Intelligent Framework for Enhancing the Quality of Online Exams based on Students' Personalization

Ayman E. khedr[1], Abdulwahab Ali Almazroi[2], Amira M. Idrees[3]
University of Jeddah, College of Computing and Information Technology at Khulais[1]
Department of Information Systems, Jeddah, Saudi Arabia[1]
University of Jeddah, College of Computing and Information Technology at Khulais[2]
Department of Information Technology, Jeddah, Saudi Arabia[2]
Faculty of Computers and Information Technology, Future University in Egypt, Egypt[3]

***Abstract*—In education sector, personalization is an evolutionary term that gained a high attention due to its effectiveness in raising the enterprise competence level. This research aims at proposing a novel model for effective smart testing, which considers the student's Facebook activities in determining the students' personality and constructing his suitable exam. The aim of this examination perspectives to ensure the reliable student evaluation according to his gained knowledge to ensure that no other factor interferes which may negatively affect the reliable evaluation. The research also applies text analytics techniques to ensure the exam balance. The proposed model has been applied and evaluated with professors' percentage equal to 96.5 % and successfully reach students satisfaction percentage with average equal to 96.63%.**

***Keywords*—Personalization; data mining; sentiment analysis; social networks; e-learning**

I. Introduction

Online education is no longer considered as an additional tool, but a vital solution that strongly supported the whole educational operation against crashing. Although this situation was not planned, however, results revealed that online education is the main factor for increasing information retention, reducing learning time, and raising the stakeholders' satisfaction level which confirmed that this adaption in the learning strategies is here to stay. The transformation of the education system towards online education has been already introduced with limits, however, this situation has moved to a significant surge forward. This shift away from classrooms does not only include the teaching classes, but it also requires other learning activities adaptation such as projects' work, practical sessions, as well as the immense need to adapt the student's assessment perspective [1]. Consequently, bolstering the online learning systems' capabilities can be currently considered a strategic objective for the educational field.

Moreover, online education has raised the alarm to focus on personalized learning as the pieces of evidence have confirmed its effectiveness of tuning the evaluation process to rely on students' personalization rather than memorization [2]. As highlighted in [3], personalized learning supports students to perceive learning with enthusiasm as it becomes more relevant and compatible with the student's characteristics [4]. Accordingly, focusing on exams personalization has become one of the goals that gained a high priority and importance as it could lead to a strong positive impact. Such an opportunistic assessment perspective in conducting the students' exams in an adequate environment based on their own pace ensures equal opportunity for all students [5]. This increasing goal for performance evaluation based on individual characteristics has been globally monitored. This recent evaluation vision has gone far beyond the traditional approach with changing the whole evaluation scheme. This research targets to intelligently transform the evaluation process from stressing, unaccommodating, and monotonic process to an effective, knowledgeable, and reliable perspective, which could be tagged as "smart testing".

Data as well as information analytics techniques play a vital role in smart testing that could successfully incorporate the personalization process into smart testing by the intervention of the behavioral students' data for tracing the suitable exam and facilitating the questions' characteristics selection [6]. On the other hand, data resources such as social networks, forums, and corporates' databases are the foundations for the personalization process for monitoring the personal behavior and characterize the student personality which consequently supports the smart testing process [7]. These resources are the pillar for revealing the student's primitive actions, his interaction preferences, as well as his trends. This revealed information feeds the testing process with the required measuring criteria for generating a suitable exam for the student [8].

This research proposes a smart model for generating a suitable exam for the student based on his personality. The student's personality has been determined based on his social network activities and educational data. The proposed model depends on the corporate database and the Facebook data as the main data resources for the personalized smart testing process.

II. Related Work

Enhancing the online education towards a more reliable process has been proposed in several researches [9] [10]. One of these researches have been presented by [11] who developed interactive learning resources with proposing to considers the learner activities during the learning process, however, the proposed enhancement focused on the closed activities cycle which was later considered by [12] could mislead the explored actions by not considering the traditional student behavior. Additionally, the research by [13] focused on tracking the student skills targeting the learning path recommendation based on a set of conducted exams. however, this approach lacked considering many exam criteria during the evaluation process such as the difficulty level.

Engaging intelligent systems in the e-learning process has been introduced from many perspectives. Different researches proposed intelligent methods for learning objectives recommendations with respect to the student progress [14]. Another research by [15] adopted the recommendation perspective to recommend the suitable department for the Fayoum university students. Other researchers have applied a variety of intelligent techniques such as the Bayes model [16], evolutionary algorithms [17], and association network [18]. In [19], Item Response Theory has been applied targeting to update the education path for the student according to his ability. Additionally, a recent research by [20] proposed a recommender system for lessons' study plan to maintain the student learning time. The proposed researches focused on the learner path; however, it is vital for an intelligent assessment method which opens the adaptation perspective using reliable criteria.

Focusing on the contribution of text analytics in the e-learning process. Text analytics has contributed to many researches in different tasks. A research in [21] proposed investigating the capability of the student in managing the exam time during the exam using text analytics, however, no consideration of other exam characteristics such as the exam level or specialty. Another research in [22] introduced text analytics in assignments' assessment for detecting plagiarism level.

Although as mentioned by [23], focusing on the student's social networking activities for discovering his behavior patterns is still considered an unexplored field, however, some researchers proposed some directions. While different empirical researches have investigated the impact of social networking and the education sector stakeholders' performance [24] [25], others have focused on the reasons that raise the power of social networking on the students in the learning process [26] [27]. It is a fact that social network influence on the educational process can take either direction, positive or negative [28], however, the success lies in lighting the shed towards the correct path [29]. Although some of the studies have tried to highlight the negative impact of the time spent in using social networking and the student's performance [30] [31], however, most of these studies revealed that there is no significant relationship between the two activities [32] [33]. Moreover, social networking extended its intervention on the learning process by offering academic resources and encourage the direct interaction among the education sector stakeholders [34]. On the other hand, researchers have highlighted that social networking users who are underage, therefore most probably students, have limited their social networking relations to their friends, not their family. Focusing on the interaction methods, some researchers argued that girls are most probably using images and share more videos on their posts more than boys [35]. More recently, the researches in [36] [37] [38] have proposed the approach of considering the Facebook activities to support the learning process by active discussion, sharing material, and continuous communication. Other researches such as in [39] [40] focused on the relation between students' engagement in Facebook activities and their willingness for class engagement. The presented researches and others have shyly considered social networking in the learning process with a limited role for continuous communication, while in the current research, social networking has a vital role and proved its effectiveness in enhancing the learning process reliability.

III. The Proposed Model for Smart Testing

The proposed smart testing model includes three main stages, "social-based exploration for the student preference", "semantic-based question bank construction", and "setting the student preference-based exam". The following sections will discuss each stage in detail.

A. *Stage One: Social-based Exploration for the Student Preference*

This stage aims at identifying the suitable type of questions for each student. Three types are available, they are illustration, long text, and short text questions. In this stage, the students' main data is collected from the faculty database including name, id, gender, email, education history (place, courses, and degrees), and Facebook account. The student's current educational status is already monitored including the registered courses, the number of credit hours gained, and remaining credit hours.

Social networks are considered the main data source in this stage. Using the Facebook account, the student's public posts are extracted and categorized to be either text or other media. This research only focuses on these two categories as the aim of this classification is to identify the suitable questions' type for the student. Moreover, the text category is also classified as short or long text. The short text category leads to the closed test questions including MCQ and T/F, while the long text leads to the open text questions including the discussion and state questions. It is vital to mention that the research depends on the student's social public data in order to avoid violating the student data privacy as social network users.

The student social activities data source is represented as follows:

The set of student's posts is represented by a set of vectors, each vector includes the post identified and its content.

$$ST\_Posts\ (STID) = \{<Post\_ID, PContent>_j \mid j \in N\}$$

All the students' posts are represented in the parent set as follows:

$$ALL\_ST\_Posts = \bigcup ST\_Posts\ (STID) = \{<STID, ST\_Posts\ (STID)>\}$$

Each post belongs to one of the five types, they are: short text, long text, illustration, long text &illustration, and short text & illustration. Detecting the post type is performed and the tagging is applied which can be represented as follows:

$$ST\_TagPosts\ (STID) = \{<Post\_ID, PContent, PType>_j \mid j \in N\}$$

The posts' types are then weighted to determine the student preferences, the performed steps are as follows:

The percentage of the posts with type "short text" referring to all number of posts

$$\text{PText (STID)} = \frac{\sum_{n=1}^{k} \text{PText(STID)}}{|\text{ST\_TagPosts (STID)}|} * 100$$

PText(STID) $\subseteq$ ST_TagPosts (STID) where PType = Short Text

The percentage of the posts with type "long text" referring to all number of posts

$$\text{PText (STID)} = \frac{\sum_{n=1}^{k} \text{PText(STID)}}{|\text{ST\_TagPosts (STID)}|} * 100$$

PText(STID) $\subseteq$ ST_TagPosts (STID) where PType = Long Text

The percentage of the posts with type "fig" referring to all number of posts

$$\text{PFig (STID)} = \frac{\sum_{n=1}^{k} \text{PFig(STID)}}{|\text{ST\_TagPosts (STID)}|} * 100$$

PFig(STID) $\subseteq$ ST_TagPosts (STID) where PType = Illustration

Then the student preferences are then arranged in descending order according to the revealed percentage. The student preference set has three ordered members, each member is a vector that includes the preference order, preference type, and percentage.

Skill (STID) = {<order, preference, Percentage> | order $\in$ {1,2,3}, preference $\in$ {short text, long text, illustration}}. In the case of equal percentages, then the student will be considered according to the equal percentages by stating the included types in the hybrid set. Although the proposed model considers the highest student's preference, however, ordering the student's skill is vital in case that the first preference does not match with the suitable type with the course questions' type. In this case, the following student preference is considered.

B. Stage Two: Semantic-based Question Bank Construction

This stage focuses on building the test bank for the subject under examination. The main source of this stage is the course curriculum. The following steps describe the construction process in detail. In this stage, a semantic-based mesh tree is built relating the questions' tags with the subject key terms according to the subject nature. Each key subject can be related to one or more question tags. Both keys; key terms and key question tags; are tagged with one of the three types; text, illustration, and hybrid; which highlight the possible type of questions for these keys. The generated tree is used for the examination of the test bank questions' suitability which is an additional step to ensure test bank stability. Additionally, the test bank questions are tagged with the suitable keywords targeting to build an ILOs based balanced exam.

1) Step 1: Key questions tags determination: The outcome of this step is determining the question tags that are included in the exams. the questions' tags set is built based on Bloom's Taxonomy Verb Chart [41]. Bloom Taxonomy has 271 verbs which are listed as Key question terms. These terms are tagged with the suitable category and skill which highlight that this term examines a certain skill and suitable for a certain category. Bloom's Taxonomy can be represented as a set of vectors, each vector includes the verb and the corresponding skill.

Bloom's Taxonomy = {<V_j, S_j>}

Where j $\in$ N

V_j is one of the Bloom verbs

S_j is the corresponding key skill, S_j $\in$ Skill, Skill = {knowledge and understanding, intellectual, practical}

The key questions' tags set is represented as follows:

KQues = {<T_i, S_i, C_i>}

Where i $\in$ N

T_i is a verb in the Bloom set which represents the question key

S_i is the corresponding key skill, S_i $\in$ Skill

C_i is the corresponding category, C_i $\in$ Category, Category = {short text, long text, figure}

2) Step 2: Key terms extraction: The main source to extract the questions' key terms is the course curriculum. The course curriculum which includes the Intended learning objects (ILOs) which describe the required topics for the course. For example, "Identify the principles of economics and management" is one of the ILOs of the database systems course. Analyzing this sentence to identify the main keywords leads to extracting a set of four keywords "identify, principles, economics, management". ILOs are analyzed to extract the main keywords of the course subject. Additionally, the course recommended textbook is also considered to expand the keywords' set. The recommended textbook is considered to match the extracted keywords with the book subjects' headings with also considering the subheadings as part of the main heading. The relation between the course ILOs and the textbook headings is the pillar of building a semantic network that fully considers the related course keywords.

Formally describing the tagged sentences is as follows:

$$\text{ILOTag } (S_i) = \{< K_1, Tag_1 >, < K_2, Tag_2 >, \ldots < K_n, Tag_n >\}$$

Where K_n is the token and tag_n is its attached tag

Extracting the subject key terms with the construction of the semantic network is presented by the following algorithmic steps.

// ILOs key terms semantic relations

For each ILO in the course description
Extract main terms
Apply terms' tagging
Identify verbs as the key question tags
Identify nouns as the key terms
Build key terms semantic relations (In-relation) where In-relation identify the terms in the same ILO
// Textbook key terms semantic relations
Extract headings' tree
For each heading level
For each heading
Extract main terms
Apply terms' tagging
Identify verbs as the key question tags
Identify nouns as the key terms
Build Level 1_Heading semantic relations (In-relation) where In-relation identify the terms in the same heading
Build Level 2_Heading semantic relations (parent-relation) where parent-relation identify the relation between headings' terms
// integrate Textbook-ILO network
For each key term in the ILO, identify synonym and antonym
Extract matched heading key term with ILO key term, synonym, and antonym
Integrate the two networks' branches
// Build Key terms/Key question tags semantic relation
For each key term in the key terms set
Identify synonym and antonym
Apply KeyTerm relation set
For each key question tag in the question tags set
Identify synonym and antonym
Apply QuesTag relation set
For each ILO
Identify ILO key term as K_i
Extract KeyTerm K_i relation set
Identify ILO verb as QT_i
Identify question tag QT_i relation set
Append Key terms/Key question tags semantic relation (K_i – QT_i)

3) Step 3: Building semantic based test bank: The test bank is a group of question sets. each set includes the questions that examine one of the course ILOs. In this step, building the test bank question sets is achieved. Each question in the test bank is tagged with an attribute vector. The vector includes time, mark, difficulty level, associated key terms set, associated key question tags set. The time, mark, difficulty level attributes are identified by the professor, while the associated key terms and questions tags are explored by applying the following algorithmic steps.

For each question in the question bank
Identify question key tags
Identify question key terms
Match question key terms with network members
If success
Tag the question with network members id
Identify the question ILO id
add question to ILO questions' set
Else
Raise an alarm

At the end of this step, each ILO id questions' set should have a group of members which are the questions that examine the ILO. If the ILO set is empty, then acquiring questions from the professor is applied.

C. Stage Three: Setting the Student Preference-based Exam

At this stage, the student exam is built according to his revealed skill. The questions are selected randomly from the corresponding categories based on the required number of questions and the determined exam time. The following algorithm steps are performed to build the required exam.

Given Student_Pref (STID)
Test_Bank = {<Pref, Skill, Difficulty, {< QID, QText, QDuration, QMark >}}
Set Exam_time
Set Exam_Grade
If Student_Pref (STID) ∈ {ShortText, LongText, illustration}
Questions_Set = select questions from Test_Bank where Category = Student_Pref (STID)
Else
Questions_Set = select questions from Test_Bank
Initiate Exam_test bank
Set courseSkillsSet
SkillTime = ExamTime / |courseSkillsSet|
SkillGrade = ExamGrade / |courseSkillsSet|
Set CourseDiffSet
While ALLQues_time < Exam_Time && ALLQues_Grade < Exam_Grade {
For each skill j in course_skills
Set ILO set
ILOTime = Skilltime / | ILO set |
ILOGrade = SkillGrade / |ILO set|
DiffTime = ILOTime / | CourseDiffSet|
DiffGrade = ILOGrade / | CourseDiffSet|
For Each ilo in ILO set
For each Difficulty i in course_Difficulty
While DiffQues_time < DiffTime && DiffQues_grade < DiffGrade {
Question = Random Choice (Questions_test bank) where Skill = j and Difficulty = I and ILO = ilo
If DiffQues_Time + Question.Question_Duration <= Diff_Time
&& DiffQues_Grade+ Question.Question_Grade <= DiffGrade
{
DiffQues_Time = DiffQues_Time + Question.Question_Duration
DiffQues_Grade = DiffQues_Grade + Question.Question_Grade
Append (Exam_Content, Question_Text)
AllQuesTime = AllQuesTime + DiffQues_Time
AllQuesGrade = AllQuesGrade + DiffQues_Grade }}}

IV. Experimental Case Study

The research has two validation milestones. First, validating the model success in exploring the suitable student's skill based on his social activities are performed while validating the constructed exam is also considered as the second milestone. The following sections discuss the case study setup, the performed steps, and the validation results.

A. Stage One: Exploration for the Student Preference

In this research, the dataset included the skills classification for 473 students. The dataset is based on the data which was provided in the research of [1]. The research of [1] included research that adapts the online system to satisfy the student. The original dataset included 752 students while the response was 631 students, and a satisfaction level with an average of 75 % of them have been satisfied with the proposed enhanced system with a total of 473 students in the online exam based on a series of conducted exams. The current research acquired the students' data who had been satisfied with a total of 473 students. The acquired data included all the personal and academic students' data. Extracting the required social data is performed through implementing a simple program and the data is stored as four attributes, student id, corresponding social user id, post content, post type. As a result of this process, the final experiment dataset included 380 students after removing the incomplete students' records.

A five-month range of public Facebook posts; starting from January 2018 to May 2018; have been gathered from the students' accounts. This short time range has been considered to avoid the large number of posts that may require extensive tools and software for big data which was not the scope of this paper. The posts' contents have been processed to detect the post type. The post type classification is illustrated in Table I.

The results have been compared with the results in [1]. This comparison has revealed 93% success for correct exploration to the student's most suitable skill. By analyzing the presented results, a focus has been performed on the incorrect classified students and the time period for their posts has been enlarged. A sample of these students' posts with a range of eight months starting from November 2017 to May 2018 has been extracted and the model has been applied for the student re-exploration. 40 % of these students have been re-classified to the correct skill. Therefore, this minor experiment revealed that the 7% failure in the correct classification was according to the short time range for the extracted social data due to the minor activity of the student in the three months on focus.

B. Stage Two: Semantic-based Question Bank Construction

This stage focuses on constructing the courses' questions' bank in a semantic-based format. This research argues that this proposed construction supports the applicability to generate a suitable balanced preference-based exam. The following subsections discuss the conducted steps in detail with demonstrating the required validation.

1) Step 1: Key questions tags determination: As previously discussed, the Bloom verbs are considered the question tags. 271 verbs are included in the key questions' tags set. For example, the key question term "Define" is suitable for the understanding skill and the text category. A sample of the taxonomy is illustrated in Table IV.

2) Step 2: Key terms extraction: The experiment focused on "systems analysis and design" course which are obligatory to the students in the information systems department. Table V illustrates the ILOs statistics for the courses on focus with examples for each course.

TABLE I. Post Types

Post Content	Type
Single Video or image	Illustration
Single text sentence where words' count is less than 10 words	Short text
Single text sentence where words' count is more than 10 words	Long text

According to this classification, the students' posts have been tagged with the appropriate class, a statistical illustration of the students' posts is presented in Table II, while another perspective of this classification was illustrated in Table III presenting the statistics of classified students based on their social activity.

TABLE II. Statistics of Posts

Type	Statistics
multimedia	445,584
Short text	420,254
Long text	239,901
Illustration & Short text	558,069
Illustration & Long text	168,704
Total	1,832,512

TABLE III. Statistics of Students

Type	Number of Students (%)
multimedia	70 (12.96 %)
Short text	62 (11.48 %)
Long text	40 (7.4 %)
Illustration & Short text	238 (44.07 %)
Illustration & Long text	130 (24.07%)
Total	540

TABLE IV. SAMPLE OF WORDNET VERBS CATEGORIES

Key Question Term	**Skill**	**Category**
write	Knowledge and Understanding	Long Text & Short Text
state	Knowledge and Understanding	Long Text & Short Text
outline	Knowledge and Understanding	Long Text & Short Text
classify	Knowledge and Understanding & intellectual	Long Text & Short Text
define	Knowledge and Understanding	Long Text
discuss	Knowledge and Understanding	Long Text
describe	Knowledge and Understanding	Long Text
identify	Knowledge and Understanding	Long Text
explain	Knowledge and Understanding	Long Text
summarize	Practical	Long Text
assess	Practical	Long Text
criticize	Practical	Long Text
differentiate	Practical	Hybrid
construct	intellectual	Hybrid
design	intellectual	Hybrid
compare	intellectual	Hybrid
solve	intellectual	Hybrid
develop	intellectual	Hybrid
apply	intellectual	Hybrid
draw	intellectual	Illustration
Sketch	Intellectual & Practical	Illustration

TABLE V. SAMPLE OF COURSES' ILOS

Course	**Skill**	**ID**	**ILOs**
Systems Analysis and Design	Knowledge and Understanding	1	Discuss specifications and strategic planning for a given project.
		2	Recognize different methods for data analysis and design.
		3	Illustrate management process for software projects and productions.
	Intellectual Skills	4	Analyze information systems problems, setting goals and requirements.
		5	Identify main ideas, patterns, components, attributes and detect relationships between these components in software analysis with different designs.
		6	Select appropriate methodologies and techniques for a given problem solution and setting out their limitations and errors
	Practical	7	Describe different analysis and design methodologies.
		8	Analyze system process and data requirements
		9	Apply different IS methodologies for analysis and design.

Text processing tasks have been applied to the courses' ILOs [42]. According to [43] the most suitable processing tasks for correctly extracting keywords that ensure avoiding conflict or missing the word's meaning are lemmatization and part of speech tagging.

Consequently, lemmatization and Part of Speech tagging (POS) are applied for the ILOs, nouns are extracted as keywords and indexed. As a result, each ILO is tagged with two references, the skill Id, and the set of corresponding keywords' Ids. For Example, ILO text "Discuss specifications and strategic planning for a given project" has the following two steps:

Lemmatization: "Discuss specification and strategic planning for a give project"

POS tagging: $\text{ILOTag}\,(ILO_i) = \{<\text{Discuss}, \text{V}><\text{specification}, \text{NNS}><\text{and}, \text{CC}>, <\text{strategic}, \text{JJ}><\text{planning}, \text{NN}><\text{for}, \text{IN}>, <\text{a}, \text{DT}><\text{give}, \text{VBN}><\text{project}, \text{NN}>\}$

The ILO is then tagged with the set of keywords' Ids which are: "specification", "planning", "project" in addition to the skill id. Moreover, synonyms and antonyms of the specified terms are identified and included in the set members. Statistically speaking, the experiment included a total of 9 ILOs, a total of the extracted keywords equal to 26. Each ILO was tagged with a range of 2 to 7 keywords. At the end of this stage, the relation between the ILOs and the corresponding keywords is revealed for each course.

3) Step 3: Building semantic based test bank: In this stage, the relation between the test bank questions and the ILOs are explored based on the extracted keywords. It is recommended that the test bank for each course included 300 questions. Each question is tagged with one of the three types (short text, long text, multimedia) according to its key question tag. Tagging each question with its corresponding keywords is then applied.

According to [44], bi-gram keywords provide the highest accurate accuracy. Therefore, uni-gram keywords and bi-gram keywords are constructed, then, the matching process is applied. Each question is tagged with two keywords subsets, the first subset includes the matched uni-gram keywords while the second includes the matched bi-gram keywords. the following example is a sample of the performed process while Table VI presents a statistical presentation with the step results.

Question: A system request will generally have these items: project sponsor; business need; business requirements; business value; special issues or constraints

Keyword (s): system, request, project, sponsor, business, need, requirement, value, issue, constraint

Matched bi-gram Keyword (s): (system, problem), (system, requirement), (requirement, problem), (problem, limitation), (problem, error), (limitation, error).

Matched ILOs ID: 4, 6, 8

Validating the tagging process has been performed by the course professors. The validation process has confirmed the higher accuracy in tagging the questions with bi-gram keywords, therefore, following the bi-gram keywords' tagging was the main path to the next phase for constructing the student's exam.

Table VII demonstrates the evaluation criteria and the evaluation percentage according to the professors' perspective. It is shown that the proposed model has succeeded in classifying the test bank questions with an average success percentage equal to 96.6 %.

TABLE VI. A STATISTICAL PRESENTATION WITH THE STEP RESULTS

	Systems analysis and design
Short text questions	150
Long text questions	94
Illustration questions	56
Average questions / ILO	33

TABLE VII. TEST BANK VALIDATION

No of questions that are classified to the correct skill(s)	582
No of questions that are classified to the suitable ILO(S)	570
No of questions that are tagged by the suitable keyword(s)	588

C. *Stage Three: Setting the Student Preference-based Exam*

As mentioned in [45], the stakeholders' satisfaction is one of the main objectives for organizations in any field. Therefore, this research targets not only moving in the right track for the smart testing paradigm but the students' satisfaction, as well as the professors' satisfaction, are also essential objectives for this research. Therefore, generating the preference-based exams for the students has been applied and validated by both the professors and the students as follows:

A focus on the successfully classified students is performed, fifty successfully classified students have been randomly selected for testing the stage of generating a suitable exam. The selection process ensured the variety of the students' preferences. As previously illustrated, five categories are considered, therefore, twenty of the students/preference/course have been targeted. Generating the exams followed the proposed algorithmic steps and the constructed tests have been reviewed by the course professors. Table VIII demonstrates the statistical measures of the conducted exams. It is shown that the proposed model has succeeded in generating a suitable exam for the students with an average success percentage equal to 96.5 %. The 3.5 % failure goes to the lack of questions that could be required to complete the exam time or the exam grade, therefore, the experiment has been revised after feeding the test bank with an additional 50 questions for each course that has a variety in the marks distribution and required time. This adaptation has filled the required gab and the exams were successfully generated based on the professors' evaluation.

On the other hand, the students' satisfaction has been measured and the results are demonstrated in this section. Conducting two generated exams have been developed, first a randomly generated exam without considering their preferences and a randomly generated exam after applying the proposed model. The results are presented in Table IX while illustrated in Fig. 1- 3.

TABLE VIII. EXAM VALIDATION

Total No. of generated exams	50
No. of exams that are correctly generated	48
Average No of questions / Student	25
Minimum No of questions / Student	19
Maximum No of questions / Student	40

TABLE IX. COMPARISON FOR THE AVERAGE STUDENTS' RESULTS

	Excellent		**Very Good**		**Good**		**Fair**		**Fail**	
	No	%	No	%	No	%	No	%	No	%
Random Exam	6	12	8	16	16	32	9	18	11	22
Model-Based Exam	16	32	10	20	14	28	5	10	5	10

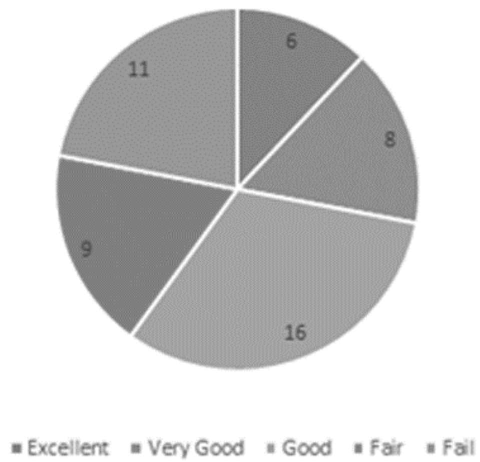

Fig. 1. Random Exam Results' Distribution.

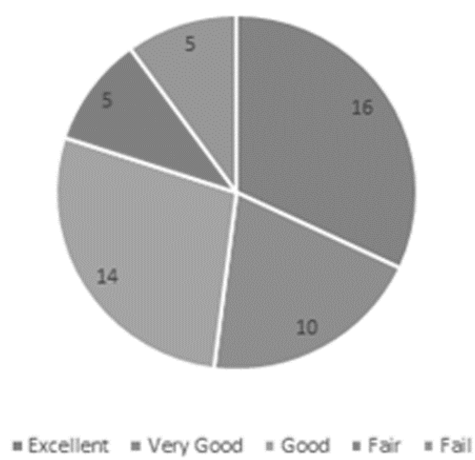

Fig. 2. Model-based Exam Distribution.

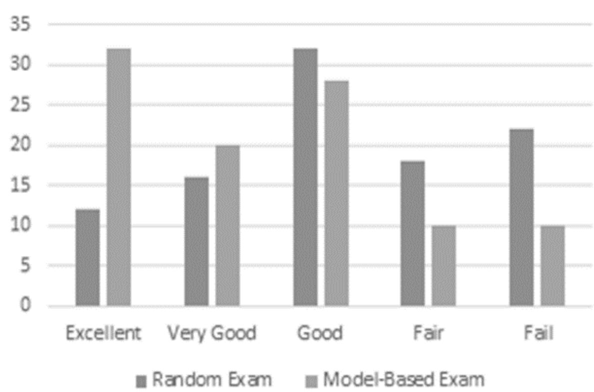

Fig. 3. Comparison between the Two Exams' Results (Random Exam and Model-based Exam).

V. Conclusion

This study proposed a student personalized exam model which is based on two main approaches. The first approach focuses on exploring the student's personalization characteristics targeting to detect his questions' preferences. This target has been on focus to ensure the questions' types suitability for the student which leads to a higher evaluation accuracy to the student learning level. The second approach utilizes text analytics techniques in different goals. It contributes to revealing the student preferences in addition to its contribution in constructing the exam contents. The proposed model considers the balance while generating the student exam according to different criteria including the difficulty level, the intended learning outcomes coverage, the required time, and the degrees' distribution in addition to the student's preferences. According to the experiment evaluation results, the proposed model succeeds in reaching 96.5% of the professor satisfaction in the constructed exams.

The proposed model confirmed its effectiveness in approaching smart testing, however, enhancement directions can further contribute effectively to the same direction. One of the proposed enhancements is considering the students' emotions which provide more accuracy to his on-time preferences. Another direction is the automated generation to the questions' banks to ensure the full course coverage. Finally, the current research relied on the highest student preference, considering the preferences according to its adequacy level could be an effective enhancement to ensure the full smart testing perspective coverage.

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AUTHORS' PROFILE

Ayman E. Khedr, Professor. I am currently a professor in the university of Jeddah, College of Computing and Information Technology at Khulais. I have been the vice dean of post-graduation and research and the head of Information Systems Department in the Faculty of Computers and Information Technology, Future University in Egypt. I am a professor in the Faculty of Computers and Information, Helwan University in Egypt. I have previously worked as the general manager of Helwan E-Learning Center. My research is focused around the themes (scientific) data and model management, Data Science, Big Data, IoT, E-learning, Data Mining, Bioinformatics and Cloud Computing.

Abdulwahab Ali Almazroi, Associate Professor, received his M.Sc. and Ph.D. in Computer Science from the University of Science, Malaysia, and Flinders University, Australia, respectively. He is currently serving as an Associate Professor in the Department of Information Technology, College of Computing and Information Technology at Khulais, University of Jeddah, Saudi Arabia. His research interests include parallel computing, cloud computing, wireless communication, and data mining.

Amira M. Idrees, Professor. I'm a professor in Data Science, the head of information systems department, faculty of computers and information technology, Future University in Egypt. I have been the head of scientific departments and the vice dean of the community services and environmental development, Faculty of Computers and Information, Fayoum University. I'm currently an associate professor in the Faculty of Computers and Information Technology in Future University and the head of University Requirements Unit. My research interests include Knowledge Discovery, Text Mining, Opinion Mining, Cloud Computing, E-Learning, Software Engineering, Data Science, and Data warehousing.