A Modified Neurofuzzy Based Quality of eLearning Model (Modified SCeLQM)

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***Abstract*: Higher Education Institutions are required to invent means and tools to meet the increasing demand of students' enrolment. ELearning is one of these potential means which indicates that the issue of the quality of eLearning models is essential. A developed two-stage, Multi-Input-Single-Output SCeQLM[a] eLearning quality model has been reviewed. SCeLQM is based on ten Critical Success Factors, CSF. Each CSF consists of several characteristics or sub-factors. Stage one models, individually, every CSF using the rule-based soft Computing, Neurofuzzy in particular, approach, where relative sub-factors are input into the models. Stage 2 feeds the outputs from the processed ten CSFs models, with equal weights, into another Neurofuzzy-based model to produce a unique value that describes the status of the quality of the eLearning system in the higher education institution under consideration. The output of SCeLQM will be one of the categories POOR, FAIR, GOOD, V. GOOD and EXCELLENT, in the ranges 1.0 to >2.3, 2.3 to <3.2, 3.2 to < 4, 4 to <4.5 and 4.5 to 5, respectively. Several metrics have been used to measure the adequacy of the SCeLQM model. 338 data sets were divided into 80% training and 20% checking data sets using the cross validation approach. The obtained consistent and promising results of these metrics, above 0.99 for Correlation Coefficient and below 1.722 for the Mean Absolute Percentage Error, suggest the suitability to apply the modeling techniques, Neurofuzzy, in this type of problems.**

This paper focuses on the weights of the ten inputs, second stage, and their impact on the overall output of the SCeLQM model. Weights of one input, PEDAGOGY CSF, have been doubled several times to obtain weights of twice, four times, eight times, sixteen times the equal weights of all other nine inputs. Similarly, the available 338 data sets have been cross validated into 80% training data sets and 20% data sets. Four measures have been used to validate and check the proposed models. These metrics include the Correlation Coefficient, CC, the Mean Absolute Percentage Error, MAPE, the Maximum Difference, MD, and the Maximum Difference Percentage, MDP. The achieved CC range between 0.999 and 0.908, MAPE values vary between 0.1382 and 6.625, MD values range between 0.061 and 0.8 and MDP values range between 1.22 and 16 for the various models. A comparison study shows that the four measures follow quadratic trend, different parameters, with the weights' variations. It is found that a 2% threshold of CC values (0.02 below the optimum value of one) yields significant changes of the overall output that corresponds to greater than or equal to the 30.8% weight case. Regarding the MAPE metric, it is found that an increase of four MAPE value thresholds (4.0 above the optimum value of zero) will produce significant changes to the overall output that are obtained at greater than or equal to the 47.1% weight cases. A rise of 0.5 MD value thresholds (0.5 above the optimum value of zero) will make significant changes of the overall output at greater or equal the 47.1% weight cases. Whereas; an increase of 8 MDP value thresholds (8.0% above the optimum value of zero) will produce significant changes of the overall output are obtained at greater or equal the 47.1% weight cases. Furtherlly, the five categories, POOR, FAIR, GOOD, V. GOOD and EXCELLENT, of the SCeLQM overall output has been addressed. It is found that these categories will be affected, either improving or worsening, when the one of the weight of an input has been set to equal or higher than four times than the equal weights of the other nine inputs. This value corresponds to 0.984 correlation coefficient, 2.437 MAPE, 0.31 MD, and 6.2 MDP values and four times (30.8%) weight of one input of the equal weight of the other nine inputs. That is, considerable contributions of the weight of one input will affect the overall model output when it is higher than four times. Additionally, the variations of CC values against the number of categories' changes follow a second order quadratic trend. The achieved promising, consistent and promising results of these metrics suggest the suitability to apply the modeling techniques, Neurofuzzy, in this type of problems. It is intended to further investigate, enhance and address the impact of the rules and develop a Web-based version of SCeLQM model in the near future.

Keywords--- eLearning, Quality eLearning Models, Quality, Higher Education, Soft Computing.

[a] SCeLQM model has been recently submitted for publication entitled "A Neurofuzzy-based Quality of eLearning Model"

I. INTRODUCTION

We are all aware of the importance of Higher Education and its crucial role for providing, developing the knowledge, understanding and skills that we all, as leaders in the communities, need to compete in the world economy. In a recent report [1] it is recommended to have 10% of the Further Education courses of our provision provided online by 2015-16, rising to 50% by 2017-19). This of course holds true for colleges, universities, adult and community education, third sector organizations, private training providers, commercial and work-based training, uniformed and public services, secure estates and independent schools. Thus, states, worldwide, should invest enough to modernize their higher education systems. Furthermore, and with the lack and shortages of resources as well as the increase in the demand for enrolment, Higher Education Institutions, HEIs, have to modernize their teaching and learning means making use of the eLearning. Generally speaking, eLearning (electronic / enhanced / engaged / enriched learning) is a broad expression that is used to describe instructional materials and/or learning experience facilitated by electronic (information and communications) technologies. In other words and in its broadest sense, eLearning is a blended and online learning. The evolution of eLearning has gone over years through several stages. The first one can be described as Passive that consisted of Videos, PC-Based Contents. The second stage had basic and limited Internet interactivity. The third stage had an Interactive with customized design that included Blended Learning and Integrating Electronic Formats with Traditional classes. Nowadays, we are witnessing the fourth stage that is characterized by Interactivity, Adaptivity and Dynamic that includes social networking, web-based learning, virtual collaborations and classes, mobile learning, simulations, augmented reality and games. ELearning models try to present the required frameworks to address the various aspects and concerns of learners together with the challenges being imposed by technology, so that eLearning can be made effective. That is, eLearning has a dual aspect, namely, the technological and the pedagogical ones. The convention within the HEIs is that there is no compromise on quality. Thus, the importance of developing quality eLearning in HEIs has been addressed and emphasized in the literature. Therefore, any quality model to be developed must be implanted upon what makes eLearning successful including the various stakeholders' viewpoints. The main purpose of this paper is to address the quality of eLearning, aiming at enhancing the quality eLearning via proposing a quality model for eLearning. The enhancement is ensured in the view of containing multi dimensions such as contents, institutions, technology, interface design, etc. In addition, this paper addresses the weights of these dimensions that might change according to the concerns of a HEI.

The ultimate goal of this research is to enhance the proposed SCeLQM quality model[a] to manage and develop quality eLearning in the Higher Education Institutions, the Palestinian case in particular, highlighting a set of essential critical success factors for constructing eLearning and their weights.

The organization of the paper is as follow: The related works is covered in section two. While section three reviews briefly the proposed Soft Computing-based, SCeLQM, model, section four addresses the changing of weights and discusses the obtained results. Section five concludes the paper and provides the future directions.

II. RELATED WORKS

The quality eLearning has been addressed by many researchers as from the 90s of the last century. Since then, several models have been proposed and adopted in the literature. Some of these studies have been conducted as guidelines and standards by governmental and semi-governmental bodies including, the Canadian Community Association for Community Education, CACE, and the Office of Learning Technologies, OLT, of Human Resources Development Canada, HRDC [2]; the Postsecondary Education Quality Assessment Board has set four standards, Program Delivery Capacity to Deliver, Academic Freedom and Integrity and Student Protection [3];

A list of several quality standards for eLearning has been developed by Bates [4]. The various published quality eLearning models and frameworks include the ACTIONS (Access, Cost, Technologies, Interactivity, Organization, Novelty, Cost and Speed) model [5]. A framework for web-based authoring systems has been proposed by Khan that includes Institutional, Technological, Pedagogical, Resource Support, Evaluation, Interface Design, Management and Ethical considerations [6]. A framework for promoting and assuring quality in virtual institutions has been proposed by Masoumi [7]. This framework includes factors like institutional, Instructional Design, evaluation, technological, pedagogical, student and faculty supports. Another proposed quality assurance framework for e-Learning [8] has considered Operational characteristics (usability, security, and reliability), Transition characteristics (portability, interoperability) and revision characteristics (testability, modularity). The adopted faculty-centered and peer review process, designed by Quality Matters to certify the quality of online and blended courses, has included 8 general standards for its Quality Matters Rubric [9] to evaluate the design of online and blended courses. These standards are course overview and Introduction, learning objectives (competencies), assessment and measurement instructional materials, learner interaction and engagement, course technology, learner support and accessibility. The eLearning concerns of the British Quality Assurance Agency lie under the headings of delivery, support and assessment [10]. The developed Context, Input, Process and product evaluation model, CIPP [11], is considered as a framework for detecting unexpected defects and strengths. CIPP has been used by researchers such as Zhang [12] and universities like Western Michigan University [13] and Catalan Open University (UOC) [14]. The e-Maturity Model (eMM) has been developed in 2004 as a quality improvement framework [15]. eMM provides a means by which institutions can assess and compare their capability to develop sustainably, deploy and support e-learning. eMM consists of 42 criteria that covers 5 dimensions. These dimensions are delivery, strategy, definition, management and optimization. It is worth mentioning that it eMM has been later treated as a benchmarking for quality improvement [16]. The Swedish National Agency of Higher Education has developed a model for quality assessment of eLearning entitled "eLearning Quality, ELQ," [17]. ELQ includes 10 quality essential aspects including Material/content, Structure/virtual environment, Communication, cooperation and interactivity, Student assessment, Flexibility and adaptability, Support (student and staff), Staff qualifications and experience, Vision and institutional leadership, Resource allocation and the holistic and process aspect. The University of Western Sydney has developed an eLearning Quality Framework that provides criteria and standards to guide the development of quality online sites [18]. The ELQ three layers basic standards, staff development and advanced standards. The Commonwealth of Learning has developed a Quality Assurance framework for Distance Education known as the Quality Assurance Toolkit [19]. The Basic Standards of this toolkit focus on technological and design aspects identifying 10 criteria that reflect the features of an Open University. These criteria are Vision, mission and planning; Management, leadership and organizational culture; the learners; Human resources and development; Program design and development; Course design and development; Learner support; Learner assessment; Infrastructure and learning resources and Research consultancy and extension services. The European Foundation for Quality in eLearning, EFQUEL [20], has developed the European Universities Quality in eLearning, UNQUe, quality criteria that contains Learning/Institutional Context (Strategy & eLearning, Commitment to Innovation and Openness to the Community), Learning Processes (quality of the offer, human resources development and assessment of learning) and Learning Resources (Resources for learning, Students, University staff and Technology & Equipment) [21]. A quality grid that focuses on the Course Design, Learning Design, Media Design and Content is currently implemented by Epprobate [22]. Kidney and co authors identified 8 strategies to assure eLearning quality [23]. These concentrate on reviews of instructional design, web development, editing, usability and accessibility, maintainability, copyright, infrastructure impact, and content and rigor. Abdous has proposed a process-oriented lifecycle model to assure quality in eLearning development and delivery [24]. The model is based on planning and analysis; design, prototype and production; and post-production and delivery. The ISO/IEC 19796-1 [25] is a framework to describe, compare, analyze and implement quality management and quality assurance approaches. Pawlowski [26] has adapted and adopted this framework in his studies. Whereas, the ISO/IEC 19796-3 [27] extends the reference framework described in ISO/IEC 19796-1 that provides a homogeneous description of the methods and metrics required to implement quality management and quality assurance systems for stakeholders designing, developing, or utilizing information technology systems used for learning, education, and training. A four-stage Planning, Development, Process and product, PDPP, evaluation has been proposed [28]. The PDPP model addresses the market demand, feasibility, target student group, course objectives, and finance during the planning stage; instructional design, course material design, course Web site design, flexibility, student-student interaction, teacher/tutor support, technical support, and assessment during the development stage; technical support, Web site utilization, learning interaction, learning evaluation, learning support, and flexibility during the process; student satisfaction, teaching effectiveness, learning effectiveness, and sustainability) during the product stage. PDPP has been used to evaluate an eLearning course on Research Methods at the University of Hong Kong covered in several universities with 60 students to measure the student satisfaction and learning effectiveness. A common framework for e-learning quality has been proposed that identifies five broad and distinct categories of infrastructure provision, technical standards, content development, pedagogic affordances and practices institutional development by Anderson [29]. A hybrid model for e-learning quality evaluation [30] has developed a model to estimate e-learning quality based on a hybrid model which involves the Analytic Hierarchy Process, trend analysis and data comparison based on ISO/IEC 19796. An e-quality framework has been developed in the cultural-pedagogical context that provides a structure to enhance and assure quality in virtual institutions [31]. This framework is based on seven factors namely, Institutional Factor, Technological Factor, Instructional Design Factor, Pedagogical Factor, Faculty Support, Student Support and Evaluation factor. A cyclical pattern conceptualized as a Five Ds has been developed for the Ministry of Education of New Zealand [32]. These 5 Ds are: Define (the training requirements), Design (the training events), Develop (the resources), Deliver (the events), and Determine (how or if e-learning can or should be used to meet the above requirements successfully). Engelbrecht [33] reviewed several papers concluding that all have emphasized issues like Needs analysis, Student profiles, Institutional support for e-learning initiatives and Pedagogical choices that meet the requirements of the subject and the needs of the target learner group. The Demand-Driven Learning model was developed by MacDonald and co-authors [34] et al that emphasized the learner demands for quality: Content, Delivery and Service. The five-stage Analysis, Design, Development, Implementation and Evaluation, ADDIE instructional design model [35] concentrates on the process and activities of learning materials. ADDIE is mainly used by training developers and instructional designers. A framework for success has been proposed by [36] that includes Technology, Content, Administration and support, Communication, and Financial analysis elements. A service quality method, SERVQUAL, has been proposed that addresses the basic dimensions of reliability, assurance, tangibles, empathy and responsiveness [37]. Based on the SERVQUAL model, the factors that lead to the quality service in eLearning has been identified for the Jordanian higher education environment that identifies [38]. These factors include interface design, reliability, responsiveness, trust and personalization. In the the Quality Matters Higher Education Rubric, Fifth Edition, 2014, a set of 8 general standards and 43 specific standards have been used to evaluate the design of online and blended courses [39]. These standards are Course Overview and Introduction, Learning Objectives (Competencies), Assessment and Measurement, Instructional Materials, Course Activities and Learner Interaction, Course Technology, Learner Support, Accessibility and Usability.

III. REVIEW OF THE PROPOSED SCELQM MODEL

An eLearning quality model namely, Soft Computing eLearning Quality Model, SCeLQM[a], has been developed to provide an enhanced, humanized and effective learning educational environment. SCeLQM is a two-stage system that models the ten input Critical Success Factors, CSFs, individually and combined their outputs to achieve an overall single eLearning Quality Model output. Stage one consists of ten individual soft computing-based models. The input of each model accepts various sub-factors inputs and produces a single output that is based on the contributions of these sub-factors. Stage two, on the other hand, accepts these ten outputs, processes them and produces a single overall output that describes the status of the quality of the institution under consideration. These processes describe the relations between the inputs and the output. In the following sections, we will briefly introduce the Soft Computing field, present the original eLearning quality model and reveal the SCeLQM model.

A. *Soft Computing Concise Introduction*

The field of Soft Computing, SC, is a set of modelling techniques that have been developed as an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision [40]. The SC terminology includes Fuzzy Logic, FL, Artificial Neural Networks, ANN, Approximate Reasoning & Derivative-Free Optimization Methods such as Genetic Algorithms, Simulated Annealing, Random search, Downhill Simplex. SC has a tremendous number of applications particularly in the engineering fields. In this paper we are proposing to make use of the SC means and tools in enhancing the developed SCeLQM eLearning quality model. The fuzzy Logic, FL, approach incorporates human knowledge and performs inferencing and decision making that uses multi-value notions of to solve problems instead of using Boolean logic. FL's basics are derived from fuzzy set theory [41]. A fuzzy system, FS, is a mapping of an input data vector into a scalar output by means of fuzzy logic, using the fuzzyfication, fuzzy inference, and defuzzification components. The fuzzyfication component maps a crisp input space into appropriate linguistic labels of fuzzy sets known as Membership Functions, MFs. The fuzzy inference machine contains a rule base that holds a selection of fuzzy rules; a database that defines the MFs used in the fuzzy rules, normalises the input and output universes of discourse and performs the fuzzy partition of input and output spaces; and a reasoning mechanism that performs the inference process upon the rules and given condition to derive a reasonable output. The defuzzification component converts the aggregated fuzzy set to a non-fuzzy output value. The artificial neural network is an information processing paradigm inspired by biological nervous systems like our brain. ANN is composed of large number of highly interconnected neurons working together. ANN learns from experience complex functional relations by generalizing from a limited amount of input/output training data observed on the system. ANN has its strength in learning and adaptation. The main supervised learning algorithm that has been implemented is the back propagation, BP, as well as the subtractive clustering approach. The combination of modelling techniques, FL and ANN is called the Neuro-Fuzzy, NF, approach that combines the reasoning feature of fuzzy logic and the learning capability of the neural networks. One of these NF approach namely, Adaptive-Network-based Fuzzy Inference Systems or Artificial Neuro-Fuzzy Inference Systems, ANFIS [42] has been implemented. Using given pairs of input/output dataset, ANFIS constructs a fuzzy inference system (structural identification), or making use of the generated clusters by the SubCluster model. These membership function parameters are tuned using either a learning rule such as the BP algorithm alone or in combination with a least squares type of method. This adjustment allows the fuzzy system to learn from the data is modelling. This is the first time that the NF approach has been implemented to address the modelling of the Quality eLearning systems as illustrated in this paper.

B. *Brief Background of the SCeLQM Model*

An eLearning Quality Model, eLQM, has been developed to provide an enhanced and effective learning [43] that ensures the success and quality of the developed eLearning environment and contents for a Palestinian Higher Education Context. The eLQM model covers the eLearning design and development processes. These processes include software quality models procedure, quality management approaches and features that are combined with instructional design strategies including the process and product perspectives [43]. The eLQM model is based on a set of several essential Critical Success Factors, CSFs. These CSFs are Institutional, Pedagogical, Technological, Student Support, Instructor, Support, Cultural, Content, Instructional Design, and Delivery factors. These ten CSFs encompass around 100 criteria that are assembled in about sixty sub factors. The Institutional factor includes vision, policy and strategy, objectives and leadership criteria. The pedagogical factor contains learner-centred, engagement, effectiveness, ease of use and collaboration criteria. The Technological factor encompasses accessibility, browsing, browsing speed, security, reliability, effectiveness and availability criteria. The Instructional Design factor covers goal and objective, interaction, personalization, learning resources and interface design sub-factors. The Content factor consists of accuracy, organization, clarity, ease of use and interactive sub-factors. The Cultural factor takes account of language, cross-culture, religious, symbols, writing styles and globalization sub-factors. The Student factor embraces motivation, technology competence, interaction and collaboration, attitudes, flexibility and learning style sub-factors. The Instructor factor comprises attitudes towards students, technical competences, instructor role and teaching style sub-factors. The Support factor involves technical tangibles, technical reliability, technical responsiveness, technical empathy, student before starting, student during course, during learning, instructor technical, instructor pedagogy and instructor training sub-factors. The Delivery factor incorporates accessibility, availability, usability, reliability, interactivity and information quality sub-factors [43]. A questionnaire has been developed and distributed to 410 students, faculty members and developers at four Palestinian Universities. 338 samples were accepted and analysed making use of the Principal Component Analysis approach. The author identified that all CSFs have almost the same significant and contribution that range between 9% and 12% [43]. Furthermore, the study reported that 95% of the respondents are in favour of using eLearning to support their learning teaching in future. The study concluded that the quality in eLearning is still in its early state and many attempts are still required to improve its quality and successful.

C. *Description of the SCeQLM model*

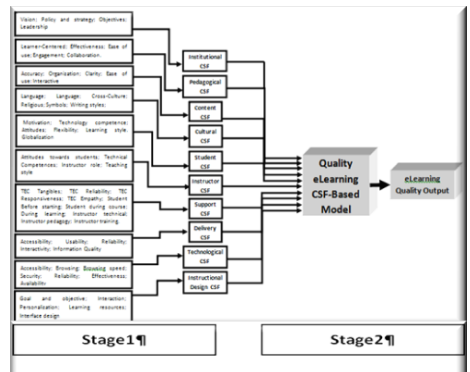

Fig. (1): The two-stage SCeLQM Model Block Diagram¶

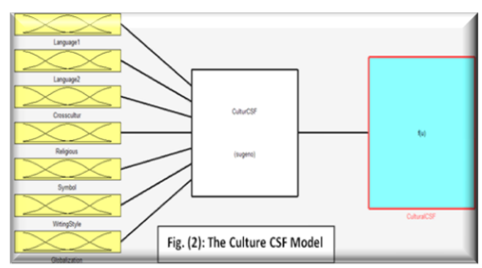

Fig. (2): The Culture CSF Model

The SCeQLM model as shown in Fig. (1) is a two -stage Soft Computing, in particular, Neurofuzzy-based system that receives ten CSFs' values, models them individually. The outputs of all of these `CSFs models are fed to the second stage. The processing of the ten inputs results in a value that describes and represents the status of the eLearning quality of a higher education institution under consideration. The following subsections will describe in more details the processing of these two stages.

1. **Stage1:** Individually, each CSF has been modelled based on the Neurofuzzy modelling technique to represent and describe the relations between all its sub factors with equal weights that can be modified according to the institutional considerations, contexts and environment. The output of each of these models represents the relations between all of the involved input corresponding sub factors and the output, taking into account the contribution of all of these inputs to produce the output. That is, such a model depicts the quality of this CSF as the linguistic terms: low, satisfactory, good and high, in the ranges 1.0–3, 2.5–4.0, 3.5–4.4 and 4.1–5, respectively. An example of these individual CSFs is the Cultural one (CulturalCSF) as shown in Fig. (2). The Culture CSF has seven sub-factors that influence its output. The relations between these seven input sub-factors namely, Language1, Language2, Crosscultur, Religious, Symbol, WrtingStyle and Globalization and the resulted output are described in this model to produce the output, CulturalCSF. With equal weights' contribution, the relationship between these sub-factors and the produced output, CulturalCSF, is described by the following rule:

Rule R_i: *if* (Language1 is $in_1cluster_i$) and (Language2 is $In_2Cllusteri$) and (Crosscultur is $In_3cluster_i$) and (Religious is $in_4cluster_i$) and (Symbol is $in_5cluster_i$) and (WrtingStyle is $in_6cluster_i$) and (Globalization is $in_7cluster_i$)

then CulturalCSF is the i^{th} linear = $p_i + q_i + r_i$ [43]

Where i indicates the i^{th} rule, that relates the i^{th} inputs terms (Language1, Language2, Crosscultur, Religious, Symbol, WrtingStylen, Globalization) with the i^{th} output (CulturalCSF)

p_i , q_i and r_i are parameters.

The tested and validated used data to verify the performance of the eLQM model [42] has been used to train and validate the SCeQLM model. For every individual model, 338 data sets have been split using the cross validation approach [45]. That is, 80% of the data has been used as the training set and the rest as the checking set (data that has not been shown to the model).

Four main measures, as displayed in Table 1, have been used to check the adequacy of these ten developed models.

TABLE 1: The MAPE, CC, Maximum Difference and its Percentage for all Individual Developed Models

CSFs	MAPE (1)	CC (2)	MD (3)	MDP (4)
Institutional	0.2161	0.9998	0.1065	2.254
Pedagogical	0.4438	0.9995	0.1359	2.718
Technological	0.4800	0.9999	0.0496	0.991
Instructional Design	1.7218	0.9905	0.4368	8.736
Content	0.2332	0.9996	0.1189	2.377
Cultural	0.0045	0.9999	0.0007	0.013
Student	0.0040	1.000	0.0003	0.006
Instructor	0.0042	1.000	0.0005	0.010
Support	0.2182	0.9997	0.1150	2.300
Delivery	0.0088	1.000	0.0036	0.073

The Mean Absolute Percentage Error, **MAPE,** is the average of the absolute percentage errors of forecasts which is calculated as in equation (1).

$$MAPE = \left(\frac{Actual_i - Predicted_i}{Actual_i}\right) \times {}^{100}/_{N\%} \qquad (1)$$

The second measure is the Correlation Coefficient; **CC. CC** determines the degree to which two variables' movements are associated and is computed as in equation (2).

$$CC_{xy} = \sqrt{\left[1 - {}^{\sum_i (y_i - f(x_i))^2}/_{\sum_i (y_i - y)^2}\right]} \qquad (2)$$

where y_i is the i^{th} actual data;

y is the average of all actual data;

$f(x_i)$ is the i^{th} predicted data.

The Maximum Difference, **MD**, calculated as in equation (3) and the Maximum Difference Percentage, **MDP**, as computed in equation (4), are the third and fourth measures.

$$MD = MAX(ABS(Actual_i - Predicted_i)) \qquad (3)$$

$$MDP = {}^{MD}/_{Max\ Value} * 100 \qquad (4)$$

TABLE 2: SCeLQM Model's Performance	
MAPE (1)	0.1508
CC (2)	0.9998
MD (3)	0.0788
MDP (4)	1.5762

TABLE3: CALCULATED CC, MD, MDP MEASURES FOR DIFFERENT WEIGNTS																	
	A				B				C				D				E
T	Actual Vs Predicted[b]				Actual Vs. Actual PED1[c]				Predicted Vs. Pred PED1[d]				Predicted VS. Actual PED1[e]				Weights of One Input
U	CC	MAPE	MD	MDP	CC	MAPE	MD	MDP	CC	MAPE	MD	MDP	CC	MAPE	MD	MDP	
V	0.998	0.379	0.326	6.528	0.909	6.650	0.797	15.948	0.908	6.112	0.800	16.00	0.909	6.095	0.799	15.98	69.6%[f]
W	0.998	0.332	0.245	4.906	0.953	4.500	0.547	10.945	0.953	4.169	0.550	11.00	0.953	4.148	0.549	10.98	47.1[g]
X	0.999	0.216	0.161	3.215	0.984	2.423	0.307	6.134	0.984	2.437	0.310	6.20	0.984	2.3402	0.309	6.18	30.8%[h]
Y	0.999	0.173	0.104	2.073	0.998	0.979	0.121	2.416	0.998	0.937	0.125	2.50	0.998	0.939	0.124	2.48	18.2%[i]
Z	0.999	0.1382	0.061	1.220	1.00[j]	0.000[9]	0.000[9]	0.000[9]	1.00[9]	0.000[9]	0.00[9]	0.00[9]	1.000[9]	0.1382	0.061	1.22	10% (Similar to all inputs)

1. **Stage2**: The outputs of all of these ten models are input, with equal weights, to the overall neurofuzzy model as shown in Fig. (4). Of course, the weights of these inputs can be modified according to the institutional concerns. This overall model describes the relationships of the fed produced outputs of the ten CSF, in the first stage, and the produced overall output of the Quality of eLearning system. It is worth mentioning that all inputs have contributed equally to produce the output of the system.

The rules that govern the overall SCeLQM model have the following form:

Rule R_i: ***if*** (Institutional is in$_1$cluster$_i$) and (Pedagogical is In$_2$Cllusteri) and (Technological is In$_3$cluster$_i$) and (Student Support is in$_4$cluster$_i$) and (Instructor is in$_5$cluster$_i$) and (Support is in$_6$cluster$_i$) and (Cultural is in$_7$cluster$_i$) and (Content is in$_8$cluster$_i$) and (Instructional Design is in$_9$cluster$_i$) and (Delivery factors is in$_{10}$cluster$_i$)

then overall is the ith linear = $p_i + q_i + r_i$ [43]

Where i indicates the ith rule, that relates the ith inputs terms (Institutional, Pedagogical, Technological, Student Support, Instructor, Support, Cultural, Content, Instructional Design, and Delivery factors) with the ith output (Overall) p_i , q_i and r_i are parameters.

Similarly, the validation and adequacy of the proposed SCeLQM system has been tested against the obtained and published results of the eLQM model [43]. These values will be called as the actual ones; whereas; the SCeLQM model's obtained output will be called the predicted values. Table 2 illustrates the performance of the SCeLQM model using various metrics.

The consistent obtained promising results of these metrics suggest the suitability to apply the modeling techniques, Neurofuzzy, in this type of problems. It has been mentioned, previously, several times that we have implemented all models with equal weights for the inputs. As previously mentioned, the focus of this paper is to study the effect of changing these weights and check their impact on the overall output of the SCeLQM model.

IV. INPUTS' WEIGHTS EFFECT

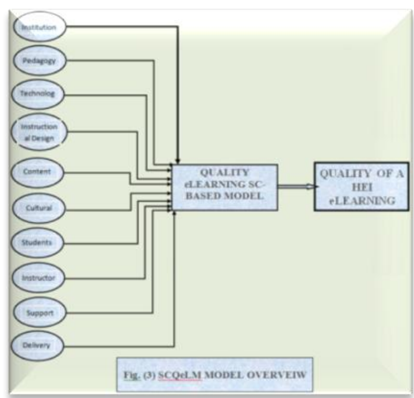

Fig. (3) SCQeLM MODEL OVERVEIW

To study the effect of changing the inputs' weights, we have limited our consideration to the second stage, Fig. (3). Since all ten models have outputs that range between 1 and 5, we have concentrated on one input, PEDAGOGY CSF (could be any input CSF). The implemented changes of the weights of

[b] The Actual Values verses the Predicted Values.

[c] The Actual Values verses the Actual value of the input PED1 (PEDAGOGY) with similar weight like the other ten inputs (10%).

[d] The Predicted Values verses the Predicted value of the input PED1 (PEDAGOGY) with similar weight like the other ten inputs (10%).

[e] The Predicted Values verses the Actual value of the input PED1 (PEDAGOGY) with similar weight like the other ten inputs (10%).

[f] The weight of one of the ten CSF inputs (PEDAGOGY) is sixteen times the equal weight of the other nine inputs (PED16). That is, its weight is 69.6%.

[g] The weight of one of the ten CSF inputs (PEDAGOGY) is eight times the equal weight of the other nine inputs (PED8). That is, its weight is 47.1%.

[h] The weight of one of the ten CSF inputs (PEDAGOGY) is four times the equal weight of the other nine inputs (PED4). That is, its weight is 30.8%.

[i] The weight of one of the ten CSF inputs (PEDAGOGY) is double the equal weight of the other nine inputs (PED2). That is, its weight is 18.2%.

[j] Both values are the same.

PEDAGOGY input are doubled several times to obtain the weights of twice, four times, eight times and sixteen times. Thus, the corresponding total weights of all inputs are 11, 13, 17 and 23, respectively. That is, these weight cases are the double, four times, eight times and sixteen times of one input, PEDAGOGY, CSF whereas the weights of the other nine CSFs inputs have the same equal weight.

Similarly, the NeuroFuzzy Modeling technique was used to develop and train several models. In particular, the Subclustering as well as a Hybrid Training methods were implemented [44]. For every individual model, 338 data sets have been split using the cross validation approach [45]. 80% of the data has been used as the learning set and the rest as the checking set (data that has not been shown to the model).

Four measures have been used to check the adequacy of these models. Namely, **MAPE,** as in equation (1), **CC,** as in equation (2), **MD**, as in equation (3) and **MDP**, as in equation (4).

V. Results and Discussions:

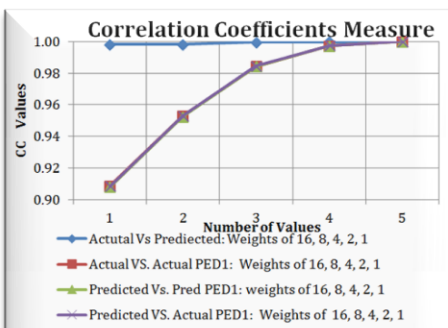

Fig. (4): The various obtained Correlation Coefficient Values

The overall results are presented in Table3. Table3 consists of five, A through E, major columns. All columns show the obtained values of metrics (CC, MAPE, MD and MDP) that have been used. Column A shows obtained values of metrics for the case to compare Actual and Predicted Values for different weights' cases. Column B illustrates obtained metrics values relating Actual Values for different weights' cases and Actual Values of the input PED1 (no changes in PEDAGOGY weight. i.e., similar weight like the other ten inputs that forms 10%. Column C reveals obtained values of the metrics linking the Predicted Values for different weights' cases and the Predicted Values of the input PED1 with similar weight like the other nine inputs (10%). Column D demonstrates the obtained values of the metrics connecting the Predicted Values for different weights' cases and the Actual Values of the input PED1 with similar weight like the other nine inputs (10%). Column E exhibits the various cases for the weights of one input out of the total ten inputs.

Table3 contains five major V through Z rows. These rows show the obtained metric (CC, MAPE, MD and MDP values for various cases. Row V illustrates the obtained metrics values for all major Columns A through D for the case when the weight of one input (PEDAGOGY) is sixteen times the equal weights of all other nine inputs (i.e., its weight is 69.6% of the overall weights of all ten inputs). Row W shows the obtained metrics values for all major Columns A through D for the case when the weight of one input (PEDAGOGY) is eight times the equal weights of the other nine inputs (i.e., its weight is 47.1% of the overall weights of all ten inputs). Row X demonstrates the metrics values for all major Columns A through D for the case when the weight of one input (PEDAGOGY) is four times the equal weights of other nine inputs (i.e., its weight is 30.8% of the overall weights of all ten inputs). Rows Y displays the obtained metrics values for all major Columns A through D for the case when the weight of one input (PEDAGOGY) is double of the equal weights of the other nine inputs (i.e., its weight is 18.2% of the overall weights of all ten inputs). Similarly, row Z reflects the obtained metrics values for all major Columns A through D for the case when the weight of one input (PEDAGOGY) is equal the weights of the other nine inputs (i.e., its overall weight is 10%). The various tabulated results are highlighted as follow:

1. The overall obtained measures:

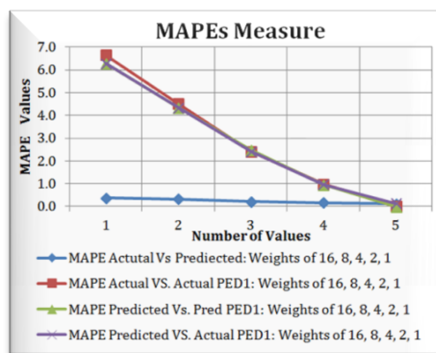

Fig. (5): The various obtained MAPE Values

1.1. The obtained CC values range between 0.999 and 0.908. Fig. (4) displays these obtained CC values. These high CC values (close to the CC optimum value of 1) suggest the high level of prediction power of the SC modeling approach to address this kind of a problem. It is worth noting that the CC values of ones were obtained since the CC metric was calculated between the same values as in CELLs: (B, Z) and (C, Z).

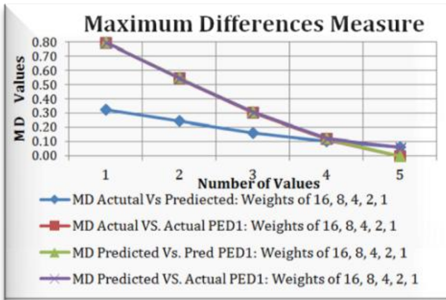

Fig. (6): The various obtained Maximum Difference Values

1.2. The obtained MAPE values range between 0.1382 and 6.625 as in Fig. (5). These low error values (adjacent the MAPE optimum value of 0) propose the high level of prediction power of the SC modeling approach to address this kind of a problem. Note that the MAPE values of zeros were obtained since the MAPE measure was calculated between the same values, CELLs: (B, Z) and (C, Z).

1.3. The achieved MD values range between 0.061 and 0.8 as in Fig. (6). These low MD values (nearby the MD optimum value of 0) suggest the high level of prediction power of the SC modeling approach to address this kind of a problem. Note that the MD values of zeros were obtained since the MD measure was calculated between the same values, CELLs: (B, Z) and (C, Z).

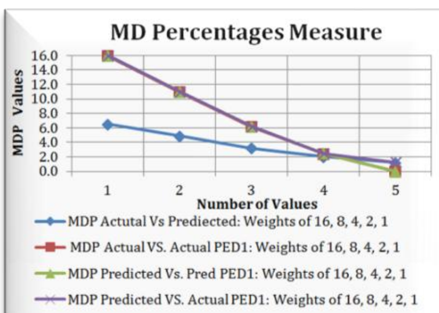

Fig. (7): The various obtained Maximum Difference Percentage

1.4. The attained MDP values range between 1.22 and 16 as in Fig. (7). These low MDP values suggest the high level of prediction power of the SC modeling approach to address this kind of a problem. It is worth noting that the MDP values of zeros were obtained since the MDP metric was calculated between the same values, CELLs: (B, Z) and (C, Z).

In conclusion, the consistency in the achieved CC, MAPE, MD and MDP measures suggests the adequacy of the Soft Computing-based modeling approach to address this kind of problem.

2. Impact of Changing the Inputs' Weights Specific Obtained results:

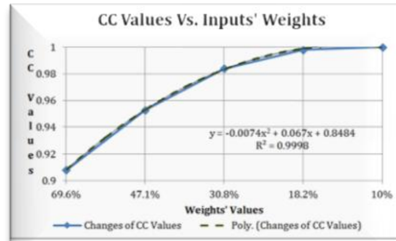

Fig. (8): The Various CC values Against Weights'

2.1. The predicted outputs for all weights' cases have been compared with the predicted output for the equal input weight cases as listed in Column C. The obtained CC values range between 1.000 for the equal weight case (CELL: Z, C) and 0.908 for the sixteen times weight case (CELL: U, C). Changes in CC values against the weight's changes has been plotted (Solid) in Fig. (8). Changes in CC values range from 1.00 for the 10% input weight to 0.984 that corresponds to the 30.8% weight. However, CC values drops down to 0.953 at 47.1% weight value and 0.908 at 69.6% weight. These changes follow the trend (Dashes) equation shown on Fig. (8). That is, Changes in CC values do not drop significantly with the changes of the weights of an input. This indicates that changing the weight of one input out of the ten inputs do not have significant impact on the output from the CC viewpoint.

2.2. Let us consider the following assumptions:

2.2.1. A 10% drop of the CC values threshold (0.1 below the optimum value of one) will have no significant effect of changing the weight on an individual input over the overall output.

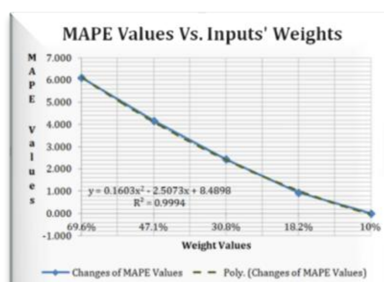

Fig. (9): The various Obtained MAPE Values against Weight Values.

2.2.2. A 5% threshold (0.05 below the optimum value of one) will make significant changes of the overall output are obtained at the 69.6% weight case.

2.2.3. A 2% threshold (0.02 below the optimum value of one) will make significant changes of the overall output are obtained at the 30.8% weight case.

2.3. Due to the obtained high CC values (CELL: Z, A), CC values shown on Columns C and D are almost identical.

2.4. Considering the MAPE measure, we have plotted the changes in MAPE values in column C verses the various weight cases as shown in Fig. (9). These values range from 0.000 (CELL: Z, C) to 6.112 (CELL: V, C).

2.5. Changes in MAPE values range from 0.00 for the 10% input weight to 2.2 that corresponds to the 30.8% weight. This MAPE trend increases polynomially 2^{nd} order to reach a value of around 6 at 69.6% weight. That is, Changes in MAPE values do not increase significantly with the changes of the weights of an input. This indicates that changing the weight of an input out of the ten inputs do not have significant impact on the output which is consistent with findings in point 2.1.

2.6. Let us consider the following assumptions:

2.6.1. A threshold of an increase of seven MAPE values (7.0 above the optimum value of zero) will have no significant effect of changing the weight on an individual input over the overall output.

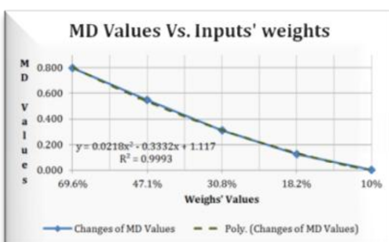

Fig. (10): The various Obtained MD Values against Weight Values.

2.6.2. An increase of four MAPE value thresholds (4.0 above the optimum value of zero) will produce significant changes to the overall output are obtained at the 69.6% and 47.1% weight cases.

2.7. Due to the obtained low MAPE values (CELL: Z, A), the MAPE values shown on Columns C and D are very close.

2.8. Similarly, for the MD measure. We have plotted the changes in MD values in column C verses the various weight cases as shown in Fig. (10). These values range from 0.000 (CELL: Z, C) to 0.8 (CELL: V, C).

2.9. Changes in MD values range from 0.00 for the 10% input weight to around 0.3 that corresponds to the 30.8% weight. This MD trend increases polonomially to reach a value of around 0.8 at 69.6% weight. That is, Changes in MD values do not increase significantly with the changes of the weights of an input. This indicates that changing the weight of an input out of the ten inputs do not have significant impact on the output which is consistent with findings in point 2.1.

2.10. Let us consider the following assumptions:

2.10.1. A threshold of an increase of greater than 0.8 MD values (0.8+ above the optimum value of zero) will lead to a conclusion that there is no significant effect of changing the weight on an individual input over the overall output.

2.10.2. An increase of 0.5 MD value thresholds (0.5 above the optimum value of zero) will yield significant changes of the overall output at the 69.6% and 47.1% weight cases.

2.11. Similarly, for the MDP measure. We have plotted the changes in MDP values in column C verses the various weight cases as shown in Fig. (11). These values range from 0.000 (CELL: Z, C) to 16 (CELL: V, C).

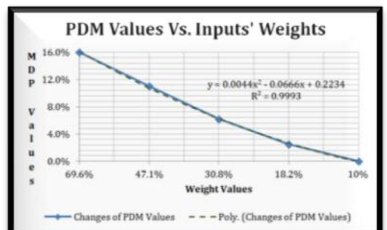

Fig. (11): The various Obtained MDP Values against Weight Values.

2.12. Changes in MDP values range from 0.00 for the 10% input weight to 6.2 that corresponds to the 30.8% weight. This MDP trend increases polonomially to reach a value of around 16 at 69.6% weight. That is, Changes in MDP values do not increase significantly with the changes of the weights of an input. This indicates that changing the weight of an input out of the ten inputs do not have significant impact on the output which is consistent with findings in point 2.1.

2.13. Let us consider the following assumptions:

2.13.1. A threshold of an increase of 16 MDP values (16.0% above the optimum value of zero) will have no significant effect of changing the weight on an individual input over the overall output.

2.14. An increase of 8 MDP value thresholds (8.0% above the optimum value of zero) will produce significant changes of the overall output are obtained at the 69.6% and 47.1% weight cases.

Basing on the consistent result of the four used measures, we may conclude that changing the weight of an input (any CSF value) will not significantly affect or bias the overall output (quality of eLearning system). However, considerable contributions of the weight of one input will affect the overall model output when it is four times or higher.

3. Considering the overall SCeLQM model output intuitively: Make the categorization according to table4. For the 67 testing sets, we have recorded several changes between categories upon varying the weights of one input (PEDAGOY) as in table3. Categories' changes include improvement such as FAIR to GOOD or worsening such as EXCELLENCE TO V. GOOD. The obtained changes presented in Table3 include the following events:

3.1. Events 1-5: Various number of categories' changes have been obtained, due to varying weights of one input (PEDAGOGY) while maintaining the rest nine inputs with the equal same weights. These values range between 0 (0%) for event 1 and 21 (31.3%) for event 5;

3.2. Events 2-5: These events report the number of categories' changes for cases: double, four, eight and sixteen times of weights as compared with the case of equal inputs' weights. These values range between 3 changes (4.5%) for event 1 to 21 (31.3%) for event 4. Recalling from table2, **CC** value for the case PED2 (CELL: Y, C) is 0.998 and **CC** value for the case PED16 (CELL: Y, C) is 0.908. This indicates the consistencies of the obtained results. Furthermore, while the 0.998 **CC** value for the case PED2 corresponds to 3 (4.5%) categories' changes, the 0.908 **CC** value for the case PED16 corresponds to 21 (31.3%) categories' changes. Regarding the thresholds assumed in sections 2.2, we have the following comments:

3.2.1. Fulfilling the proposed 10% threshold of CC value (section 2.2.1), we need to neglect higher than 21 (31.3%) categories' changes. Of course, this is not reasonable.

3.2.2. Concerning the 5% threshold of CC value (section 2.2.2), we need to ignore 21 (31.3%) categories' changes. This is also, not reasonable.

3.2.3. Regarding the 2% threshold of CC value (section 2.2.3), we need to disregard 3 (4.5%) categories' changes. Of course, this is a perfect case.

3.2.4. However, if we allow a value of 6 (9%) categories' changes threshold, this might be reasonable and realistic. This value corresponds to 0.984 correlation coefficient, 2.437 MAPE, 0.31 MD, and 6.2 MDP values and four times (30.8%) Weight of one input of the equal weight of the other nine inputs (PED4 case).

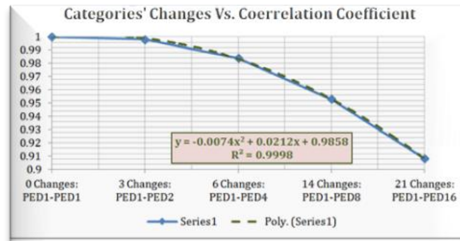

Fig. (12): Correlation Coefficient Values vs. Number of Categories' Changes Plot.

Fig. 12 illustrates the variations of CC values against the number of categories' changes. A second order polynomial trend model and line (dotted greenish) are shown on Fig.12

TABLE5: The SCeLQM overall output Categories' Changes in response with Weights' changes

Events	Description of Weights	Number of Categories' Changes	% of Categories' Changes	Correlation Coefficient
1	Changes Between Cases: PED1 and PED1	0	0	1.000
2	Changes Between Cases: PED1 and PED2[8]	3	4.5	0.998
3	Changes Between Cases: PED1 and PED4[7]	6	9.0	0.984
4	Changes Between Cases: PED1 and PED8[6]	14	20.9	0.953
5	Changes Between Cases: PED1 and PED16[5]	21	31.3	0.908

TABLE4: Intuitive Categorization of the SCeLQM overall output

Values' Range	Category
1.0 - < 2.3	**POOR**
2.3 - < 3.2	**FAIR**
3.2 - < 4.0	**GOOD**
4.0 - < 4.5	**V. GOOD**
≥ 4.5	**EXCELLENT**

as well. Y designates the CC values whereas; x indicates number of categories' changes. R-Square (**R^2**) indicates the goodness of fit. As shown in Fig. (12), the reasonable and realistic threshold categories' changes that corresponds to a CC value of 0.984.

VI. CONCLUSION AND FURTHER WORK

Several Quality eLearning models have been suggested in the literature. A new ten input single output two-stage proposed SCeLQM eLearning quality model has been reviewed. A two-stage SCeLQM is based on suggested tens of criteria that are composed into ten Critical Success Factors along with their relative corresponding sub-factors. In stage one; every CSF is modelled using the rule-based Neurofuzzy approach. In the second stage, the outputs of these processed ten CSFs models have been fed into another Neurofuzzy model to produce a unique value that describes the status of the quality of the eLearning system in the higher education institution under consideration. Several metrics and have been used to measure the adequacy of the SCeLQM model. These metrics include the Correlation Coefficient to indicate the degree to which the actual and the predicted value's movements are associated, and the Mean Absolute Percentage Error that is used as a measure of accuracy. The consistent obtained promising results of these metrics suggest the suitability to apply the modeling techniques, Neurofuzzy, in this type of problems.

A weight factor has been introduced to the inputs so as to study this change impact on the overall output. The weight of one input (PEDAGOGY CSF) has been doubled several times. That is, twice, four times, eight times and sixteen times. Several models have been developed making use of the same 338 data sets. Using the cross validation technique, 80% have been used for training the models and the rest 20% (67 Data sets) have been used for checking the performance of the models. Similarly, the same four metrics have been used. While, the obtained CC values range between 0.999 and 0.908, the obtained MAPE values range between 0.1382 and 6.625. Furthermore, the MD and MDP obtained values range between 0.061 and 0.8, and 1.22 and 16, respectively. Again, the consistency in the achieved CC, MAPE, MD and MDP measures suggests the adequacy of the Soft Computing-based modeling approach to address this kind of problem. When, the CC values have been compared with the weights changes, it is found that the trend of the change follows a quadratic shape. The 2% threshold of CC values (0.02 below the optimum value of one) makes significant changes of the overall output that corresponds to the greater than or equal the 30.8% weight case. Regarding the MAPE metric, it varies with the input weights in a quadratic form. An increase of four MAPE value thresholds (4.0 above the optimum value of zero) will produce significant changes to the overall output are obtained at greater than or equal to the 47.1% weight cases. Similarly, for the MD and MDP, they follow a quadratic trend. A rise of 0.5 MD value thresholds (0.5 above the optimum value of zero) will yield significant changes of the overall output at greater or equal the 47.1% weight cases. Whereas; an increase of 8 MDP value thresholds (8.0% above the optimum value of zero) will produce significant changes of the overall output are obtained at greater or equal the 47.1% weight cases. The overall SCeLQM model's output has 5 categories: POOR, FAIR, GOOD, V. GOOD and EXCELLENT. While varying the weights of one input, significant changes have been obtained, either improvement or worsening, in the categories. These changes follow a polynomial trend. A reasonable and realistic case is achieved by allowing a value of 6 (9%) categories' changes threshold is. This value corresponds to 0.984 correlation coefficient, 2.437 MAPE, 0.31 MD, and 6.2 MDP values and four times (30.8%) weight of one input of the equal weight of the other nine inputs (PED4 case).

In conclusion, the categories of the SCeLQM overall output will be affected (changed) when the one of the weight of one input has been set to equal or higher than four times than the equal weights of the other nine inputs. That is, considerable contributions of the weight of one input will affect the overall model output when it is higher than four times.

Although, we have achieved these promising and potential results that support the adequacy and potential of the modelling approach and the impact of implementing the weights of the inputs, it still needs further investigation. The future work and investigation include Further work will be carried out focusing on changing the rules themselves and of course, implementing the SCeLQM model with hundreds of data. In addition, we intend to implement the SCeLQM model at several regional and global higher education institutions, get the feedback and accordingly enhance the model. Furthermore, a web-based SCeLQM will be developed and uploaded for global use.

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