect manner: Upper)*

Average score being taken into consideration with the range taken is 0-20.

(d) Score in soft skilled Multiple Choice Questions evaluation: *(Effect manner: Upper)*

Average score being taken into consideration with the range taken is 0-20.

To handle this complex problem, a modelling and methodology tool, Multiple Criteria Decision Making (MCDM) is used. Grey situation decision is a method to choose the decision with optimum effect from multiple decision and objectives, with the prerequisite that decision
information should have grey elements. As the uncertainty exists in the group of data, the grey element is used as the situations described are grey, hazy of fuzzy. In the light of this development and to forecast the initial competency skill of the learner, Grey theory and Multi Objective Programming are used. This inspired us to use Multi-objective Grey Situation Decision-making theory (MGSD)[35].

As discussed earlier, the MGSD uses three types of effect measures: upper, lower, central limit. The upper limit is used to find the maximum deviation data i.e. higher the better mechanism.

$$r_{ij} = \frac{u_{ij}}{u_{max}}$$

Where \(u_{ij}\) is the actual effect measure for \(S_{ij}\), \(u_{max}\) is the maximum data in \(S_{ij}\). \(u_{ij} \leq u_{max} ; r_{ij} \leq 1\)

The lower limit is used to find the minimum deviation data i.e. lower the better mechanism.

$$r_{ij} = \frac{u_{min}}{u_{ij}}$$

Where \(u_{ij}\) is the actual effect measure for \(S_{ij}\) and \(u_{min}\) is minimum data in \(S_{ij}\). \(u_{ij} \geq u_{min} ; r_{ij} \geq 1\)

The central effect measure takes the value near by the specific goal as consideration scope [33] and [34].

$$r_{ij} = \frac{\min(u_{ij}, u_0)}{\max(u_{ij}, u_0)}$$

Where \(u_{ij}\) is the actual effect measure for \(S_{ij}\), \(u_0\) is the reference point and \(r \leq 1\).
The effect measure of $k^{th}$ objective is remarked by $r^{(k)}_{ij}$. The corresponding decision unit given by $S_{ij}$. The decision column is $\delta^{(k)}_i$, the decision row $\delta^{(k)}_j$ and the decision matrix $D^{(k)}$ [34] [36].

\[
\begin{bmatrix}
    r^{(1)}_{11} & r^{(1)}_{12} & \cdots & r^{(1)}_{1m} \\
    S_{11} & S_{12} & \cdots & S_{1m} \\
    r^{(2)}_{21} & r^{(2)}_{22} & \cdots & r^{(2)}_{2m} \\
    S_{21} & S_{22} & \cdots & S_{2m} \\
    \vdots & \vdots & \ddots & \vdots \\
    \vdots & \vdots & \ddots & \vdots \\
    r^{(n)}_{n1} & r^{(n)}_{n2} & \cdots & r^{(n)}_{nm} \\
    S_{n1} & S_{n2} & \cdots & S_{nm}
\end{bmatrix}
\]

The comprehensive matrix is created for all the students present in the system based on the effect measure for the criteria determined. This comprehensive matrix then is evaluated to calculate new effect measure which is considered as the cluster effective measure. The multi-objective situation decision value can be calculated by the following equation.

\[r^{(0)}_{ij} = \frac{1}{N} \sum_{k=1}^{n} r^{(k)}_{ij}\]

The values of $i$, $j$ are taken as $n$ where $n$ is number of students in the cluster.
Table: 4.3 Elements of VCLE in MGSD (Full length paper)

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Effect manner</th>
<th>Minimum (Weight)</th>
<th>Maximum (Weight)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Existing level of understanding scale</td>
<td>Upper</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Score for the analysis type questions</td>
<td>Upper</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Score for the understanding type questions</td>
<td>Upper</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Score for the remembering type questions</td>
<td>Upper</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Score for the aptitude evaluation (MCQ)</td>
<td>Upper</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Score for the subjective evaluation (MCQ)</td>
<td>Upper</td>
<td>0</td>
<td>20</td>
</tr>
</tbody>
</table>

To calculate quantitative and qualitative assessment, we have registered three students with their details and asked to have hands on to the system. At the end of the prescribed time given to them, the sample calculation performed on the above mentioned criteria for them. The calculation for the same is shown below with their actual data:
Table: 4.4 Sample elements of VCLE in MGSD (Full length paper)

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Sample-1</th>
<th>Sample-2</th>
<th>Sample-3</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Existing level of understanding scale</td>
<td>0.73</td>
<td>0.45</td>
<td>0.33</td>
<td>1</td>
</tr>
<tr>
<td>Score for the analysis type questions</td>
<td>12</td>
<td>10</td>
<td>6</td>
<td>20</td>
</tr>
<tr>
<td>Score for the understanding type questions</td>
<td>10</td>
<td>8</td>
<td>6</td>
<td>20</td>
</tr>
<tr>
<td>Score for the remembering type questions</td>
<td>15</td>
<td>12</td>
<td>7</td>
<td>20</td>
</tr>
<tr>
<td>Score for the aptitude evaluation (MCQ)</td>
<td>13</td>
<td>8</td>
<td>7</td>
<td>20</td>
</tr>
<tr>
<td>Score for the subjective evaluation (MCQ)</td>
<td>11</td>
<td>10</td>
<td>7</td>
<td>20</td>
</tr>
</tbody>
</table>

The assessment of quantitative and quantitative assessment for three sample dataset calculations is shown as under:

\[
r_{ij}^{(1)} = \begin{bmatrix} 0.73 & 0.45 & 0.33 \end{bmatrix},
\]

\[
r_{ij}^{(2)} = \begin{bmatrix} 12 & 10 & 6 \end{bmatrix},
\]

\[
r_{ij}^{(3)} = \begin{bmatrix} 10 & 8 & 6 \end{bmatrix},
\]

\[
r_{ij}^{(4)} = \begin{bmatrix} 15 & 12 & 7 \end{bmatrix},
\]

\[
r_{ij}^{(5)} = \begin{bmatrix} 13 & 8 & 7 \end{bmatrix},
\]

\[
r_{ij}^{(6)} = \begin{bmatrix} 11 & 10 & 7 \end{bmatrix}.
\]
Calculating the comprehensive measure:

\[ r_{ij}^{(\Sigma)} = [r_{ij1}^{(\Sigma)}, r_{ij2}^{(\Sigma)}, r_{ij3}^{(\Sigma)}] = [0.638, 0.475, 0.33] \]

Here the comprehensive measures for three sample dataset are 0.638, 0.475, and 0.33 respectively. The aggregate for these three sample data is \textbf{0.481} that falls in the criteria-III as shown in the below table 4.5. With above mentioned criteria, with comprehensive measures effect, the criteria are decided for the full length paper generation. As shown in the decision table below in table 4.5, the lists of condition with their respective values are mapped with the list of conclusions. As the value is nearer to 1, the learning effectiveness of group of learners seems to be better and as the value nearer to 0, the learning effectiveness of the group learners seems to be lower.

<table>
<thead>
<tr>
<th>Range</th>
<th>Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 0.35</td>
<td>I</td>
</tr>
<tr>
<td>0.30 – 0.70</td>
<td>II</td>
</tr>
<tr>
<td>0.65 – 1.0</td>
<td>III</td>
</tr>
</tbody>
</table>

The fuzzy membership functions for the above situation is demonstrated in the following figure 4.2.
The criteria here are basically used to give priority for the types of question to be fetched as well as complexity level of the question. Here the question extraction is based on the following priority:

(a) Weightage of the unit/chapter in the syllabus;
(b) Number of times the question being used/fetched previously;
(c) Discriminate index of the question;
(d) Type of question; and
(e) Complexity level of the question.
### Table: 4.6 Criteria for fetching question as per effect measure

<table>
<thead>
<tr>
<th>Type</th>
<th>Level</th>
<th>Difficult</th>
<th>Moderate</th>
<th>Easy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Effect measure:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Criteria – I</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Analysis</td>
<td>8.33%</td>
<td>8.33%</td>
<td>16.66%</td>
<td></td>
</tr>
<tr>
<td>Understanding</td>
<td>3.37%</td>
<td>13.33%</td>
<td>16.66%</td>
<td></td>
</tr>
<tr>
<td>Remembering</td>
<td>8.33%</td>
<td>8.33%</td>
<td>16.66%</td>
<td></td>
</tr>
<tr>
<td><strong>Effect measure:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Criteria-II</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Analysis</td>
<td>8.33%</td>
<td>16.66%</td>
<td>8.33%</td>
<td></td>
</tr>
<tr>
<td>Understanding</td>
<td>10%</td>
<td>10%</td>
<td>13.36%</td>
<td></td>
</tr>
<tr>
<td>Remembering</td>
<td>16.66%</td>
<td>8.33%</td>
<td>8.33%</td>
<td></td>
</tr>
<tr>
<td><strong>Effect measure:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Criteria-III</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Analysis</td>
<td>16.66%</td>
<td>8.33%</td>
<td>8.33%</td>
<td></td>
</tr>
<tr>
<td>Understanding</td>
<td>11.66%</td>
<td>18.33%</td>
<td>3.37%</td>
<td></td>
</tr>
<tr>
<td>Remembering</td>
<td>16.66%</td>
<td>8.33%</td>
<td>8.33%</td>
<td></td>
</tr>
</tbody>
</table>

The details for the decision table shown in the table 4.5 with their conclusions are shown in the table 4.6 based on the criteria as per the aggregate effect measure range with their difficulty level and type of question. The conclusions are taken by consulting the various evaluating experts from various academic institutions. As we know that intelligence cannot be measured in any physical units; we try to measure it by means of various parameters. One of the parameter which helps us in identifying it is by using intelligent tests. To have proper justification to the learner’s learning capabilities, the tests are configured accordingly. The evaluation tests are generated by taking into consideration different parameters like type and level of the questions. The outcome of the evaluation parameter is used again by the agent to generate the next evaluation pattern.