Design and Implementation of a SMART Learning Environment for the Upskilling of ICT professionals in Mauritius

Abstract:

Teaching and Learning confined to within the four walls of a classroom or even online Learning through Massive Online Courses (MOOCs) and other Learning Content Management Systems (LCMS) are no longer seen as the optimal approach for competency and skills development, especially for working professionals. Each of these busy learners have their own training needs and prior knowledge. Adopting the *one-size-fits-all* teaching approach is definitely not effective, motivating and encouraging. For some learners, the content might be too easy and for others, it might be too difficult. This is why this research presents the use of SMART Learning Environment that makes use of *Intelligent Techniques* to personalise the learning materials for each learner. It has been observed that on one hand the country is not able to provide the required number of IT professionals with the desired skills and on the other hand, the number of unemployed graduates in areas other than IT is increasing. This mismatch in skills is becoming a pressing issue and is having a direct impact on the ICT Sector, which is one of the pillars of the Mauritian Economy. This research, therefore, besides proposing a novel approach to learning, also attempts to address an issue of national importance. The major findings of this research were that personalisation of learning materials through the use of a SMART Learning Environment can be used to address the training needs of Cybersecurity professionals in Mauritius, by offering a more effective, engaging and motivating learning experience.

Keywords: SMART Learning Environments, Cybersecurity, Design Science Research Methodology (DSRM), Artificial Neural Networks (ANN), Backpropagation (BP) Algorithm.

I. INTRODUCTION

The Republic of Mauritius is a small Island in the Indian Ocean, situated around 2000 Km off the East of the African Continent and has a total population of around 1.3 million inhabitants. The ICT sector has been able to position itself as one of the major pillars of the Mauritian Economy. A number of ICT companies engage in BPO activities and software development. As per ITU's ICT Development Index 2017, Mauritius ranks itself 72nd in the world and 1st in Africa with an ICT Development Index (IDI) of 5.88 (ITU, 2017). The ICT/BPO sector presents tremendous opportunities for Mauritius in its endeavour to become a high-income economy. The Economic Vision 2030 of the Government of Mauritius aims at transforming the ICT industry into a key sector by fostering innovation & creativity and developing a sustainable & high value added-economy that will provide more accessible and higher-value opportunities for Mauritian citizens (Economic Development Board, 2018).

The Information and Communication Technology/Business Process Outsourcing (ICT/BPO) sector remains a buoyant and growing one for economic growth and employment in Mauritius. Given the dynamic and fast-paced nature of the sector, the skills of the workforce also need to concurrently keep up with the pace. Human talent with the right skill sets will continue to be the key, among other factors, for the building of a vibrant and diversified ICT/BPO sector in Mauritius (HRDC, 2017). The Human Resource Development Council (HRDC) of Mauritius has been vested with the responsibility to look after and promote the development of the labour force in Mauritius in line with the requirements of a fast growing economy (HRDC, 2017). The ICT/BPO industry has maintained its strength towards high-end activities. Total employment in the ICT-BPO industry has crossed the 20,000 threshold and stood at 23,000 in 2016 as shown in figure 1 below.

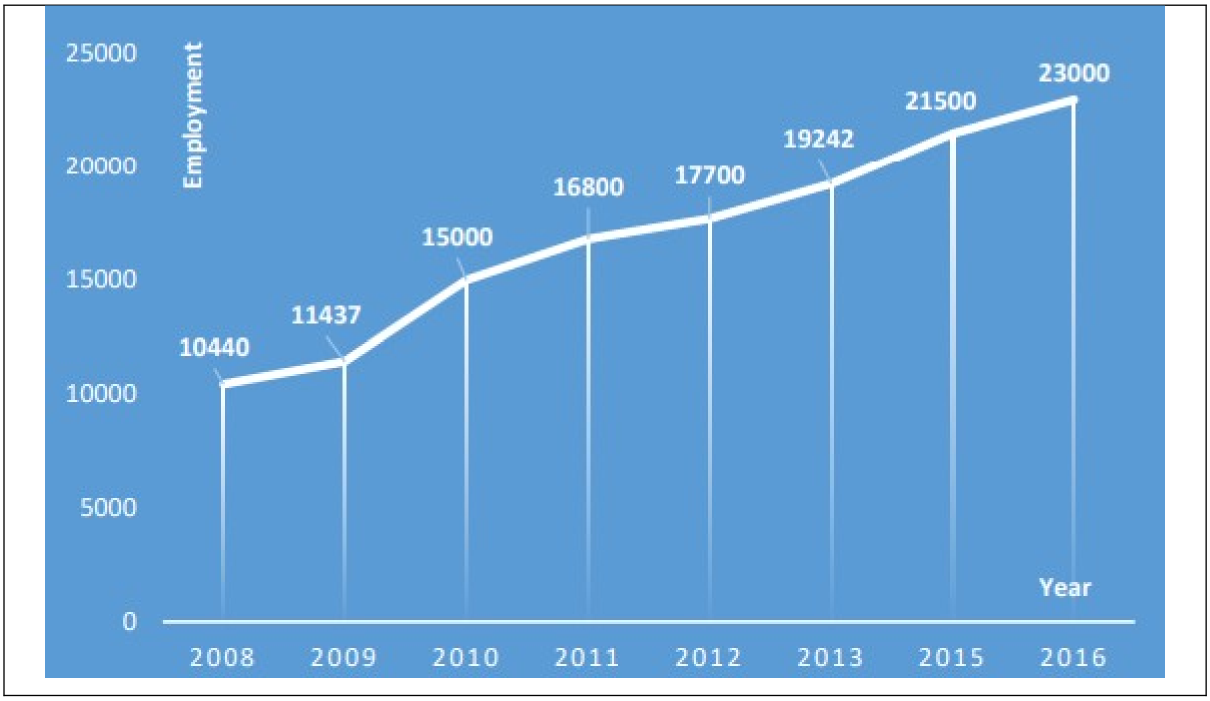

Figure 1: Employment in the ICT Sector of Mauritius (2008-2016)

(Source: Adapted from Industry Review 2016 ICT/BPO, BOI 2016)

Mauritius has to remain competitive in the IT industry by ensuring that the ICT labour force is kept up-to-date with the latest technologies. Employer demand for a skilled workforce in the ICT Sector will continue in the global competitive marketplace and it is important that education and training supply produces people in the right number with relevant skills and qualifications to meet this demand (HRDC, 2017).

Statement of the problem

The current problem with the ICT/BPO sector of Mauritius is the lack of trained professionals with the proper skills to respond to the needs of this bustling sector. This has often been described as 'Skills Mismatch' and is very detrimental for the ICT sector whereby a number of businesses prefer to move their businesses to other locations where the people are skilled and properly trained. This has been described in a report carried out by the Human Resource Development Council (HRDC) of Mauritius where it is mentioned that "skills mismatches in the ICT labour pool are a particular concern given the importance of this sector in the Government's growth strategy" and further elaborates by mentioning that "…the persistent and growing mismatch between workers' skills and market needs that plagues the economy generally is also apparent for the ICT labour pool" (HRDC, 2017). The HRDC has also carried out a survey where it was found that the enterprises operating in the ICT sector are not satisfied with the level of preparedness of the potential recruits, whether 'freshers' or those having work experience.

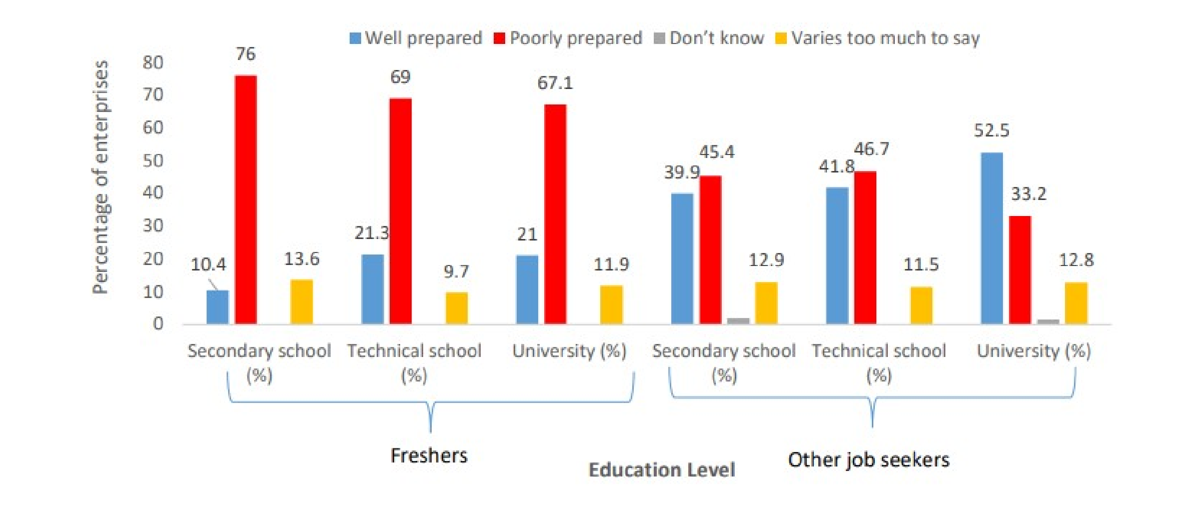

Figure 2: Perception of employers w.r.t preparedness of last 2 years recruits

(Source: HRDC – skills study report for the ICT Sector, 2017)

Even the World Bank Group has recognized this mismatch by stating that "employer surveys suggest that the ICT sector is facing a labour shortage that is expected to continue or worsen over the next five years, and for which the key factors are a lack of sufficient work experience and low qualifications in both technical and soft skills" (HRDC, 2017). The Ministry of Technology, Communication and Innovation (MTCI) of Mauritius has reaffirmed the above and is even considering this as a major problem by stating that "like many countries, Mauritius is suffering from a workforce mismatch phenomenon in ICT where the requirements of the industry concerning labour are not being met. At the Ministry, this is a priority and we are actively working on solutions to this major problem," and further argues that "the Mauritian Government is fully conscious that the lack of ICT Professionals in the job market is a serious impediment to the development and expansion of the ICT/BPO sector." (MCTI, 2018)

Continuous learning and constant up skilling of the ICT labour force is a must for this crucial sector of the Mauritian economy. Face-to-face learning, e-learning, and other traditional methods are necessary, but do not appear to be sufficient to address the skills gap in the case where training needs and learning styles of everyone is different. A **'one-size-fits-all approach'** is not beneficial and does not encourage learning effectiveness and efficiency as well. Some learners might be learning concepts that are too easy for them whereas others might be learning concepts that are far too complex for them to start. Some recruits in this sector already have some experience and require some minor up skilling whereas some recruits are completely new in this field, doing a conversion programme and would require a complete coverage of the concepts, starting from the very basics. This leads to a situation where the learner ends up being frustrated and does not eventually meet the learning objectives or pathways initially set. This situation is depicted in the figure below, where it should be understood that every learner has their own specificities and abilities.

This phenomenon is even more clearly visible with the concept of Massive Open Online Courses (MOOCs) e.g. Coursera or edX where the dropout rate is high and very often the learners are 'disconnected'. Top Universities in the world such as Harvard and MIT joined the MOOC bandwagon to propagate knowledge. Despite the millions of subscription for the Harvard MOOC, only 10% of students were completing the courses. Feedback from students show that the content of the courses did not suit their current knowledge level and that the way the course content was presented decelerated their learning rate. Onah et al (2014) argues that although thousands of participants enrol on MOOC courses, the completion rate of most of these courses is below 13%. Hence the concept of “one size fits all” was questioned by researchers who brought forward the concept of learning styles and prior knowledge relationship to learning process.

II. LITERATURE REVIEW

Career Paths in the area of Cybersecurity in Mauritius

With the world becoming more and more connected and with technology evolving at such a pace, the area of Cybersecurity currently faces many challenges and is highly dynamic one. Very often, the skills of hackers and other cyber criminals can outpace that of the professionals in the organisation. Hence the need for constant up-skilling of these professionals. The Government of Mauritius has identified Cybersecurity as one of the areas where professionals would be in high demand in the years to come (HRDC2017). For the purpose of this research, only one area, namely that of Cybersecurity has been considered. Information about this area was collected, compiled, summarised and then analysed. This shows that the main job profiles of Cybersecurity professionals in Mauritius include that of

Information Security Officer, Information Security Analyst, Information Security Consultant and Chief Information Security Officer.

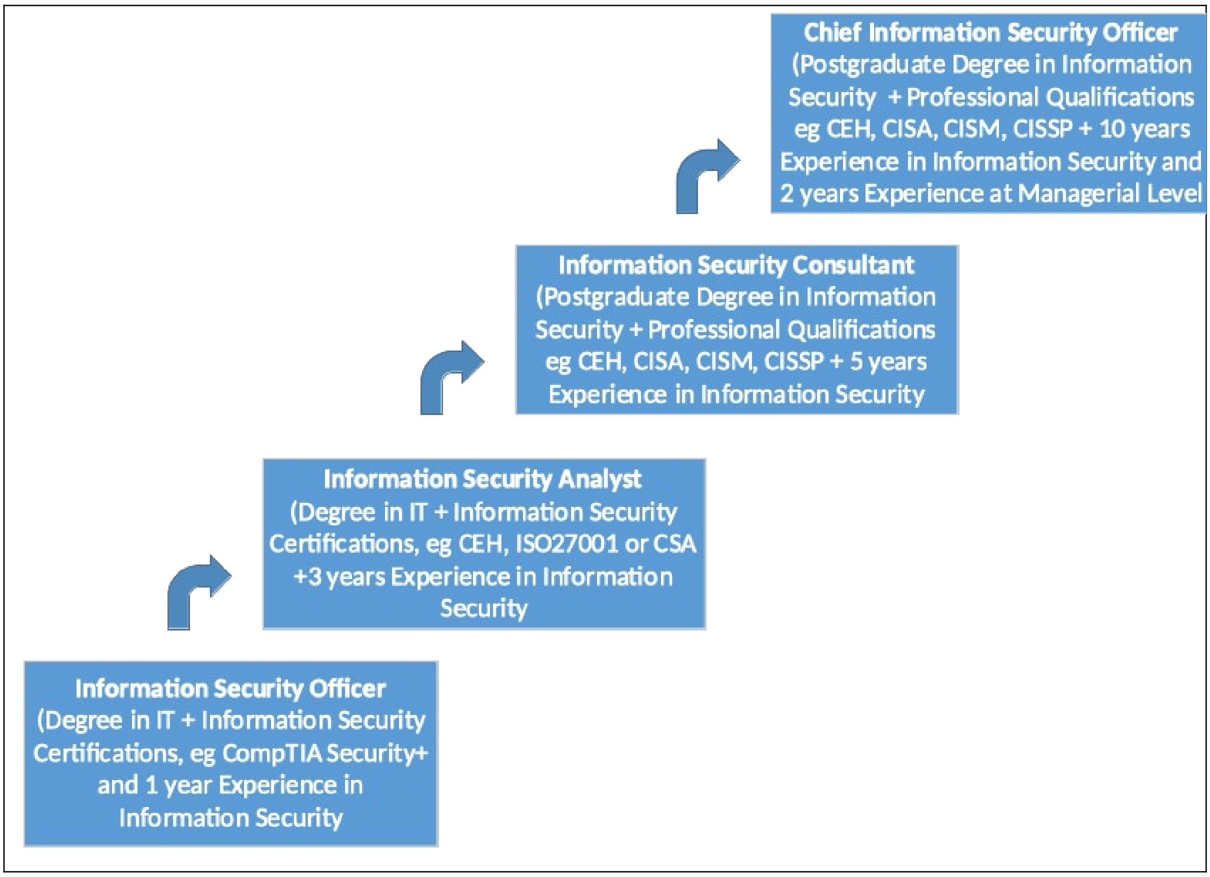

Figure 3: Career Path in the field of Cybersecurity in Mauritius (Adapted from HRDC, 2017)

Related Works on SMART Learning Environments

Developing SMART Learning Environments is at this stage still predominantly being done in Research Institutions and rarely for commercialization purposes (Yau and Joy, 2017). The learner is always considered to be as the focal point of the SMART learning environments and the rationale is to be able to provide self-motivated, self-learning and personalized services whereby the learners can attend courses at their own pace and are able to access the personalized learning content according to their personal circumstances (Kim et al. 2012). Koper (2014) suggests that SMART learning environments can be seen as physical environments that are enriched with context-aware, digital and adaptive devices, to promote faster and better learning. Spector (2014) describes a SMART Learning as one that is engaging, efficient and effective. Hwang (2014) suggests that an interesting feature of a SMART learning environment may include context-aware services that are able to offer instant and adaptive support to the learners. The necessary learning guidance is here seen as a very important component of the SMART Learning Environment. The section that follows describes some of the past attempts to implement SMART Learning Environments. The inherent limitations and the challenges encountered are also critically analysed.

A. Two-Source Adaptive Learning (TSAL) (Tseng et al, 2008)

Tseng et al (2008) proposed an Intelligent Tutoring Environment having personalisation carried out in two phases as described in its two-source learning (TSAL) component. Firstly, it monitors the student's learning styles and secondly the student's learning behaviours. This differs from previous Adaptive Learning Systems which mostly used only one source of data to provide personalisation. The different learning styles and learning behaviours used in the research of Tseng et al. (2008), are summarised in Figure 4. TSAL allowed instructors to create adaptive learning materials for science courses. The results of experiments carried out show that providing adaptive learning materials to the learners helped to enhance the learning efficacy and improve learning achievements (Tseng et al., 2008). The challenge, however, remained that multiple versions of the learning materials had to be created to suit the different categories of personalisation information obtained. A modular approach was adopted and the architecture of TSAL is shown in Figure 5.

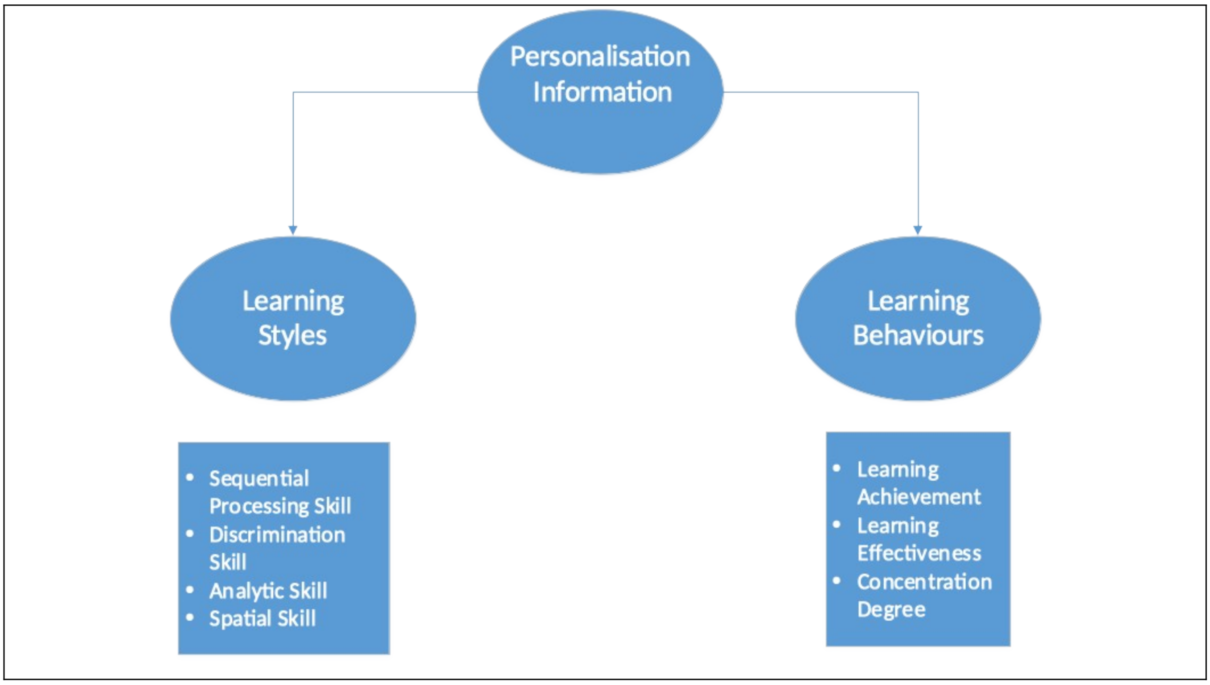

Figure 4: TSAL Features

(Source: Adapted from Tseng et al., 2008)

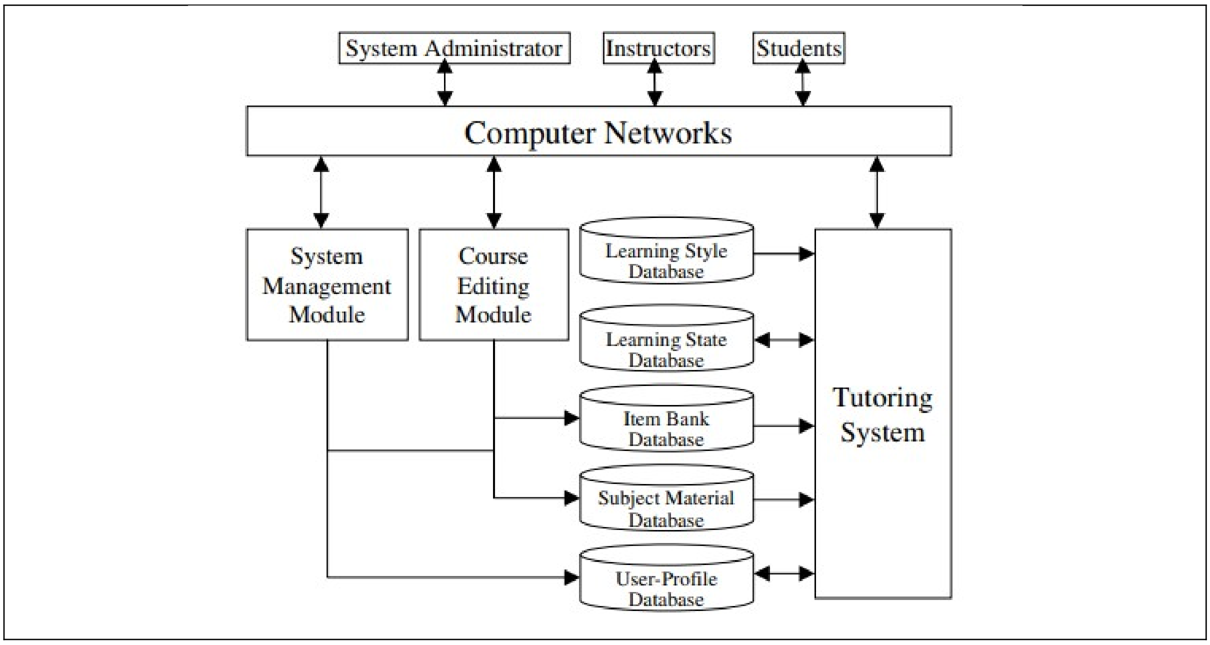

Figure 5: TSAL Architecture

(Source: Adapted from Tseng et al., 2008)

B. Intelligent learning system with personalized learning path guidance (Chen, 2008)

Chen (2008) proposed an intelligent learning environment which utilizes a genetic-based algorithm to construct the personalized learning path which focuses on the level of difficulty of the course and at the same time, the learning process.

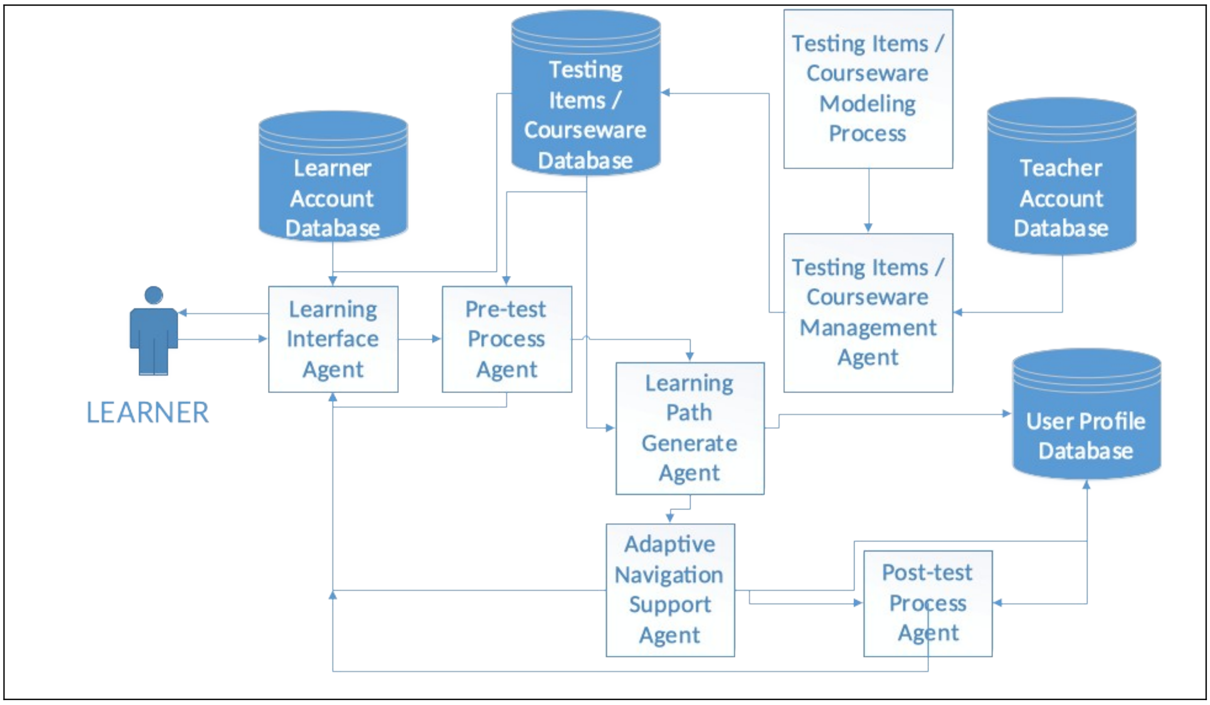

Figure 6: Architecture of Genetic-Based Personalised e-learning systems

(Source: Adapted from Chen, 2008)

Moreover, this algorithm generates suitable learning paths according to the incorrect answers of a student in a test. Based on the marks of test, the learning system can conduct personalized syllabus sequencing through simultaneously considering the difficulty level of the course material and the steadiness of learning paths to support web-based learning. An architecture of the system is shown in Figure 6 above. The proposed system makes use of software agents.

C. The Adaptive Learning System based on Learning Style and Cognitive State (ALS-LSCS) (Cheng and Zhang, 2008)

Cheng and Zhang (2008), depicted an Adaptive Learning System based on Learning Style and Cognitive State. This adaptive learning system focuses on the traits of the learner's personality, like for instance the style of learning and allows teachers to monitor the learning phase of the students. The learning style is determined through the use of Felder-Silverman's categorisation, which includes the following learning style categories; (i) Sensing v/s Intuitive Learner (ii) Visual v/s Verbal Learner (iii) Active v/s Reflective (iv) Sequential v/s Global.

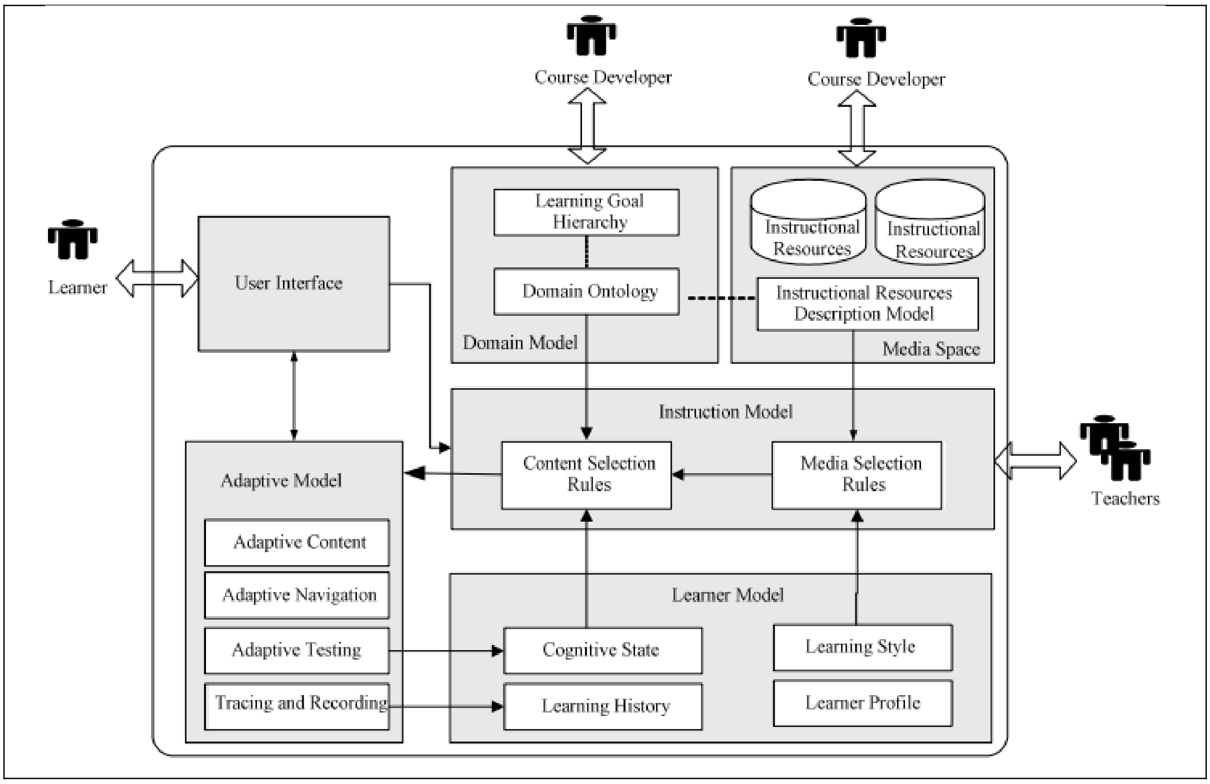

Figure 7: Architecture of ALS-LSCS

(Source: Adapted from Cheng and Zhang, 2008)

The cognitive state of the learner is captured through a multi-layered overlay model which takes as parameter several factors such as whether the learning material has been visited, whether the learner has finished the concept to be studied and whether the learner has taken part in adaptive tests. Both the learning style and cognitive state captured, thereafter enabled the construction of a learner model which is dynamically updated as and when learning takes place. Besides the learner model, the proposed system by Cheng and Zhang (2008) also consists of several other components such as Media Space, Domain Model, Instruction Model, Adaptive Model and the User Interface. The architecture of the system is based on 'A Reference Model to Support Adaptive Hypermedia Authoring Model' (AHAM model) and is shown in Figure 7 above. The proposed system encourages collaborative learning and 'learning by doing'. Another interesting aspect is the reuse of domain knowledge and the use of Domain Ontology which is built around knowledge components and their relationships.

D. Intelligent, Adaptive learning or Tutoring System (IATS) (Gowri et al., 2011)

In another study, Gowri et al. (2011) put forward an adaptive learning tutoring system that uses agent based technology. The proposed system model was developed using the Organization-based Multiagent Software Engineering (O-MaSE) development approach model which basically allows for custom agent-oriented processes to be designed by using a set of method fragments. To accomplish this, OMaSE was defined in respect to a Meta model, a set of guidelines and a set of method fragments. The OMaSE Meta model specified a set of analysis, design and implementation approaches whereby each set has a set of constraints. The adaptive behaviour of the system was achieved by grouping together all the similarities between the student such as their skills, learning styles and other criteria. Using this method, the course contents of each user were displayed to them according to their position in the clusters. The clustering was done using the Fuzzy C-Means algorithm which allows data to belong to multiple clusters. To represent the content of the course, a tree like structure was constructed and whereby the student was at certain level of the course, only the content which corresponded to that tree would be displayed to the student. The learning materials are further categorised as HTML, audio, video, flash or any other combination of these types.

E. Context-Aware and Adaptive Learning Schedule (CALS) (Yau and Joy, 2017)

Yau and Joy (2017), developed a tool for new computer science students at the university level to help them to learn the Java language effectively. The Context-Aware and Adaptive Learning Schedule (CALS) provided the students with appropriate learning content and available time and location based on the student's daily activities which they had to input. The tool consisted of five main components which are described below.

1. **Learner Schedule** for capturing and scheduling learner activities.
2. **Learner Profile** for storing learner preferences.
3. **Learning Object Repository** where the learning materials are stored.
4. **Learning Profile Adaptation** module which provides adaption in different forms. This is delivered by three sub-modules, namely Learning Priorities adaptation, Learning Style adaptation and Knowledge Level adaptation
5. **Context-Aware Adaptation** Module which provides adaptation based on the learner's location and time s/he is available.

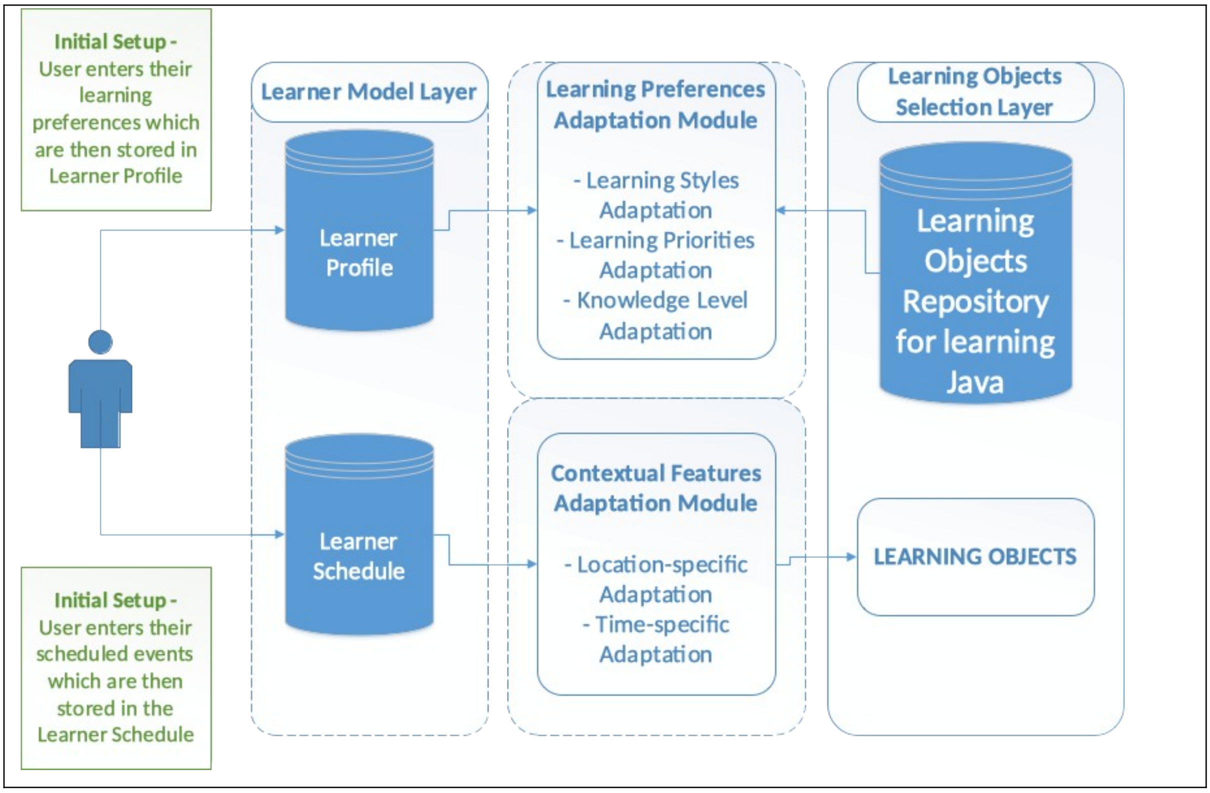

Figure 8: System Architecture of CALS

(Source: Adapted from Yau and Joy, 2017)

The architecture of the system is shown in Figure 8. The learner is responsible for inputting accurate information, in terms of scheduled events and learning preferences. The system also depicts some interesting features such as the ability to measure the noise level through a sensor and to be able to determine the level of concentration accordingly.

F. Data mining for adaptive learning in a TESL-based e-learning system (Wang and Liao, 2011),

Wang and Liao (2011) proposed using **A**daptive **L**earning for **T**eaching **E**nglish as a **S**econd **L**anguage (AL-TESL) in Chinese Taipei. A data mining technique, Artificial Neural Network (ANN) using the back-propagation (BP) algorithm was used to construct the system. ANN comprises of processing elements namely: nodes, neurons and the connections. The nodes are related layer-wise. The BP algorithm uses a neural network of layers, that is, the input layer, the hidden layer and the output layer. Three different levels of teaching for grammar, vocabulary and teaching was used in the research of Wang and Liao (2011). The learner is prompted to enter information about his personality type (introverted = 1, mildly introverted = 2, neutral = 3, mildly extroverted = 4, and extroverted = 5) and his/her level of anxiety (high anxiety = 1, moderate anxiety = 2, and low anxiety = 3) and gender. This research explains that student anxiety pertaining to the learning of a foreign language can be viewed from three perspectives; anxiety related to tests, communication apprehension and fear of negative feedback and evaluation. The system also highlights that different learning paths are able to accommodate the differences and needs of each learner. Learners using the AL-TESL were then evaluated and compared with other learners who were using the conventional way of teaching, which involved delivery in a regular online course. Results show that learners using the AL-TESL performed much better. The researchers also argue that one major obstacle for the development of such adaptive learning system is the high cost for developing learning materials in Taiwan. This research also presents adaptive learning as a means for promoting learners' motivation and puts forward that future works can include the use of such systems for the training of disadvantaged learners or for continuing education.

G. Alta Adaptive Learning Technology (Knewton, 2020)

Alta Adaptive Learning Technology (Knewton, 2020) is an example of a personalised learning environment that has been put on the market by Wiley. Alta is a web learning platform which focuses on adaptive sequences and provides a fully integrated courseware. It records feedback and responds to changes on a real time basis. Accordingly, the learning materials are built on thousands of observations consisting of theories, structure, and difficulty level. Alta analyses these learning materials and uses sophisticated algorithms to render the most appropriate content to the user. The developers of Alta also argue that data is collected from a network of students and this data is recorded, analysed and applied to optimize the next output for each student (Knewton, 2020). Alta promotes the concept of Adaptive Learning and argues that its main strengths lies in (1) Dynamic and ongoing remediation that encourages just-in-time learning (2) Instructor Control and (3) Student Responsiveness. The major weakness of using Alta as a case-study for this research is the complete opacity as far as its development architecture, technology and processes are concerned. This can be attributed to the fact that Alta is a commercial product.

Critical Discussion of Current Research in the area of SMART Learning

Having examined the design and conceptualisation of SMART Learning Environments, a critical discussion of the above is deemed to be important by the researcher. The interesting features and inherent limitations of each of these systems are discussed in the table below.

Table 1: Comparison of existing systems in the area of SMART Learning

(Source: Researcher's own construction)

System	Strengths	Weaknesses
1. Two-Source Adaptive Learning (TSAL) (Tseng et al, 2008)	• Two-source personalisation (learning behaviour and learning style) • Presentation of learning materials with different levels of difficulty • System developed using a modular approach	• The concept of using Learning Style is debatable and has been criticised by numerous researchers, including (Newton ,2015); Newton and Miah, 2017; Singal, 2015; Goldhill, 2016) • The major limitation lies in the need to develop six

		versions of learning materials to meet personalization requirements • With the advances in the field of Artificial Intelligence, a more effective means of providing personalised learning materials can be envisaged.
2. Intelligent learning system with personalized learning path guidance (Chen, 2008)	• Use of AI-related techniques, more specifically the use of Genetic Algorithms and Intelligent Software Agents which bring a new dimension to the concept of personalisation • Use of Sharable Content Object Reference Model (SCORM) which helps towards the standardisation of learning materials.	• The application is completely in Chinese with no translation possible. • Lack of feedback to the learners. • Visualisation to see learner's progress is not available.
3. The Adaptive Learning System based on Learning Style and Cognitive State (ALS-LSCS) (Cheng and Zhang, 2008)	• The system positively considers the different stakeholders in the learning process. • The research presents an interesting approach to learning style by using the Felder-Silverman's learning style categorisation.	• This research does not give any insight about the effectiveness of the adaptation taking place • Proposed system is limited in the sense that it appears to be only a framework which has been developed.

	• Encourages 'learning by doing' • Makes use of Domain Ontology and encourages reuse of Knowledge Domain	
4. Intelligent, Adaptive learning or Tutoring System (IATS) (Gowri et al., 2011)	• Use of AI-related techniques such as Agent Technology, Clustering and Fuzzy Logic. • The learning materials are presented in different formats including audio, video, HTML and flash. • The system is developed using a well-defined process, namely Agent Oriented Software Engineering which gives it a certain industry acceptance and credibility.	• No provision is made for learning materials in the form of large video file size. Video files need to be split for effective storage and retrieval • No experiment / testing is done to determine the degree to which the system is effective in providing adaptive behaviours for different learners.
5. Context-Aware and Adaptive Learning Schedule (CALS) (Yau and Joy, 2017)	• System is developed using a modular approach and has a number of modules. • Features such as the ability to measure the noise level through a sensor and to be able to determine the level of concentration accordingly.	• The onus of inputting accurate information in the system lies on the learner. • It also appears that the amount of information to be input in the system such as preferred learning style, location, time available, and others may be time-consuming

		• The learner might enter incorrect information for example incorrect learning style
6. Data mining for adaptive learning in a TESL-based e-learning system (Wang and Liao, 2011)	• This research attempts to bring adaptive learning to a completely new domain which is the teaching of English as a secondary language • The comparison of an experimental sample of learners using AL-TESL with a sample of 'normal learners' reinforces the statement that one-size-fits-all learning is not motivating and fruitful.	• The information that the learner is expected to input (personality type, level of anxiety) is highly subjective and if not correctly input in the system, will lead to incorrect output. • The learning materials to be developed in this context proved to be very costly
7. Alta Adaptive Learning Technology (Knewton, 2020)	• Dynamic and ongoing remediation that encourages just-in-time learning • Instructor Control • Student Responsiveness.	• Complete opacity as far as development architecture, technology and processes are concerned

SMART Learning environments provide a number of benefits as compared to traditional technology-enhanced learning. As demonstrated by previous research (Tseng et al, 2008; Chen, 2008; Cheng and Zhang, 2008; Gowri et al., 2011; Yau and Joy, 2017; Wang and Liao, 2011; Knewton, 2020), personalisation of contents, different learning pathways for learners, customised guidance and feedback are some of the interesting features of SMART Learning Environments which greatly contribute to make the learning process more effective, engaging and enriching. On the other hand, the development process of SMART Learning

Environments appears to be complex, requiring a deep understanding of AI-related concepts and other related technologies. Yet another challenge remains in bringing the concept of SMART Learning Environments beyond the so-far experimental and academic setting to a more applied and real-life scenario, which is that of the training and up-skilling of Cybersecurity Professionals in Mauritius. So far, what is also seen is that SMART Learning Environments have been restricted to mostly research in academia and to very few commercial products. The inherent features of SMART Learning Environments also make it suitable for learners with a certain degree of maturity who can learn by themselves and who would like to feel in control with their learning process. So far, researches and conceptualisation of SMART Learning Environments have not reached out to working professionals who are in need of constant up-skilling or reskilling.

Design Science Research Methodology (DSRM)

Science may be viewed as the process of designing theories (Walls et al., 1992). While science is concerned primarily with analysis, design is oriented towards synthesis. A scientist becomes a designer when instruments are designed to test theories, and a designer sometimes becomes a scientist when scientific theories are applied in implementing the designs. The purpose of a theory is prediction or explanation of a phenomenon (Adebesin et al., 2011). Design science have been widely used in engineering and computer science and recently researchers have succeeded in bringing design research into the Information Systems (IS) research community (Peffers et al. 2007). The figure below show the Peffers et al. (2007) Design Science Research Methodology (DSRM) Process Model.

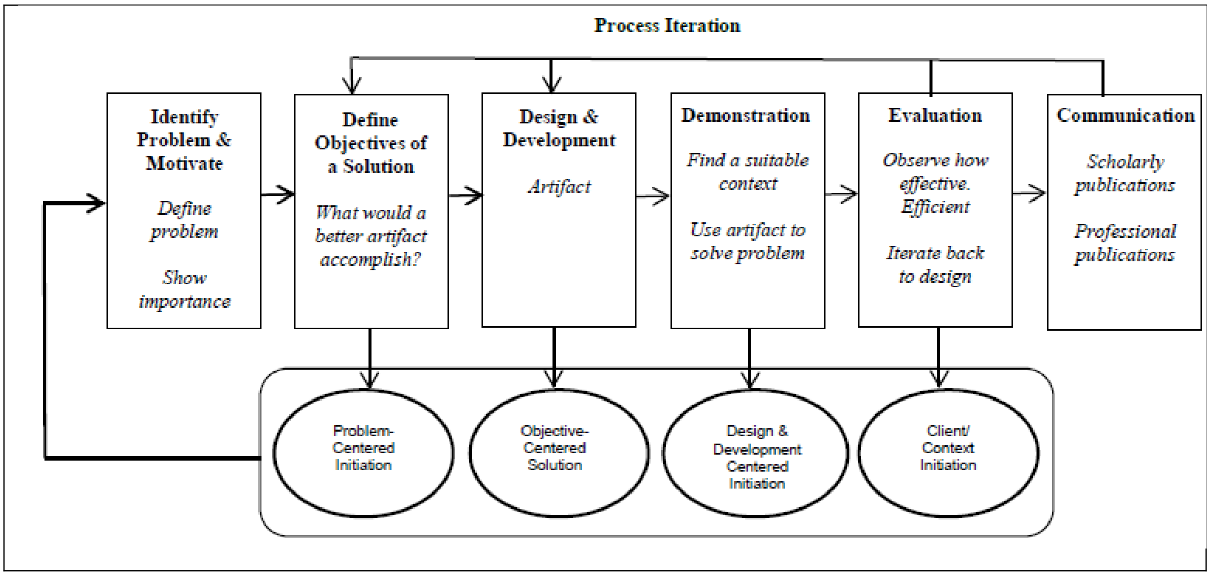

Figure 9: Design Science Research Methodology Process Model

(Source: Extracted from Peffers et al. 2007)

III. PROPOSED SOLUTION

Figure 10 below illustrates the process model for the research study.

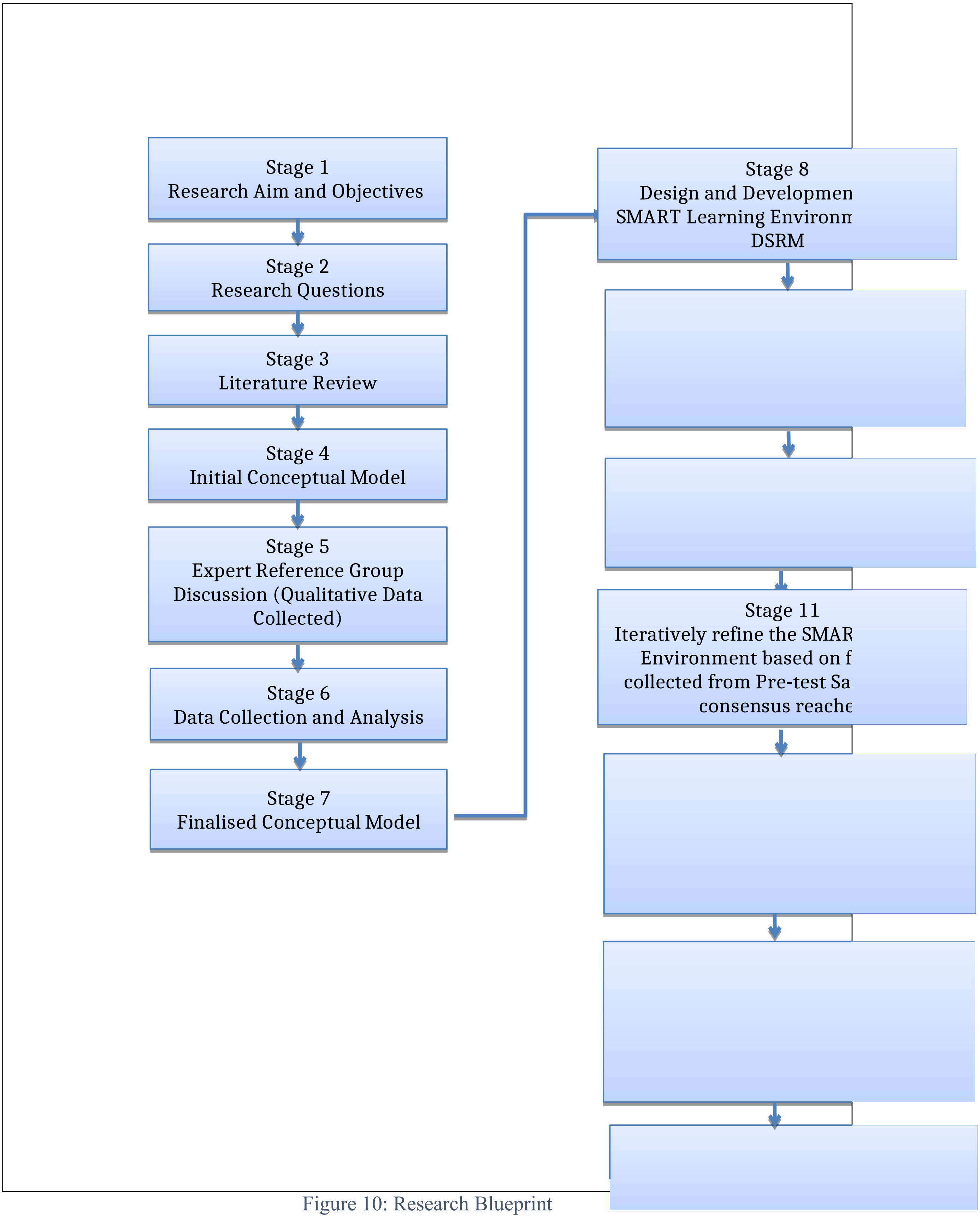

Figure 10: Research Blueprint

Framework of Proposed SMART Learning Environment

The proposed framework of the SMART Learning Environment is further expanded as shown in the figure 11 and consists of the modules listed in table 2. A modular approach is preferred for a number of reasons. A modular approach brings in a certain flexibility in terms of code reuse, debugging and future modifications.

Table 2: Modules of the SMART Learning Environment

	Modules	Description
1	Curriculum Design Module	This module will help content specialists, instructional designers and trainers prepare and set questions to eventually monitor the progress of the learner
2	Initial Competency Level Determination Module	This module will help determine the prior knowledge of the learner
3	Learning Performance Evaluation Module	This module evaluates the learner's performance through the use of online tests and other learning activities. Results of the activities carried out will thereafter be stored for analysing at a later phase.
4	Personalised Learning Module	This module adapts the learning contents, materials and tasks based on the learner's prior knowledge, performance and learning objectives. With the help of this module, the learner will be provided content and activities that would be most appropriate to him or her and would ensure that the learning process is most effective, efficient and customised according to his or her needs
5	Visualisation and Feedback Module	This module will provide, through data collected, appropriate visualisation that eventually would help in delivering timely and appropriate feedback to the learner
6	Recommendation of Learning Tools, Strategies and Feedback Module	The purpose of this module is for Individual Learners to reach desired level through Learning Analytics. This Module will recommend to the learner the most appropriate learning strategies, activities and contents so as to reach desired level and objectives
7	Ubiquitous Computing Module	This will help reach out to the learner and ensure that the learning process can take place anytime and anywhere

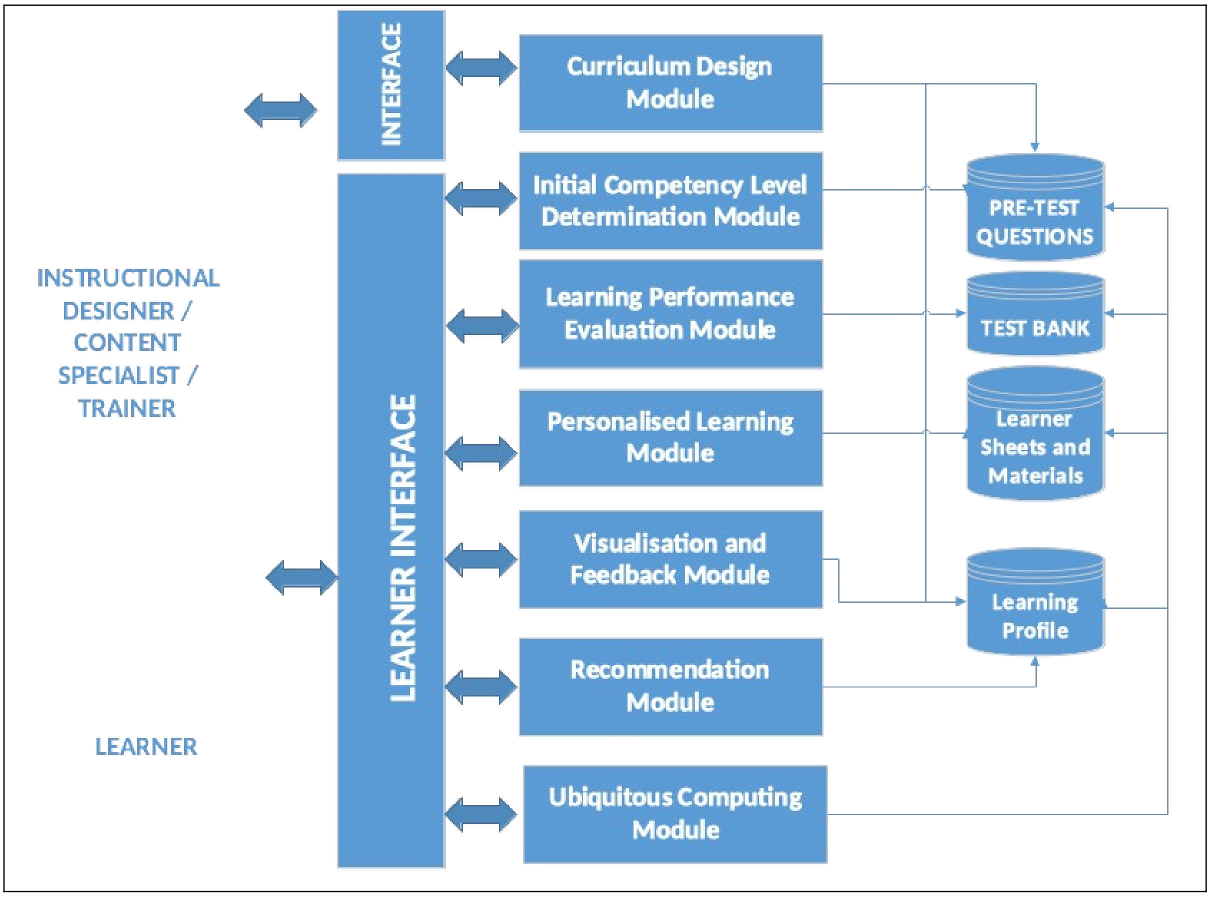

Figure 11: Proposed Architecture of SMART Learning Environment

A data mining approach was used to construct the SMART Learning Environment, more specifically, a four-step approach on an artificial neural network (ANN) core data mining technique. Moreover, a back- propagation (BP) algorithm selected from the ANNs will be used for the supervised cluster classification of student learning performances namely; the Test Score obtained from the Initial Competency Level Determination (Pre-test) and the Time Taken to complete the test.

After choosing the weights of the network randomly, the Backpropagation algorithm is used to compute the necessary corrections. The algorithm can be broken down in the following four steps:

- Feed-forward computation
- Backpropagation to the output layer
- Backpropagation to the hidden layer
- Weight updates

The algorithm stops when the value of the error function becomes sufficiently small. In addition to this, a training set of data has been implemented so that the neural network can be trained. Moreover, the flowchart of how to train the network is illustrated below.

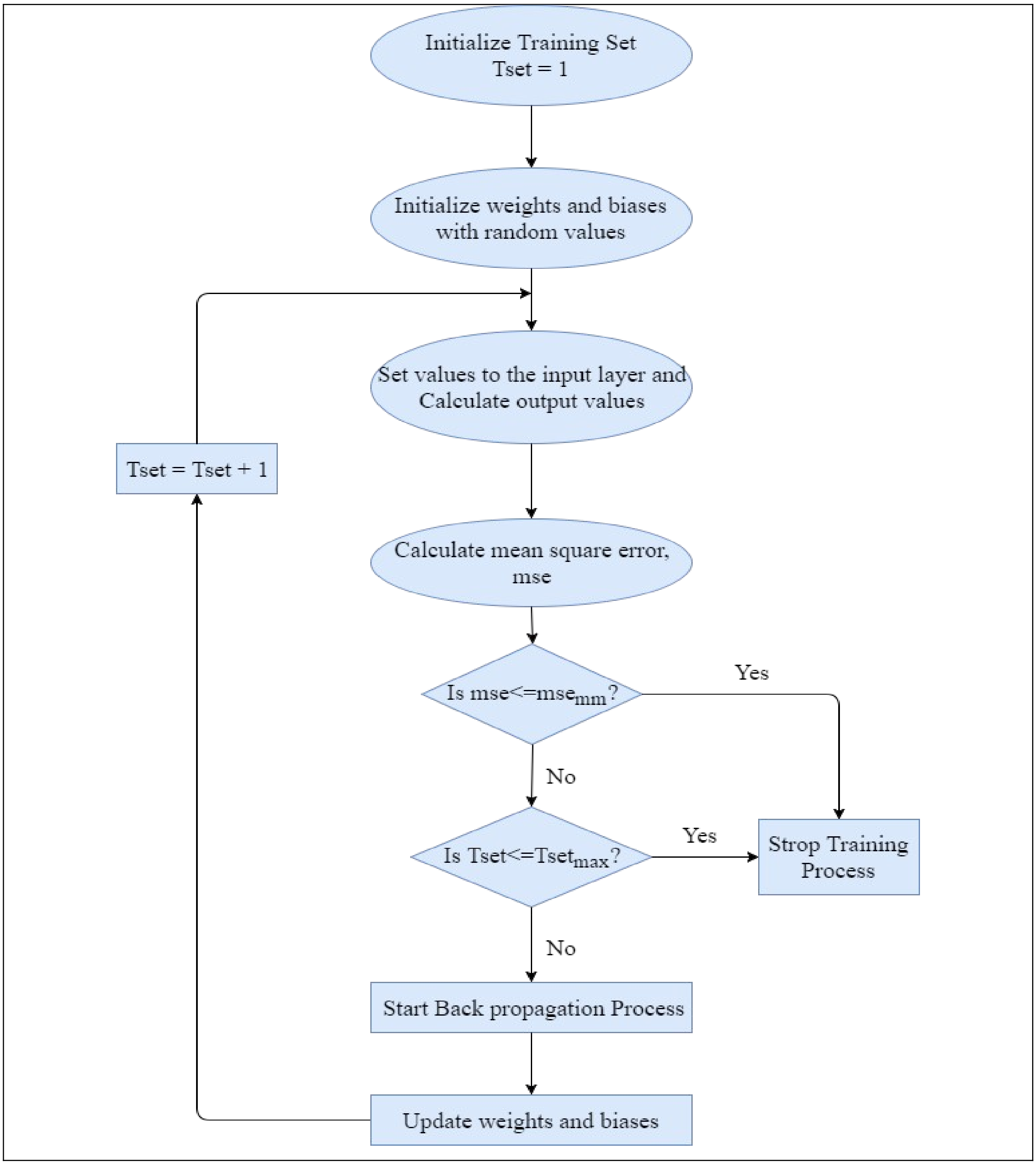

Figure 12: Artificial Neural Network Training Flowchart

After the Artificial Neural Network has been trained, the SMART Learning Environment is able to generate the personalised learning pathway for the learners. The Personalised Learning Module consists of 6 levels of Learning Materials, Level 1 to 6, each level increasing in the complexity of the learning material. After a learner has completed the materials for a particular level, he/she is subjected to a post-test for that particular level. Again, the parameters of the test score and the time taken to complete the test will be considered. If the learner clears the test, the learner is promoted to the next level. In case the learner fails the post-test, the learner will be made to learn the same learning materials again.

Also, the pseudocode for the Backpropagation Algorithm is shown below.

```
initialize network weights (often small random values)
 do
   for each training example named β
     prediction = neural-net-output (network, β) // forward pass
     actual = α-output (β)
     compute error (prediction - actual) at the output units
     compute wi for all weights from hidden layer to output layer // backward pass
     compute wj  for all weights from input layer to hidden layer // backward pass continued
     update network weights // input layer not modified by error estimate
 until all examples classified correctly or another stopping criterion satisfied
 return the network
```

Figure 13: Pseudocode for BackPropagation Algorithm

(Source: Adapted from Chattopadhyay and Bandyopadhyay, 2007)

Creating Neural Network on Neuroph Studio

To implement the SMART Learning Environment, a Multi-Layer perceptron which is a type of neural network that can be used in prediction and recognition has been used. This is very often used in situations where problems are not linearly separable. It is a feed forward neural network with a single or multiple layers separating the input and the output layer. The Multi-Layer Perceptron is trained with the Backpropagation Learning algorithm which has been explained above. The dataset was then created which will eventually be used to train the neural network. Before inserting the training elements in the training sets, normalization is performed by scaling each value between 0 and 1. The formulae below has been used to perform this operation.

$$Normalized\ (e_i) = \frac{e_i - E_{min}}{E_{max} - E_{min}}$$

where

E_{min} = the minimum value for variable E

E_{max} = the maximum value for variable E

Figure 14: Normalization

After normalising each value, the training set is created by entering the training elements with the input neurons and their output neurons respectively. To train the neural network, 50 training sets have been used. Training the network with the training sets was then performed while specifying the learning rate and momentum. Figure 15 below demonstrates that the training stops after 1500 iterations with total error under 0.01.

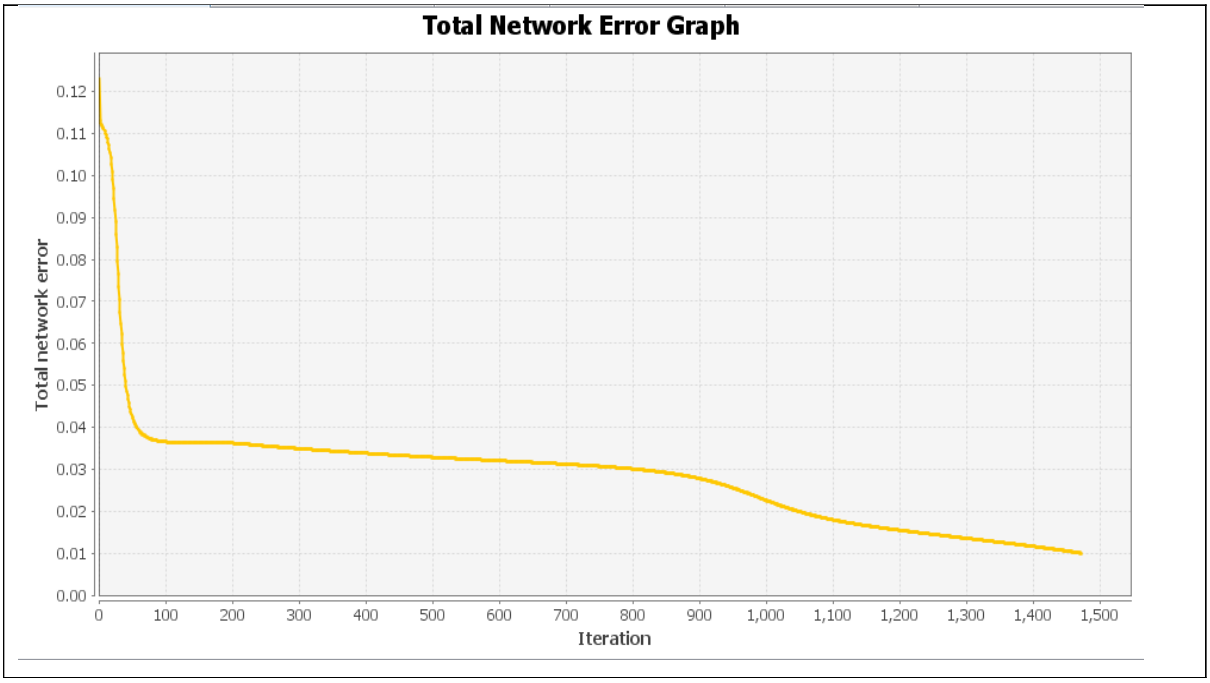

Figure 15: Total Network Error Graph 1

After adjusting the learning rate of the training, the results can be observed below.

The training stopped after just 210 iterations with total error under 0.01.

IV. DISCUSSIONS

The learning pathway which can also be described as the learning routes or learning flows and allows the learner to dynamically evolve through the learning contents.

Figure 16: Learning Pathway for Learner X

Experimental Scenario 2

Learner Y, based on his score obtained and time taken, has been tagged as an average learner by the SMART Learning Environment. His progress through the learning materials is depicted in the table below.

Table 3: Performance of Learner Y

Tests	Pre-Test	Post-Test1	Post-Test2	Post-Test2	Post-Test3
Marks	6	7	3	6	6

It is observed that Learner Y, on his first attempt, fails Post-Test 2 and is required to do Post-Test 2 again. Appropriate learning materials from level 2 is provided in the form of consolidation materials for Learner Y and the latter is also provided with supplementary learning activities. Learner Y then retakes Post-Test 2 again where he successfully clears this level and then takes post-test 3 where he passes the test.

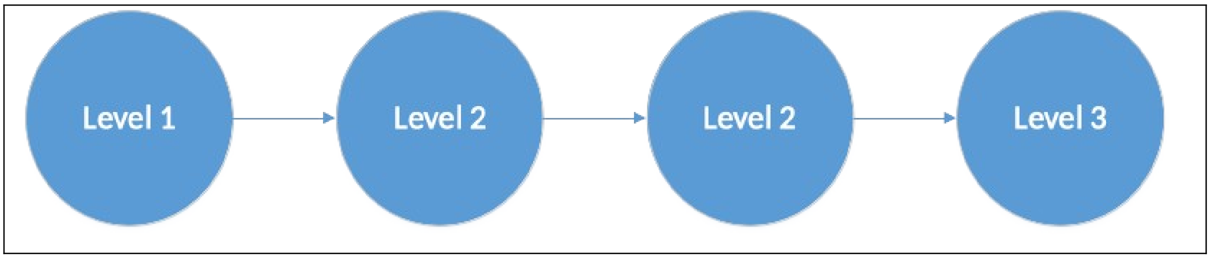

Figure 17: Learning Pathway for Learner Y

Experimental Scenario 3

Learner Z is categorised as weak as per his performance shown below.

Table 4: Performance of Learner Y

Test	Pre-test	Post-Test1	Post-Test1	Post-Test2	Post-Test3	Post-Test3	Post-Test3
Marks	3	3	5	5	2	3	6

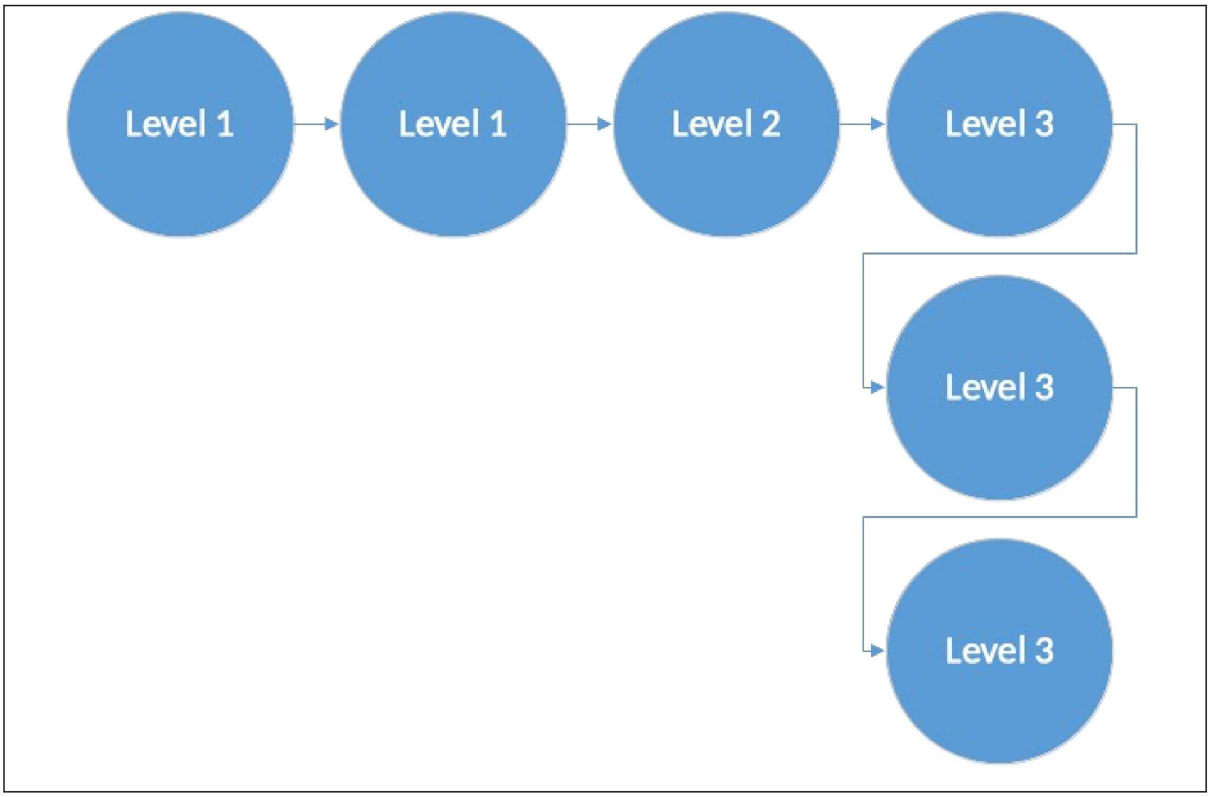

Figure 18: Learning Pathway for Learner Z

It is being observed that Learner Z is definitely a weak learner and clears post-test 3 with much difficulty after 3 attempts. The SMART Learning Environment provides Learner Z with elementary materials (which are identified through the use of tagging applied to learning objects) and further consolidates on the learning process of Learner Z by making him carry out a number of learning activities for the level he fails to clear.

Evaluation of the SMART Learning Environment using the Technology Acceptance Model (TAM)

The SMART Learning Environment developed was then evaluated using constructs of the TAM model.

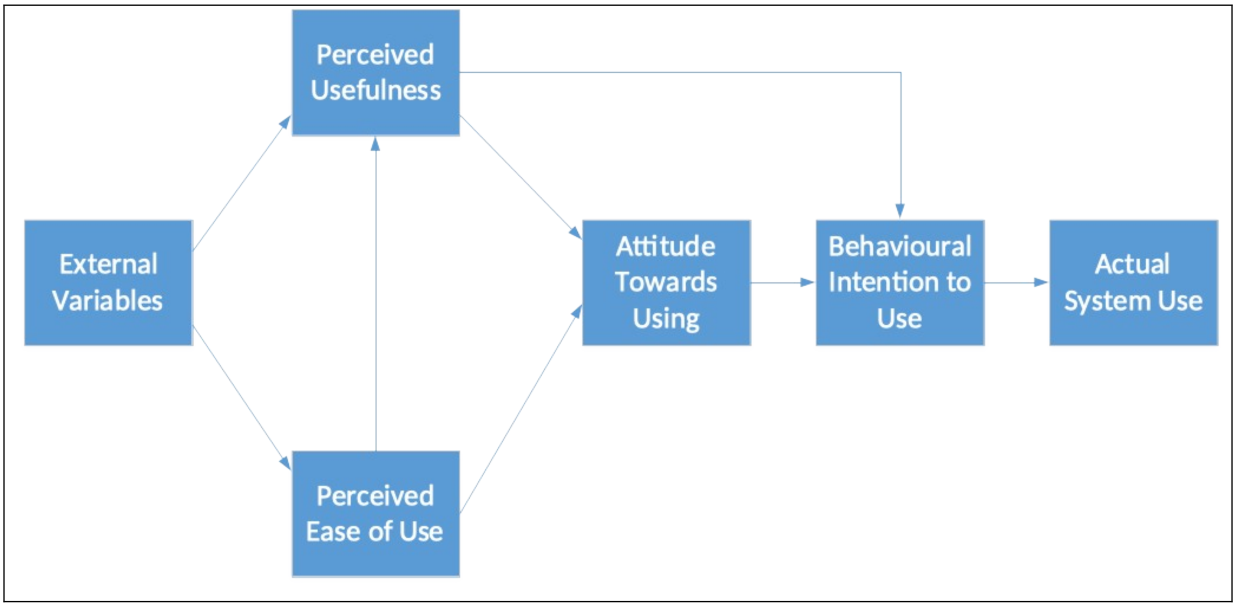

Figure 19: First modified version of Technology Acceptance Model

(Source: Adapted from Davis et al, 1989)

This section presents the findings from the survey carried out with the sample of 63 Cybersecurity professionals in Mauritius.

A. Perceived Ease of Use of the SMART Learning Environment

This section highlights the results as far as 'Perceived Ease of Use' of the SMART Learning Environment is concerned.

Table 5: Perceived Ease of Use of the SMART Learning Environment

	1	**2**	**3**	**4**	**5**	**Total**
Statement	**Strongly Disagree**	**Disagree**	**Not Sure**	**Agree**	**Strongly Agree**	
1. The User Interface of the SMART Learning Environment promotes easy use.	1 (1.59%)	5 (7.94%)	8 (12.70%)	35 (55.56%)	14 (22.22%)	63 (100%)
2. The SMART Learning Environment is easy to use.	1 (1.59%)	3 (4.76%)	6 (9.52%)	37 (58.73%)	16 (25.40%)	63 (100%)

Discussions

The *Perceived Ease of Use* (PEOU) of the SMART Learning Environment is one of the factors that influences the Cybersecurity professionals' intention to use the system. The user should feel that while using the SMART Learning Environment, the effort use is minimal and some researchers even describe the desirable usage of the system as free from effort (Davis, 1989). PEOU has a direct impact on the second variable that is *perceived usefulness*. The PEOU together with the *Perceived Usefulness* of the SMART Learning Environment is determining in ensuring the eventual *attitude towards use*, *behavioural intention to use* and *actual use.* The *Perceived Ease of Use* of the SMART Learning Environment was examined from two perspectives or viewpoints; the user interface promoting easy use and the SMART Learning Environment as a whole being easy to use. In both situations, positive and encouraging feedback was collected. 77.78% of the respondents either agreed or strongly agreed that the user interfaces of the SMART Learning Environment promote easy use. 84.13% of the respondents agreed or strongly agreed that the SMART Learning Environment is easy to use.

B. Perceived Usefulness of the SMART Learning Environment

Section D depicts the 'Perceived Usefulness' of the SMART Learning Environment.

Table 6: Perceived Usefulness of the SMART Learning Environment

	1	2	3	4	5	Total
Statement	**Strongly Disagree**	**Disagree**	**Not Sure**	**Agree**	**Strongly Agree**	
1. The SMART Learning Environment is effective in providing personalised learning materials.	1 (1.59%)	2 (3.17%)	5 (7.94%)	45 (71.43%)	10 (15.87%)	63 (100%)
2. The SMART Learning Environment is correct in its operations.	1 (1.59%)	1 (1.59%)	4 (6.35%)	41 (65.08%)	16 (25.40%)	63 (100%)

Discussions

Perceived Usefulness, one of the constructs of the Technology Acceptance Model can be seen, as the degree to which a user believes that the usage of the SMART Learning Environment (SLE) would enhance his or her job performance. This construct, in this particular context, was examined from two viewpoints or perspectives. Perceptions that were collected are firstly, whether the SMART Learning Environment (SLE) is effective in providing personalised learning materials and secondly, whether the SLE is correct in its operations. 87.30% of the respondents either agreed or strongly agreed that the SMART Learning Environment is effective in providing personalised learning materials and 90.48% of the respondents found that the SMART Learning Environment is correct in its operations. These two viewpoints are very helpful in establishing the perceived usefulness of the SLE and the results collected are very encouraging.

C. Attitude towards Using the SMART Learning Environment

This section shows the results collected as far as the attitude towards using the SMART Learning Environment is concerned.

Table 7: Attitude towards Using the SMART Learning Environment

	1	**2**	**3**	**4**	**5**	**Total**
Statement	**Strongly Disagree**	**Disagree**	**Not Sure**	**Agree**	**Strongly Agree**	
1. The SMART Learning Environment offers a motivating and engaging learner experience.	1 (1.59%)	1 (1.59%)	3 (4.76%)	44 (69.84%)	14 (22.22%)	63 (100%)
2. The SMART Learning Environment provides a better learning experience as compared to existing methods of training.	1 (1.59%)	1 (1.59%)	4 (6.35%)	38 (60.32%)	19 (30.16%)	63 (100%)

Discussions

The *Attitude towards using the SMART Learning Environment* (SLE) was gauged by looking at two viewpoints. In the first instance, the researcher tried to figure out whether the SLE offered a motivating and engaging learning experience. Then the researcher collected data to try to understand whether the SLE provided a better learning experience as compared to existing methods of training in the respective workplace of the Cybersecurity professionals. 92.06% of the respondents mentioned that the SLE offered a motivating and engaging learning experience. As far as comparing the SLE with existing methods of training in the workplace of the professionals, 90.48% highlighted that the SLE offered a better learning experience.

D. Intention to Use the SMART Learning Environment

Section F presents the results about the intention of the sample surveyed to eventually use the SMART Learning Environment.

Table 8: Intention to Use the SMART Learning Environment

	1	2	3	4	5	Total
Statement	**Strongly Disagree**	**Disagre e**	**Not Sure**	**Agree**	**Strongly Agree**	
1. The SMART Learning Environment can be used for the training of Cybersecurity Professionals in Mauritius.	1 (1.59%)	1 (1.59%)	3 (4.76%)	42 (66.67%)	16 (25.40%)	63 (100%)
2. The SMART Learning Environment can be used for the training of ICT Professionals in other areas such as Networking and Software Engineering	1 (1.59%)	1 (1.59%)	4 (6.35%)	43 (68.25%)	14 (22.22%)	63 (100%)

Discussions

Data collected in this section helped the researcher understand the *intention to use* the SMART Learning Environment (SLE). This has been determined by analysing the data from two different viewpoints. The first one was to determine whether the SLE can be used for the training of Cybersecurity professionals in Mauritius. 92.07% of the respondents believed that the SLE could be used for this purpose. Another viewpoint that was considered was whether the SLE could be used to train ICT professionals in other areas (such as Networking and Software Engineering) which are in high demand in Mauritius. 90.47% of the respondents either agreed or strongly agreed that this can be the case.

V. CONCLUSION

Currently, there is a pressing need to re-invent the way training is done for working professionals in the field of Cybersecurity in Mauritius. Indeed, it has been observed that continuous professional development is a must for these professionals since they have to keep pace with the latest development in the highly dynamic cybersecurity field. These professionals have to be trained to become lifelong learners and 21st century learning implies a complete shift in the teaching and learning process. A complete re-engineering of the training process has to be envisaged and this is why this research puts forward a novel approach which personalises the learning experience by considering the prior knowledge and aptitude of the learner.

The proposed SMART Learning Environment presents a number of interesting features and functionalities, much appreciated by Cybersecurity professionals who have experimented with the system. The ability to personalise the learning contents through the use of 'Intelligent Techniques' such as Artificial Neural Network is interesting and novel. It addresses the problem of 'one-size-fits-all' described by numerous researchers in the area of education and pedagogy. The research undertaken has numerous implications for researchers, industry practitioners, the Business Sector and the Government through governmental bodies falling under the aegis of the Ministry of Technology, Communication and Innovation (TCI) of the Republic of Mauritius. From a researcher's perspective, this research has enabled to help further understand the training needs of Cybersecurity professionals in Mauritius, to formulate and evaluate a new emergent conceptual model and to experiment with a novel approach of training through the use of a SMART Learning Environment making use of AI Techniques. It can also be said that this has positively contributed to research in the area of Technology Enhanced Learning, Information Systems and Technology.

From a practitioner's point of view, this research has enabled the Cybersecurity professionals to experience a more engaging, motivating and effective means of training. The results collected from the sample of Cybersecurity Professionals were quite encouraging. The business world is highly competitive and demanding. Cybersecurity Practitioners have to remain abreast of latest technologies, techniques and developments in the area of Cybersecurity. For the Business Sector, training in the form of up-skilling and re-skilling happens in a more effective way, thereby minimising disturbance at work, ensuring productivity and therefore minimising costs. It can also be said that by adapting the learning materials present on the SMART Learning Environment, the system can be modified for the training of other ICT professionals in other areas such as networking and software engineering.

From the Government's (Republic of Mauritius) perspective, it can be said that the research has helped address a problem of national interest. The Government of the Republic of Mauritius is spending much through conversions programmes to the field of IT. In the Government Programme 2020-2024 of the Republic of Mauritius, in the section of 'Education and Skills for the World of Tomorrow' the Government has reiterated that Education and Training be at the core of the Government's inclusiveness agenda. This report also continues by adding that 'as the country enters the next phase of its development, Government will create an environment conducive to learning through modern digital technology and latest best practices' (Government Programme 2020-2024, 2020). The situation depicted in this section is very much in line with Triple Helix Model of Innovation where interactions and cooperation between Academia, Business and the Government is seen as the agent of change that will foster economic and social development. Here in this context of research, it is the provision of adequate training to ensure the competency of the professionals in the field of Cybersecurity by the help of actors in the Triple Helix Model of Innovation that will eventually ensure economic and social development.

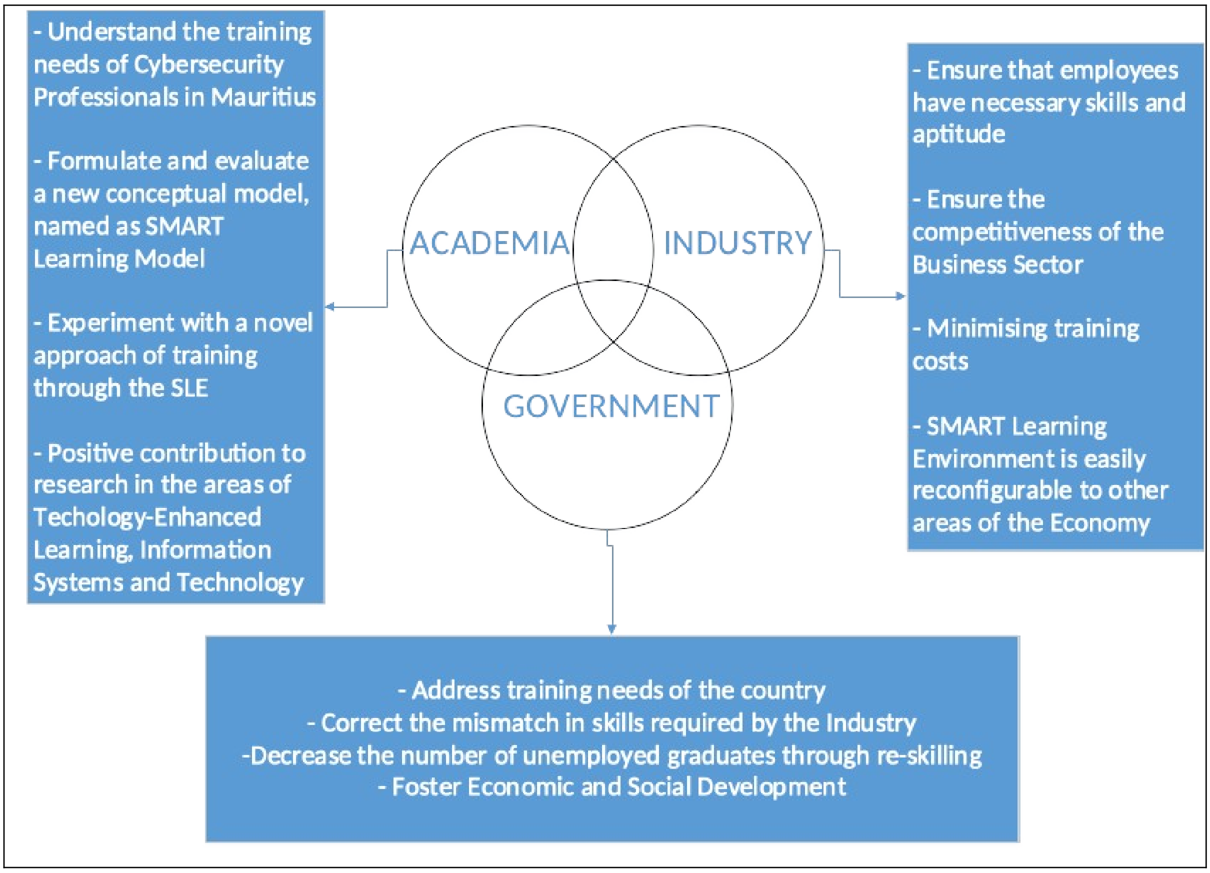

Figure 20: Implications of the study and Triple Helix Model of Innovation

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