Intelligent Decision Support in Automating ABET Accreditation Processes: A Conceptual Framework

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Abstract

In the era of knowledge-based decision-making, there is an increasing need for administrators and instructors of engineering degree programs to make informed decisions on the currency, relevancy, and efficacy of instructional efforts. Academic accreditation through ABET provides the best practices and the means to establish the requisite quality improvement processes. Various regulatory and funding agencies for these engineering degree programs also actively call for accreditations. Nevertheless, the tedious, time-consuming, resource-intensive, and knowledge-based nature of these processes and decisions pronounces the need for a knowledge-based tool to intelligently support and automate various pertinent activities. Such activities span from information collection, aggregation, and analysis to decision analysis, support, and monitoring of outcomes. We propose a conceptual framework for researching, designing, and developing such a knowledge-based system. The proposed conceptual framework seeks to automate not only various tedious and complex activities but also facilitate knowledge-based decision analysis/support in continuous quality improvement processes. The focus is on the decisions, processes, and activities related to Course Assessments, Course Learning Outcomes, and Student Outcomes. This framework is expected to deliver systems that promise significant improvement in the efficiency and efficacy of instructors, administrators, and accreditors.

Keywords: Expert Systems, Decision Support Systems, Intelligent Systems, Soft Computing, Academic Accreditation, ABET Accreditation

Introduction

Continuous Quality Improvement (CQI) in academic programs is widely seen as the key to currency, relevancy, and efficacy of academic plans and efforts as well as the means of encouraging impactful and innovative modifications. Academic accreditation through such established and forward-looking agencies like Accreditation Board for Engineering and Technology (ABET) provides the best practices as well as the means of establishing and improving the requisite CQI processes. Accreditation is a voluntary, non-governmental process that includes an external review of the ability of a school to provide quality programs. Accreditation reviews consist of self-evaluations, peer-reviews, committee-reviews, and the development of in-depth strategic plans along with reviews of a school's mission, operations, faculty qualifications and contributions, curricula, and other critical areas [1-4]. As such, academic program accreditation is often deemed a strategic management process. Consequently, the process in itself is frequently considered an important and desirable practice, as it involves all stakeholders in consciously seeking CQI and efficacious innovation [5, 6]. ABET also underscores accreditation as a value-added process providing "assurance that the [graduating] professionals who serve us have a solid educational foundation and are capable of leading the way in innovation, emerging technologies, and in anticipating the welfare and safety needs of the public" [7]. Academic program accreditation is also treated as evidence that a degree program has not only meets certain necessary standards but also produces graduates who are ready to enter their professions. In this regard, the fundamental process undertaken by institutions striving for ABET accreditation is shown in Fig. 1.

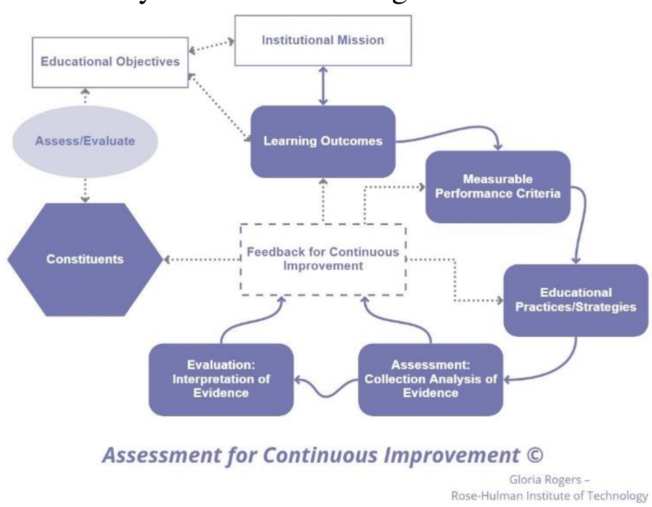

Fig. 1. Basic processes involved in ABET Accreditation (©Rogers)

Accreditation provides students assurance that the quality of education they receive meets the standards of the profession. The pursuit of accreditation provides an opportunity for academic institutions to not only demonstrate their commitment to maintaining and improving the quality of their programs but also directly and consciously involving faculty and staff in processes ensuring the currency and the relevancy of programs as well as service to its mission. The intensive team efforts involved in ABET accreditation review processes furnish valuable information that programs can use to deliver the very best education as well as formalize and reinforce a commitment to continuous quality improvement, innovation, and scholarship. Moreover, accreditation provides benefits to the faculty and staff at the accredited schools by attracting quality students, providing greater research opportunities, and allowing for global recognition. It also assures the government and public that the public money is being used prudently. However, obtaining and maintaining accreditation is an extensive, tedious, and resource-intensive exercise, sometimes making it prohibitively costly. Still, such a resource intensity and tedium do not undermine intrinsic or extrinsic value of accreditation [6].

The complex and tedious nature of CQI/Accreditation processes has long made researchers and practitioners suggest some kind of computerized automation solutions [8-14]. The most ambitious of these propositions involve the vision of developing and integrating technologies for monitoring, identifying, tracking student performance and program/curriculum management as well as data collection, processing, and reporting aspects outlined in [12]. Still, little work has been done in actually automating the CQI/Accreditation processes.

Literature Review

This research draws from literature in a wide array of synergistic disciplines including, but not limited to, knowledge-based systems, decision support systems, systems analysis and design, algorithm design, education management, etc. Here we focus more on the education management from the perspective of ABET accreditation, highlighting the gap in the existing work and the need for automating and supporting various CQI/Accreditation processes and decisions.

The sole purpose of all learning assessments is to improve the learning of students [12]. This is achieved by collecting evidence from the learning assessments, analyzing the evidence, identifying weak areas, and taking decisions based on the outcomes of the analysis aimed at improving student learning. All these processes and decisions demand a systematic approach and a workable plan that is implemented in the form of a closed-loop feedback system. In short, learning assessment plans involve three components: developing goals, collecting credible evidence, and using the evidence for improvement [6, 12]. The highly complex ABET assessment process emphasizes the use of assessment to improve programs [15]. Since the process is complex, it has a considerable overhead in terms of information collection, information processing, and decision-making [8].

The Learning Assessment Process

The basic components of an effective plan for assessment of learning are available in the literature [12, 16-20]. A typical hierarchy is listed below and shown in Fig. 2: Program Mission/Goals, Program Educational Objectives (PEOs), Student Outcomes (SOs), Course Learning Outcomes (CLOs), Course Topics (CTs) [15, 21, 22].

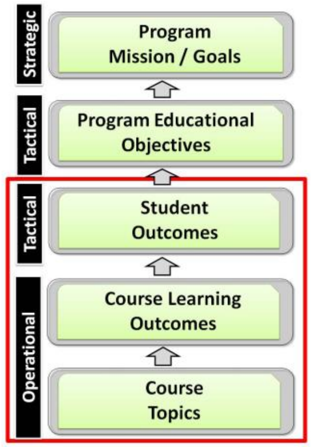

Fig. 2. Scope of the proposed decision support system

At the outset of all assessment plans, there are goals and objectives at various levels which should be clearly identified and documented. Within the hierarchy of an assessment process, PEOs and SOs are defined at the program level while CLOs are defined at the course level. Program Mission and PEOs are developed with input from all the constituencies, subject to regular reviews and updates, and consist "broad statements describing the career and professional accomplishments the graduates will achieve few years after graduation" [7]. Subsequently, SOs are derived from the Program Mission and PEOs. Essentially, SOs describe "... what students are expected to know and be able to do by the time of graduation" [23]. Fundamentally, PEOs and SOs relate to the knowledge, skills, and behaviors that learners acquire as they progress through the academic program.

At an advanced operational level, CLOs provide a formal statement of what students are expected to learn in a course. These statements refer to specific knowledge, practical skills, areas of professional development, attitudes, higher-order thinking skills, etc. that faculty members expect students to learn, develop, or master during a course [24]. Simply stated, CLO statements describe what faculty members want students to know and be able to do at the end of the course. CLOs must be observable, measurable, and student-outcome focused. These CLOs, in turn, map to one or more SOs [11, 12, 19]. However, at the very basic operational level, CTs are the actual topics covered by instructors in a specific course. Indeed, instructors often design the course assessments by considering the CTs covered in the course. Operationally, these CTs serve one or more CLOs. Depending on the pedagogy of the instructor, these CTs are covered in a course at various levels learning, such as those specified in Bloom's Taxonomy.

Limitations of SO-based Learning Assessments

ABET requires measuring the performance of learners on all SOs. However, the approach of designing assessments/questions that directly address SOs has multiple inherent limitations [11, 12]. For instance, a typical instructor would not necessarily be motivated to design assessment questions to address the SOs, as the process may be complex and non-intuitive. Furthermore, if the assessment questions are not carefully designed, the scores that students would get might not truly reflect the learning of relevant outcomes. Usually, there are only one or two SO-related assessment questions in some of the assessments, such as those on an examination. The rest of the problems in the assessments may not be necessarily addressing any of the outcomes. In addition, it is possible that am assessment question designed to address the relevant outcomes was trivial enough to not fully assess skills and learning of the student. Moreover, assessment components may occasionally be focused so much on SOs that assessment may be only remotely related to the actual course content. Consequently, the assessment would fall short of truly indicating the ability of the learner in relevant technical concepts specific to the course [6].

Benefits of CLO-based Learning Assessments

Designing CLO-based learning assessments is relatively simpler and more intuitive, as in most cases this can be done without defining performance benchmarks and is intuitively much closer to the course contents [22]. Detailed discussions on the importance and benefits of CLOs and CLO-based learning assessments can be found in [12, 22, 25]. Primarily, a typical instructor is more comfortable with, and inclined towards, designing questions addressing CLOs, an approach that is easier and more intuitive. Furthermore, CLOs derive directly from the course contents, and the learning assessments consist of questions based upon actual course contents.

SO Assessment Using CLO Assessments

Imam and Tasadduq [12] proposed a new but pragmatic and effective approach for resolving the issues involved in the direct assessment of SOs. In this approach, the instructor focuses only on the CLOs and designs assessments that directly address CLOs. All the CLOs are, in turn, mapped on specific SOs. Consequently, an instructor may indirectly address SOs by directly addressing the CLOs. This traditional CLO-based approach to assessment of learning is easier and intuitive for the instructor. Moreover, due to CLOs being closer to the actual CTs and contents than SOs, the CLO-based assessment appears more relevant to the course and its contents from the perspective of students. Consequently, the performance ratings of a student on the assessments present a relatively more authentic picture of outcome-based learning in a specific course [15].

Indeed, data collected from direct learning assessments in various courses in the program need to be aggregated, analyzed, and evaluated. This is a time consuming and cumbersome, nevertheless, extremely important process, where the extents to which students have learnt the outcomes should be ascertained as accurately as possible. Conceivably, there is a significant opportunity for automating various activities and processes. Indeed, several publications discuss this issue of lack of tools for converting CLO-based assessments to SO-based assessments. Still, there are no broad-based and knowledge-based software tools available to facilitate accurate and meaningful results [15].

Imam and Tasadduq [12] proposed a new but relatively more pragmatic and effective approach to resolve the issues involved in the direct assessment of SOs. They also provide a new algorithm for closing the CLO-SO gap and presented a simple spreadsheet-based implementation for automating this conversion. In the proposed approach, the instructor focuses only on the CLOs and will design questions and assessments that directly address CLOs. All the CLOs are, in turn, mapped on specific SOs. Consequently, an instructor may indirectly address SOs by directly addressing the CLOs. However, this approach also has several drawbacks, as discussed in the following.

CLO-SO Conversion Approach: Limitations

Despite all the merits of CLO-SO conversion process highlighted above, this scheme suffers from its own drawbacks as discussed here. For instance, the conversion from CLO-specific data to SO-specific data is very crude. Either a CLO fully addresses one or more SOs or it does not. When a given CLO maps to more than one SO, at times an instructor designs a question that addresses only one of the SOs. Since one must tag the question to the CLO, the question will incorrectly be linked to all the SOs connected with the CLO, even though the question is not focused on other SOs at all. Instructors may find it cumbersome to tag every question to one of the CLOs. Consequently, instructors must be mindful from the beginning of the course and ensure questions in all their assessments be tagged to one of the CLOs. When instructors fall short of task, it becomes extremely tedious to go back, tag the questions of their assessments and enter CLO-wise student marks to be converted to SO-wise marks. If an instructor wishes to give an assessment to students, such as a project, where the individual projects will address a different CLO, it will become almost impossible to aggregate CLO-wise student marks for this assessment and apply the conversion algorithm. When one specific CLO maps to more than one SO, a question designed to address the CLO will also address all the SOs. Many ABET evaluators show their reservations when a question addresses more than one SO [21, 22, 26].

The Need for Using CT-based Assessments

In order to address the pressing issues, we propose a new and better approach that will be integrated in the proposed automation system. In the new approach, individual CT will be tagged so as to belong to a Bloom's Level (BL), some CLOs, and some SOs. The tagging will be done in such a way that it would also take care of any subjectivity in relationships between CLOs and SOs. For example, a CT might address a given SO very strongly with another CT loosely coupled with the same SO. In such cases, tagging may also specify some subjective strength of relationships such as strong, medium, weak, etc. The proposed system will employ an intelligent fuzzy mechanism for taking care of such subjectivity and uncertainty in the relationship strengths among CTs, BLs, CLOs, and SOs.

Such an approach of CT-based assessments and employing tags to link CTs to BLs, CLOs, and SOs has many advantages. For instance, instructors are much more comfortable in linking their questions to CTs rather than to CLOs or SOs than mapping questions to CLOs. Tagging is an intuitive and increasingly popular approach used by computer and social networking web site users. The issues arising from a question addressing multiple SOs will be resolved. The issues arising from incorrectly tagging a question to some SO will be resolved. The mapping of CT-based questions to CLOs and SOs will be not only highly intuitive but also highly effective. Assessment data received from instructors will be more reliable, rendering actions taken on basis of this data more efficacious. It will have a both positive and enduring impact on CQI, student learning and tracking, and instructor tracking.

Automation for Academic Accreditation Process

At the strategic level, CQI processes involve measuring and monitoring the overall efficacy, currency, and relevancy of the academic program offered. Accreditation standards form the basis for evaluating the mission, operations, faculty qualifications and contributions, programs, and other critical areas. At the tactical level, accreditation processes include self-evaluations, peer-reviews, committee-reviews, and the development of in-depth strategic plans. These activities also include internal and external reviews of a school's mission, faculty qualifications, and curricula. At the operational level, accreditation processes involve measuring and monitoring outcome-based learning through CLOs and SOs. Indeed, accreditation processes at all these levels require sophisticated knowledge-based decision support and automation. Fig. 2 depicts these strategic, tactical, and operational levels of decisions and actions. The objectives of the automation would include:

- Automating various critical processes pertinent to continuous quality improvement and accreditation in engineering and technology programs
- Designing and implementing centralized database and knowledge-base of pertinent data and knowledge for facilitating automation and knowledge-based decision support
- Automating the conversion of student performance data on CLOs to SOs for ABET accreditation
- Automating the performance tracking, in terms of learning and teaching, of learners and instructors concerning various CLOs and SOs
- Automating the generation of course reports, course improvement plans, and remedial plans for learners

Conceivably, in the era of knowledge-based decision-making, there is an ever-increasing need for administrators and instructors in engineering and technology degree programs to have access to advanced decision support and automation tools. The need for automation is more pronounced in the areas of CLOs and SOs. As per ABET, student performance on various SOs in different courses must be assessed [15, 26]. Conceivably, if the assessment questions are not carefully designed then the performance of students may not truly reflect student learning of the relevant outcomes, defeating the purpose of the whole CQI/Accreditation exercise [11]. Nevertheless, designing course learning assessments directly relevant to SOs or CLOs is neither intuitive nor trivial due to the cognitive and information overload faced by the instructors. Various other drawbacks of such an approach of directly measuring performance on various SOs are discussed in [12]. In addition, there are drawbacks of both CLO- and SO-based assessments, strongly pointing towards a CT-based assessment approach [22, 26].

In short, a CT-based assessment of student performance is highly recommended. However, the conversion of CT-based assessments to CLO- or SO-based assessments is neither intuitive nor automatic. In order to address these pressing issues, we propose a new approach that will be integrated in the proposed automation system. In the new approach, individual CTs are tagged with specific CLOs, SOs, as well as the relevant Bloom's Level (BL) in the Bloom's taxonomy [27]. Naturally, these CT-based assessments would be converted to CLO, SO, and BL pertinent numbers. However, a typical undergraduate program contains around seven SOs and spans around 40 courses. In addition, each course typically has 6-12 CLOs and 10-20 broad CTs. Furthermore, each CT and CLO, in turn, belongs to one of the six BLs. Conceivably, the combinatorial complexity of connections reaches in tens of thousands or more. Consequently, it renders accurate and inclusive manual conversion of CT-based assessments to CLO- and SO-based assessments beyond normal cognitive and information processing capabilities of humans. Nevertheless, the comparison between the traditional and the proposed approaches with reference to student learning clearly supports the intuitiveness as well as the effectiveness of the proposed CT-based assessment approach [12].

Naturally, processes involving such tedium require specialized tools for automating information collection, analysis, and aggregation as well as for furnishing sophisticated decision support. We propose to research, design, and develop such a sophisticated knowledge-based automation and decision support tool. The proposed system for automation and knowledge-based decision support will employ intelligent soft computing and fuzzy inferencing mechanisms to take care of the subjectivity and uncertainty in the data specifying relationship between CTs and CLO, SO, BL, etc. The scope of the framework spans the automation and knowledge-based decision support in operational and tactical processes and activities related to CTs, CLOs, and SOs, as depicted in Fig. 2. It involves developing and implementing novel methodologies for generating CLO- and SO-based performance data utilizing CT-based assessments. Strategic-level activities, often comprising highly subjective decision-making, are currently excluded from the scope.

ABET / CQI Automation: Existing Research

Existing work on automating CLO-based learning assessments to SO-based learning assessments include the one described by [12], which uses a new algorithm for converting the CLO-based data into SO-based student performance indicators. They also present a spreadsheet-based tool that makes this conversion simpler for instructors and facilitates data entry, aggregation, and analysis. Despite its limitations discussed later, the spreadsheet-based tool has been used in various departments of Umm Al-Qura University. The successful use of the tool justifies the investment in researching, designing, developing, and deploying a knowledge-based system for automating CQI/Accreditation processes (KSA-Accredit) and providing effective decision support to instructors and administrators.

In [15], fuzzy logic has been applied to evaluate student performance. It has been shown that useful data on student learning can be obtained on ABET SOs using the proposed approach. Expert system can also be used to assess the student learning outcomes. This has been shown in [28]. Continuous improvement of a program is an essential element of ABET accreditation. Therefore, it is important to devise strategies that make this task easy for the faculty. Authors in [21, 26] have shown that an expert system can be used to generate course improvement plans automatically. Equally important is designing effective assessments. In another article [22], the same authors have shown the designing of effective assessments using an expert system.

As mentioned, spreadsheet-based tools have some major limitations. First, spreadsheets quickly become cumbersome when dealing with a large amount of data coming from many courses. Second, dealing effectively with multiple themes of data and knowledge, as is the case in CQI/Accreditation processes, requires the use of some kind of database component in the system [29]. Creation of centralized database and knowledgebase for CT-, CLO- and SO-pertinent data and knowledge would enable integrated performance views of each student, instructor, CT, CLO, SO, etc., as discussed in subsequent paragraphs.

Centralized Knowledge-base/Database

Creation of a central database of all course and program information and assessment results has the promise of offering the much-desirable data integrity, data availability, data transparency, as well as collaborative and data mining capabilities [6, 29, 30]. It will facilitate making the desired information available at the requisite level of details/granularity [29].

In CQI/Accreditation processes and decisions, the need for a knowledge-based decision support system cannot be overemphasized. The existing approaches towards some kind of automation in course reporting processes are devoid of knowledge-based decision support capabilities [12]. However, the knowledge-intensive nature, absence of accurate models capturing complex decision-making dynamics, and non-availability of expert advice in a timely or economical fashion highlight the need for resorting to some knowledge-based decision support and expert system methodologies in CQI and accreditation processes [31, 32]. Indeed, decision support and expert system technologies have been successfully developed and deployed in such diverse disciplines as Engineering, Business, Mining, Medicine, etc. [32-34]. However, little efforts have been expended in employing decision support and expert system methodologies in the important area of CQI and academic accreditation.

It is important to note that the proposed KSA-Accredit, by virtue of its knowledge-based decision support capabilities, will help identify any CT-, CLO-, or SO-specific weaknesses in individual students and furnish an opportunity to academic leaders and facilitators about making informed, objective, and timely remedial decisions and actions [6]. In the same league, KSA-Accredit will provide useful information on instructor-specific performance in terms of success in achieving various CLOs and SOs. This would not only enable instructors to set up their own professional development goals but also enable administrators conduct informed conversations with individual instructors on their professional performance as well as opportunities for improvement and professional development/support.

ABET / CQI Automation: Existing Automation Solutions

As already mentioned, in an assessment plan, the data collected from direct assessments in various courses need to be aggregated, analyzed, and evaluated. Such an evaluation process is time consuming and arduous for both instructors and administrators. Indeed, several publications discuss this issue of time and resource intensity of these processes as well as propose automation solutions. For example, Burge and Leach [9] present a tool based on Excel macros to allow automatic determination of the degree to which individual students meet the learning objectives that indicate how well students meet the course objectives and program directives which is equivalent to evaluating the CLO and SO satisfaction.

Essa et al. [10] present a web-based software tool called ACAT (ABET Course Assessment Tool) to keep students' records and generate various reports. Ringenbach [35] presents another web-based tool Web-CAT (Course Assessment Tool) that mainly manages students' data. Despite relatively more user-friendliness and richness of features compared to ACAT, Web-CAT lacks the functionality for effectively assessing the CLOs and SOs required for ABET accreditation. Haga et al. [36] and Morrell et al. [37], present a database management system for tracking course assessment data and reporting related outcomes for program assessment. Urban-Lurain, et al. [38] also present a database management system has for storing large assessment data of students. These systems are useful in keeping track of historical data, querying stored information, and managing large amounts of data. However, these systems lack not only the requisite knowledge-based analysis and mining facilities but also tangible decision support capabilities in automating the CLO- and SO-related activities and processes.

Imam and Tasadduq [11] report a spreadsheet-based course reporting and CLO-SO conversion system that automates some tedious course assessment and reporting activities related to CQI/Accreditation. The system has been successfully used in various programs at Umm Al-Qura University, Saudi Arabia. Despite users' reported acceptance of the system, the system has various laggings, including the cumbersome and error-prone nature of various requisite manual processes. The most advanced system available so far is proposed in [12]. This system was implemented as a commercial software with the name CLOSO [39]. CLOSO automates the course-reporting process and provides instructors the convenience of entering most of the requisite data through various selections and file upload operations. It also allows instructors to enter student survey data as well as their own feedback. Experience of using this software in various programs at Umm Al-Qura University, Saudi Arabia, indicates substantial efficiency in the course reporting processes as substantial enthusiasm towards using the software. However, CLOSO only performs direct conversion of CLO-data to SO-data, which has its own inherent limitations, as discussed earlier. Furthermore, the user interface of CLOSO is not very effective and offers opportunities for improvement. In addition, CLOSO does not provide any knowledge-based decision support to instructors and administrators. Nonetheless, the experience of using the CLOSO by [12] in the actual operating environment is considered a proof of concept for KSA-Accredit. Indeed, this system is expected to fill many remaining gaps in the existing systems.

The existing automation solutions described earlier have severe limitations [11, 12]. Most existing systems are little more than an attempt to automate or formalize course record-keeping activities while relying on a large amount of manual data inputs in an error-prone manner using ineffective user interfaces [6]. The absence of the requisite scalability, collaborative tools, and CQI decision support limits the use at large universities. The situation is complicated due to the lack of error detection, error correction, error reporting, or data validation facilities. Above all, these systems do not offer any functionality to convert CT-based assessments to BL-, CLO-, and SO-based assessments required for CQI/Accreditation processes. The absence of an intelligently designed centralized database, knowledge-base, and the requisite data mining capabilities is another handicap [6]. In addition, existing systems do not provide any integrated reporting mechanism for assessing the overall achievements of individual learners on various SOs. The unavailability of tools for choosing the requisite information level and granularity for various levels of decisions severely limits objective and informed interventions aimed at the professional development of learners and instructors [6].

Framework for Intelligent Automation

This framework builds on the Expert System (ES) paradigm for facilitating intelligent decision support in automating accreditation processes. The emphasis on the development of tools that could supplement the knowledge, experience, design intuition, and cognition of human experts. This choice of ES as the bases for the framework emanates from such inherent characteristics of an ES as the encoded knowledge, the separation of domain knowledge from the control knowledge, the ability to reason under uncertainty, the explanation facility, the knowledge acquisition capability, and the interactive user interface. These characteristics will be elucidated within the discussion on the proposed framework.

Automation can be realized to different degrees at various levels. It can include automation in the generation of assessments. It can also include calculation of the satisfaction level on various CLOs for individual learners as well as for a group of learners. Further, automation could involve the calculation of the satisfaction level on various SOs for individual learners as well as for a group of learners. In addition, automation may span generation of course improvement plans. Moreover, some automation in generation of remedial plans for individual learners is a possibility. Indeed, the scope of such automation is only limited by the capabilities incorporated into the system. Once again, these plans will serve as decision alternatives, which can be interactively adapted by the human decision-maker. Consequently, such a system will only serve as an interactive and intelligent decision support tool.

The proposed system, depicted in Fig. 3, consists of several modules working in tandem to provide intelligent decision support in automation and streamlining of ABET accreditation processes. Here we provide a somewhat generic discussion on various components of the framework.

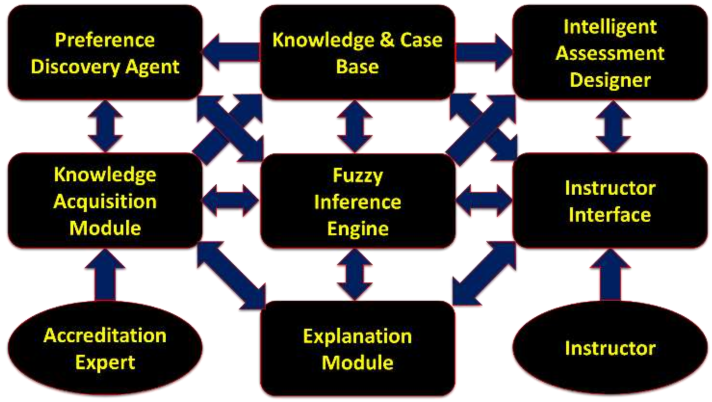

Fig. 3. The RandD Framework for the proposed system (KSA-Accredit)

Intelligent Assessment Designer (IAD)

We envisage a Genetic Algorithm (GA) based approach for building an IAD by employing various rules and heuristics. The intelligence aspect comes from the employment of penalties/rewards or preference weights, furnished by a fuzzy inference module (FIM), to evaluate the fitness value. The primary task involved in automating the assessment process is to produce superior assessment alternatives for further consideration by assessors [40]. In similar complex problems, studies indicate GAs are a promising search and optimization approach [41]. The system should incorporate expert knowledge and user preferences in the process through composite fitness functions of the IAD. This fitness function would utilize crisp preference weights furnished by the FIM.

For instance, IAD could generate several alternative assessments for an instructor to choose and modify. This modification could come in as simple form as the user selecting or deselecting certain assessment components/questions while observing the degree to which assessment is linked to different CTs, CLOs, and SOs, etc. The interactive UI will permit the user to interactively adapt elements of the task at hand while observing the impact of those changes on various performance measures. For instance, while preparing an assessment, the user could adapt the assessment components based on individual perspective and preferences, all the while monitoring the effect of those changes on the degree to which assessment is meeting various criteria such as the degree to which the assessment covers certain CLOs or SOs.

Fuzzy Inferencing Module (FIM)

Here we provide discussions on modeling of, and inferencing from, subjective and uncertain preferences as well as the design, implementation, and working of the FIM. An inference engine is the brain of any ES and contains general algorithms capable of manipulating and reasoning about the knowledge stored in the knowledge base by devising conclusions [34]. Ideally, the inference engine is distinct from the domain knowledge and is largely domain independent.

Frequently, the major problem in building intelligent systems is the extraction of knowledge from human experts who think in an imprecise or fuzzy manner. The same is true with the assessment design problem where the associated knowledge is often imprecise, incomplete, inconsistent and uncertain. Within the context of KSA-Accredit, the term imprecision refers to values that cannot be measured accurately or are vaguely defined. Likewise, incompleteness implies the unavailability of some or all of the values of an attribute, inconsistency signifies the difference or even conflict in the knowledge elicited from experts, and uncertainty suggests the subjectivity involved in estimating the value or validity of a fact or rule. For instance, fuzzy logic (FL) will help convert subject evaluation of learning achievements (like high, medium, low or grades like A, B, C) to crisp quantitative values for decision-making regarding these achievements. Another instance could be related to the CLO-SO map, where crisp connection weights between a CLO and an SO can be generated using the subjectively specified low/medium/high connections between a CLO and an SO [15].

The inherently vague, imprecise, and possibly conflicting nature of many assessment preferences implies FL as a strong option for not only modeling the system dynamics but also implementing FIM. Indeed, the ability of FL to work with imprecise terms has efficaciously been employed in automated reasoning in ES for various subjective work-domains. As such, the underlying core in KSA-Accredit inferencing uses an FIM comprising of fuzzy sets, rules, and preferences for obtaining penalties and rewards in the assessment fitness evaluation function for ranking and comparison purposes as well as for the automatic generation of assessment alternatives. The potential arises from the fact that FL provides a very natural representation of human conceptualization and partial matching. Indeed, the human decision-making process inherently relies on common sense as well as the use of vague and ambiguous terms. FL provides means for working with such ambiguous and uncertain terms [32]. Consequently, an FL-based FIM is expected to deliver much flexibility in the automated accreditation process. As such, we deem FIM as one of the core components, along with IAD, in tackling and automating the accreditation process as well as in furthering the research in this important area.

The core concept involves employing a FIM comprising of fuzzy sets, rules, and preferences in obtaining penalties and rewards for the hybrid fitness evaluation functions as well as various critical parameters for IAD and preference discovery module (PDM) – explained in IV-C. The primary benefit of a fuzzy rule-based system is that its functioning mimics more of human expert rules. The traditional rigid and myopic fitness functions do not serve well in such complex, subjective, and uncertain problem domains. Indeed, multi-criteria fitness functions are deemed more appropriate for automatic generation, evaluation, and comparison of assessment alternatives. Indeed, KSA-Accredit could have provisions for decision-makers to specify parameters in both crisp and fuzzy manner, thereby increasing the flexibility and the ease with which decision-makers may creatively adapt their preferences.

Preference Discovery Module (PDM)

The reliability and effectiveness of FIM significantly depends on the reliability of preferences. The task of extracting knowledge from experts is extremely tedious, expensive, and time consuming. In this regard, the implicit and dynamic nature of preferences, as well as efforts required for building and updating an ES, underscore the need for automated learning. Indeed, learning is an important constituent of any intelligent system [32]. However, a traditional ES cannot automatically learn preferences or improve through experience.

An automated learning mechanism can improve the speed and quality of knowledge acquisition as well as the effectiveness and robustness of ES. Incidentally, Artificial Neural Networks (ANN) have been proposed as a leading methodology for such data mining applications. ANN can especially be useful in dealing with the vast amount of intangible information usually generated in subjective and uncertain environments. The ability of ANN to learn from historical cases or decision-makers' interaction with assessment alternatives can automatically furnish some domain knowledge and design rules, thus eluding tedious and expensive processes of knowledge acquisition, validation and revision. Consequently, the integration of ANN with ES can have the ability to solve tasks that are not amenable to solution by traditional approaches [32].

Fortunately, the problem at hand is amenable automatic learning of non-quantifiable and dynamic design rules from past cases. Furthermore, it is possible to automatically and incrementally learn some decision-makers' preferences from their evaluation and manipulation of accepted or highly ranked assessments using some online ANN or Reinforcement Learning based validation agent. For instance, some supervised learning mechanism using user ratings of some past assessments/cases can learn about the individual preferences of the user and use this learning to generate more personalized assessment alternatives. Further, some unsupervised learning mechanisms can learn from interaction data captured during changes made by the user and adapt preferences related to the individual.

Knowledge-Base (KB)

Indeed, knowledge is deemed the principal ingredient in an ES [42]. The conceptual model of the elicited knowledge is converted to a format amenable to computer manipulation through a process called the Knowledge Representation [32]. Typically, knowledge elicitation continues throughout the lifecycle of the ES development and deployment as knowledge may be incomplete, inaccurate, and evolutionary in nature. The knowledge of KSA-Accredit will consist of facts and heuristics or algorithms. Further, it will contain the relevant domain specific and control knowledge essential for comprehending, formulating, and solving the underlying problems. There are various ways of storing and retrieving preferences/rules, including 'If-Then' production rules. Representing knowledge in the form of such traditional production rules enhances the system's modularity and prompted us to adopt this approach. However, conventional logic-based representation does not allow the simple addition of new decision rules to the ES without any mechanism for resolving conflicts, thus resulting in inflexibilities that are not conducive to the proposed system. This furnishes another reason for our vision of using FL modeling preferences and building the FIM.

Within the context of ABET accreditation, the KB contents would include, but not limited to, CTs, CLOs, SOs, CLO-SO maps, relevant tagging, course syllabi, course survey instruments, a pool of actual assessment questions and answers, rules of determining achievements on relevant CLOs and SOs, etc. Indeed, KB would more likely be a growing body that could be adapted to changes and innovations in aspects of curriculum.

Knowledge Acquisition Module (KAM)

Knowledge acquisition is the accumulation, transmission, and transformation of problem solving expertise from experts or knowledge repositories to a computer program to create and expand the knowledge base [34]. It should be noted that knowledge acquisition is a major bottleneck in the development of an ES [43]. It is primarily due to mental activities at the sub-cognitive level that are hard to verbalize, capture, or even become cognizant while employing the usual cognitive approach of knowledge acquisition from experts [32]. As such, the task of extracting knowledge from an expert is extremely tedious and time consuming. For instance, knowledge elicitation through interviews generates an estimated two to five usable rules a day [43].

Knowledge could be derived from domain experts, the existing knowledge, as well as through some automated machine learning mechanism. We propose to build PDM in a manner that could provide knowledge about user preferences in a form that is readily usable by IAD and FIM. More likely, the KAM is accessible to the domain expert, the program accreditation coordinator, who add CTs, CLOs, SOs, Course Syllabi, course survey instruments, etc. to the KB. Another instance could be the entering of CLO-SO map. The Subject Matter Experts may also use KAM to add to the pool of assessment questions, CTs, tagging of CTs with relevant CLOs, tagging of CLOs with relevant SOs, and so on.

Explanation Module (EM)

The ability to trace responsibility for conclusions to the sources is crucial to transfer of expertise, problem solving, and even acceptance of proposed outcomes [21]. The EM should trace such responsibility and explain the behavior of the ES by interactively answering questions. For instance, the EM could enable a user determine why a piece of information is needed or how conclusions are obtained. In its simplest form, EM could furnish the sequence of rules that were fired in reaching a certain decision. Indeed, the capability of an ES to explain the reasoning behind its recommendations is one of the main reasons in choosing this paradigm over other intelligent approaches for the implementation of our concept. EM is crucial not only from system development but also from user acceptance and adoption perspectives.

Once again, a well-designed, interactive, and effective user interface is an important ingredient in enabling a good explanation facility. In addition, incorporation of effective explanation capabilities is elusive without conducting a meticulously designed empirical study with actual users.

User Interface (UI)

The UI delimits the manner in which systems interact with the user. The need for an interactive and user-friendly UI is deemed to be an important factor in rendering the system easy to learn and easy to use "… since to the end-user the interface is the system" [44]. Furthermore, research has shown that interface aesthetics, as well as interactivity, perform a larger role in users' attitudes than users will admit [45]. As such, the perceived usefulness of the interface, or users' perception about the usefulness of the interface in a given work domain, plays an implicit role in longer-term user acceptance and performance [45, 46]. Accordingly, we envision an adaptive and interactive graphical user interface (GUI) for the system [47-60].

The UI would have the ability to accept input for the assessment design from data files. It should have the provision for manual data entry or overriding of preferences from decision makers. Moreover, it should enable easy, fast, informed and interactive manipulation of assessment alternatives by the decision-maker [61-69]. *We propose the UI be designed,* developed, and tested, using the philosophy of Ecological Interface Design and various Usability and Human-Computer Interaction guidelines. Further, the UI design should afford information about the context through various textual, graphical, analogical, and iconic references.

The Synergy of Intelligent Components

The proposed framework differs from a traditional ES in various intelligent components. Consequently, we deem it beneficial to elaborate the philosophy and synergic potential of such intelligent components. This is because of our belief that these components furnish a significant amount of realizable automation in generating and manipulating superior assessment alternatives by addressing the core issues in building the whole system. Furthermore, these components furnish a vehicle for carrying out further research in this direction [70-74].

The need for intelligent components arises from limitations of conventional systems design techniques that typically work under the implicit assumption of a good understanding of the process dynamics and related issues. Conventional systems design techniques fall short of providing satisfactory results for ill-defined processes operating in unpredictable and noisy environments such as assessment design. Consequently, the use of such non-conventional approaches FL, ANN, and GA is required. The knowledge of strengths and weaknesses of these approaches could result in hybrid systems that mitigate limitations and produce more powerful and robust systems [32, 47, 48]. Indeed, the potential of these technologies is limited only by the imagination of their users [75-83].

Among the intelligent components of KSA-Accredit, IAD generates superior assessment alternatives based on pre-specified and user-specified constraints and preferences as well as preference weights furnished by FIM. The FIM incorporates the soft knowledge and reasoning mechanism in the inference engine. The PDM complements the IAD and the FIM by automatically discovering and refining some preferences. In this synergy, the FIM receives fuzzy preferences and rules from various sources including domain experts, the knowledge base, and the PDM. These fuzzy preferences and rules are defuzzified by the FIM through its inferencing mechanism, furnishing crisp weights for use in the IAD. The IAD generates superior assessment alternatives for ranking and adaptation by users. The assessment alternatives generated by the IAD could be validated by the user or by the PDM. Consequently, the experts' ranking of assessment alternatives would serve as learning instances for updating and refining the knowledge-base, fuzzy rules, and preferences. Incremental learning technologies like Reinforcement Learning might prove useful here [6].

These intelligent components combine powers of the three main soft computing technologies representing various complementary aspects of human intelligence needed to tackle the problem at hand [48]. The real power is extracted through the synergy of expert system with fuzzy logic, genetic algorithms, and neural computing, which improve adaptability, robustness, fault tolerance, and speed of knowledge-based systems [32, 47, 48]. We have deliberately kept our discussion on individual modules in KSA-Accredit largely generic in character. The rationale is that the actual details of an accreditation process automation would depend on the goals of the actual system, which would be different from system to system.

Conclusion

We have described the problem of accreditation process automation, its significance and relevance, and the role intelligent systems and soft computing tools can play in improving the efficacy and efficiency of the automation of the accreditation processes. In particular, we have framework for a novel intelligent approach to solving this important and intricate problem. Our framework involves the use of human intuition, heuristics, metaheuristics, and soft computing tools like artificial neural networks, fuzzy logic, and expert systems. We have explained the philosophy and synergy of the various intelligent components in the framework. The framework contributes to the domain of intelligent automation of accreditation processes by enabling explicit representation of experts' knowledge, formal modeling of fuzzy user preferences, and swift generation and refinement of superior assessment alternatives. This framework would help develop systems that would significantly improve the efficiency and efficacy of instructors and administrators involved in continuous quality improvement and accreditation activities at engineering and technology related academic programs. Further, it would promote acceptance of similar activities in other disciplines.

Data Availability

No data were used to support this study.

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