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RESEARCH ARTICLE

A Smart Testing Model Based on Mining Semantic Relations

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ABSTRACT Engaging personalization in the education process is considered one of the success factors for raising the educational process quality by altering the educational institutions' vision for gaining more flexibility while attaining the institution's objectives. It is a fact that the situation of the COVID-19 pandemic is one of the main reasons that forwarded attention to online learning as an obligatory path rather than being optional until the arisen situation of the COVID-19 pandemic. This situation has altered the educational institutions' perspective permanently. This research proposes an intelligent model which considers the personalized student characteristics in exploring the student learning styles variation, then considering this variation in building the student exam. Following this model ensures the compatibility of the conducted exam with the student's capabilities as well as the course Intended Learning Outcomes (ILOs) coverage. The balance in building the exam with covering the course objectives as well as the appropriateness with the student's personalized characteristics is the main objective of this research. The proposed model has been applied and proved its applicability in enhancing the students' exam results to 92.36% and raising the exam quality level.

INDEX TERMS Students' personalization, text mining, e-learning, similarity, term frequency, intended learning outcomes (IOLs), learning styles.

I. INTRODUCTION

Online education is currently no longer a luxury path to follow [1]. There are many situations in which the online educational systems could be considered as the survival obligatory path for educational process continuity [2]. One of these situations is the COVID-19 pandemic which forced all educational institutions to hold the on-campus education process and lead to apply the online educational systems. However, the vital effect of applying online education is not only restricted to crisis situations, but it also proved its applicability and effectiveness in the educational process. This situation has led the decision-makers to announce their intention for strategic adaptation to continue working in the same direction [3]. This strategic transformation revealed the necessity not only for applying the teaching process using online systems but for the evaluation process as well. Therefore, different approaches could contribute to supporting education through intelligent mining techniques [4], [5], [6].

On the other hand, although personalization is not a novel term to highlight, however, engaging the personalized characteristics of the educational field stakeholders is a factor that many researchers tackled as a significant research direction [7]. Focusing on students, personalizing students' engagement in the learning process leads to raising the success level for the process milestones [8]. Personalization may be introduced in the educational process, material, learning method, as well as evaluation process. As discussed in [9], engaging the students' characteristics in the process ensures the students' willingness and enthusiasm. Focusing on the students' online exams, the authors claim that personalizing the students' exams to be more relevant to the student's personality as well as capabilities strongly leads to raising the evaluation process quality [7]. Education personalization has positively affected the learning process as discussed in prior

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research such as in [10]. The direction of personalizing the students' exams leads to a focus on evaluating the students' information accumulative degree by removing all the tackles such as the inappropriate questions' distribution or style [11] which ensures equal opportunities for all students [12]. The exams' personalization direction has been recently tackled as in [13] which confirmed that personalizing a preparatory exam for the students supports them in raising their grades in the following exams. In addition, research in [14] confirmed that students could predict their scores in exams which highlight the students' applicability in identifying their weaknesses and strength either in the scope or in their ability to respond to questions. This research [14] was one of the motivations for the authors of the current study to investigate the students' applicability in identifying the suitable exam questions' types with neutralizing the course scope. Moreover, the study in [15] discussed the impact of exam-taking strategy on the students' scores that reflect their course performance. The study highlighted the lack of research in this area and investigated different factors affecting exam scores. Although the research focused on this vital research area with the scope of the behavior during the conducted exam, however, it highlighted the direction of investigating the students' affecting factors for raising their performance. The research gap was highlighted in [16], which tackled the fact that prior research focused on personalization in the learning material by highlighting whether test fairness would lead to higher student performance. The research was one of the inspiring research which raised the current research question that focused on test fairness by introducing the concept of test personalization.

The remaining of the research discusses the related work in section II, then the proposed model is discussed in section III followed by the experimental study in section IV. The results, discussion, and implications are discussed in sections V and VI respectively. Finally, the conclusion is discussed in section VII.

II. RELATED WORK

The online education process has been tackled by many researchers such as in [17], [18], and [19]. The research in [20] focused on the operating learning process and proposed that the student's activities have performed during the ongoing process. Although their proposed approach could positively tackle the required activities, however, it was later criticized by the research in [21] which highlighted the weakness of the previously proposed approach by not considering the routine student's behavior. Another research by [22] applied a tracking approach to reveal the student learning style by conducting a set of exams. Although the approach was successfully applied, however, it did not consider other factors including the strength level and the exam variations.

Moreover, research in [21] focused on the students' improvement by proposing a set of recommendations. Another research by [23] also focused on the same recommendations' objectives but from another perspective, the research applied the proposed approach at Fayoum University to highlight the suitable educational direction for students individually. Other intelligent techniques are applied in different research such as associations in [24], Bayesian technique [25], and evolutionary algorithms [26]. Additionally, the student learning path has been on focus of the research [27], the path was determined by identifying the student learning capabilities. In the same direction, research by [28] proposed a plan recommendation for the student, however, the focus was only on the learning process without considering the evaluation path. As intelligent techniques included text analysis, some research highlighted this direction contribution such as in [29] which proposed a method for estimating the appropriate time exam by the exam content analysis, the research considered only the exam time with not considering other criteria whether in the exam or the examinee. Text analysis also contributed to identifying the plagiarism percentage in the students' exams' responses which was a direct application to the field of text analysis [30].

Additionally, students' personalization approach has been discussed from different perspectives. A direction in identifying the student's personality during conducting exams, others focused on social activities [31], [32], while a third direction targeted the student's daily activities [33], [34]. An example of research that targeted personalization is in [35] by conducting a set of questionnaires. More recently different research papers supported online education such as in [36] which aimed at identifying the adequate learning strategy plan for individuals in International Computer Driving License courses (ICDL) for enhancing their level. Another recent research [37] confirmed the deep learning contribution to more effective stakeholders' interactions in online education.

A literature review has been provided in [38] which discussed different research for e-learning. As discussed in [38], most of the research focused on the courses' contents, while few researchers tackled the exams' aspects. In [39], machine learning algorithms have been applied to raise the accuracy percentage in predicting the students' results, however, the current research tackles the exams' aspects in building the exam as a pre-step to ensure the students' high performance. Another research tackled the same direction in [40], which tracked the student activities participation, interaction level, and utilization level. The main target of the research was to explore the teaching method and student activities during the education process.

Different research such as in [41] has confirmed the effectiveness of applying machine learning approaches in digital education for performing intelligent tutoring, raising prediction tasks' performance, working with learning styles, and automation in general.

As mentioned in [42], although automated tests could be considered a vital advance in e-learning, however, to date, the use of automated methods for item development and test construction has been limited. The same research also tackled the perspective of personalized learning which is characterized to be meaningful and relevant to learners, driven by their interests and often self-initiated. Education personalization has been recently discussed in [43] for generating the students' study plan and confirmed the need for personalized learning.

The research in recent literature in [44] provided comprehensive literature about personalization in education and discussed the affecting factors for successful personalized learning and highlighted the research issues which included that emerging technologies in personalized education are still an open area for research. It is confirmed in different research that is discussed in [44] that previous studies focused only on learning methods and material while other aspects are vital that still require more investigation, these aspects include the use of technology, the assessment of students, and others. In the current research, the aspects of using recent intelligent methods to improve the students' assessment are tackled following the open issues in the education personalization field.

III. THE PROPOSED SMART TESTING MODEL BASED ON MINING SEMANTIC RELATIONS

The proposed approach focused on exploring the relationship between three parties, which are the student's personalized data represented in his/her previous grades' history and response to questionnaire's questions, the learning styles variation, and the available test bank questions. The proposed approach aims at providing the student with an exam that follows the available learning styles with respect to the student's preferences. The main contribution of the proposed approach is that it considers all the learning styles of the student based on their weight rather than following one learning style. The following subsections discuss the proposed approach in detail.

A. DESCRIPTION OF THE PROPOSED APPROACH

The description of the main parties is illustrated as a set of members. The learning styles questionnaire which is one of the main sources in exploring the student style is identified as a set of questions. It is a fact that different learning styles models are previously introduced, however, the current research follows the VARK model (visual, auditory, reading and writing, and kinesthetic) as one of the pioneers. Formula 1 represents the formal description of the VARK questionnaire. The general description of the learning styles set is identified in formula 2 with no limitation for the number of the set members. As the current research focuses on the VARK model, therefore, the learning styles set included four members.

The set of VARK questionnaire questions

$$\mathrm{VARK} = \{\mathrm{vq}_1, \mathrm{vq}_2, \ldots .\mathrm{vq}_{16}\} \tag{1}$$

The set of all learning styles

$$\mathrm{LS} = \{\mathrm{LS}_1, \mathrm{LS}_2, \ldots, \mathrm{LS}_\mathrm{x}\} \tag{2}$$

On the other hand, focusing on the course details, the course ILOs description is represented as a set of ILOs members in formula 3, while the question bank is described in formula 4 as a group of sets, each set representing the set of questions that follow a defined learning style. Finally, the complete question bank is represented in formula 5.

The set of the course ILOs

$$\mathrm{ILOS}\ (\mathrm{C}) = \{\mathrm{ILO}_1, \mathrm{ILO}_2, \ldots, \mathrm{ILO}_\mathrm{g}\} \times \text{where c is the course under study} \tag{3}$$

Question bank (qb) description for each learning style

$$\mathrm{qb}(\mathrm{LS}_\mathrm{x}) = \{q_{\mathrm{x}1}, \mathrm{q}_{\mathrm{x}2}, \ldots, \mathrm{q}_{\mathrm{xy}}\} \tag{4}$$

The complete question bank (QB) description for all learning styles

$$\mathrm{QB} = \bigcup\nolimits_{i=1}^{x} qb(LS_x) \tag{5}$$

Moving to the processed data representation. The questions are identified as a set of individual tokens, then these tokens are then transformed into a set of key terms. Formula 6 and 7 represent the mentioned descriptions, respectively. The key terms set description follows the approach proposed in [45] which identified that the acceptable n-gram of the key term is to be a maximum of two targeting the highest possible accurate results. Formula 8 formally represents all the learning styles' key terms while formula 9 represents the complete set of key terms in the questions that belong to the question bank and follows any of the associated learning styles.

The complete description of the test bank including all the questions that belong to all learning styles is described in formula 8

The question q_{xy} tokens' set

$$\mathrm{Tokens}(q_{\mathrm{xy}}) = \{\mathrm{Tok}_{\mathrm{xy}1}, \mathrm{Tok}_{\mathrm{xy}2}, \ldots, \mathrm{Tok}_{\mathrm{xyz}}) \tag{6}$$

The question q_{xy} key terms' set

$$\mathrm{KT}(\mathrm{q}_{\mathrm{xy}}) = \{\mathrm{KT}_{\mathrm{xy}1}, \mathrm{KT}_{\mathrm{xy}2}, \ldots, \mathrm{KT}_{\mathrm{xyz}}) \tag{7}$$

where:

Generally, $\mathrm{KT}_{\mathrm{xyz}} = < \mathrm{Tok}_{\mathrm{xya}}, \mathrm{Tok}_{\mathrm{xy(a+1)}}, \ldots, \mathrm{Tok}_{\mathrm{xyb}} >$, $\mathrm{b} = \mathrm{a+f}$

$\mathrm{KT}_{\mathrm{xyz}} \in \mathrm{Tokens}(\mathrm{q}_{\mathrm{xy}})$, $1 <= |\mathrm{KT}_{\mathrm{xyz}}| <= 2$ (meaning $\mathrm{f} = 1$)

The set of all learning style key terms

$$\mathrm{KT}(\mathrm{LS}_\mathrm{x}) = \bigcup\nolimits_{i=1}^{y} KT(q_{xi}) \tag{8}$$

The set of all question bank key terms

$$\mathrm{KT}(\mathrm{QB}) = \bigcup\nolimits_{i=1}^{x} KT(LS_x) \tag{9}$$

Identifying the set of tokens for each ILO as well as the set of key terms follows the same approach. The representation of both sets is described in formula 10 and 11 respectively, while the complete key terms set for all ILOs is represented in formula 12.

The ILO_g tokens' set.

$$\text{Tokens}(ILO_g) = \{Tok_{g1}, Tok_{g2}, \ldots, Tok_{gf}) \quad (10)$$

The ILO_g key terms' set.

$$KT(ILO_g) = \{KT_{g1}, KT_{g2}, \ldots, KT_{gd}) \quad (11)$$

where

Generally, $KT_{gd} =< Tok_{ga}, Tok_{g(a+1)}, \ldots, Tok_{gb} >$, b = a+f

$KT_{gd} \in$ Tokens (ILO_g), 1 <= | KT_{gd}| <= 2 (meaning f = 1)

The set of all ILOs' key terms.

$$KT(ILOS(C)) = \bigcup_{i=1}^{g} KT(ILO_i) \quad (12)$$

Formula 13 represents the set of questions that support a defined ILO while the set of all questions with their associated ILO is represented in formula 14. It is worth highlighting that the model followed the non-redundancy approach in associating the questions with ILOs. This means that each question is associated with only one ILO. In case a question satisfies more than one ILO, then it is associated with the highest weighted one. Nominating the question to be a member in the questions' set of a defined ILO is performed by executing a set of steps that are described in section III-B.

The set of questions for ILO_g following the learning style 'LS_x'

$$qb(ILO_g|LS_x) = \{q_{g1}, q_{g2}, \ldots, q_{gv}\} \quad (13)$$

where $qb(ILO_g) \subseteq qb(LS_x)$, $LS_x \in LS$

The set of questions for each ILO (ILO_g) follows all learning styles.

$$QB(ILOS(C)) = \bigcup_{i=1}^{g} qb(ILO_i) \quad (14)$$

B. EXAM SETUP

The exam is prepared by applying two main phases. The first phase focuses on identifying the learning styles' weight for each student individually based on his/her personalized data and the course data. Moreover, phase 2 focuses on preparing the exam for each student based on the explored weighted learning styles in phase 1. The remaining of this section identifies the processed steps in an algorithmic representation.

1) PHASE 1: BASIC EXAM DATA IDENTIFICATION

Step (1): Identify the set of ILOs ILOS (C) of course 'C'

Identify the set of Learning styles LS of course 'C', |LS| = t

Identify the required number of questions for the exam 'e' (qr_e)

for each student 'St_i'

Step2: calculate learning styles weight 'qw_{xi}' of each learning style 'ls_x' (weight ($ls_x|St_i$) = qw_{xi}) based on the questionnaire response where $\sum_{e=1}^{x} qw_{ei} = 1$

Retrieve student St questionnaire response Ans (St) = $\{a_1, a_2, \ldots a_{16}\}$ where each answer a_x is the answer for the corresponding question vq_x, 1<=x<=16

For each questionnaire learning style LS_x, weight 'qw_{xi}' = Total Number of answers following the learning style LS_x/ |VARK|

Step3: calculate learning styles weight 'ew_{xi}' of each learning style 'ls_x' (weight (ls_x|$student_i$) = ew_{xi}) based on the student's previous exams' grades where $\sum_{e=1}^{x} ew_{ei} = 1$

Retrieve student i grades for the courses' exams' questions

The exam questions for the course Ci = $\{q_b, \ldots q_w\}$

The exams questions' set for all courses EC = $\bigcup_{j=1}^{i} C_j$

All questions grades for all courses grades

grades (i) = $\bigcup_{i=1}^{s}$ grades($i|C_x$)

For each course, grades (i| C_s) = {<q_{s1}, $grade_{s1}$ >, ..., <q_{so}, $grade_{so}$ >}

For each question q_{so} in course C_s exam where < q_{so}, $grade_{so}$ >∈ grades (i),

Identify the similarity set for the question q_{so} and each learning style LS_x

Similarity (q_{so}) = $\{sim_{so1,\ldots} sim_{sox}\}$ where

sim_{sox} = similarity (($KT(LS_x)$, $KT(q_{so})$), $Tag(KT(q_{so}))$ = VB

The learning style LS_v for the question q_{so} where

$W(LS_v|\, q_{so})$ = earned grade/max grade

$QSet(LS_v) = QSet(LS_v) \bigcup q_{so}$

For each learning style LS_x

$EW_{xi} = \sum_{i=1}^{o} Wqs_i)/\ |QSet(LS_v)|$

Step 4: The final LS_x learning style weight for student i is:

$W(LS_{xi}) = Avg((EW_{xi}+qw_{xi}))$

Step5: The set of learning styles weight for student i is:

LS (i) = $\{W(LS_{1i}), \ldots, W(LS_{xi})\}$

Step6:

Identify the number of questions (qr_{ex}) for each learning style 'LS_x' based on the learning style weight. qr_{ex} = $qr_e \times W(LS_{xi})$

Identify the number of questions for each ILO 'ILO_g' following the learning style 'LS_x' ($QILO_{gx}$) where $QILO_{gx}$ = qr_{ex}/g, g is the number of ILOs.

2) PHASE 2: EXAM CONTENTS PREPARATION

Step1: Prepare the learning style LS_x questions' set

For each question q_{xy} where $q_{xy} \in$ QB, q_{xy} is nominated to be a member in $qb(LS_x)$ where

$\exists \mathbf{t}, \mathbf{t} \in KT(LS_x) \wedge \mathbf{t} \in KT(q_{xy}) \wedge$ Tag (**t**) = **"VB"**

Step 2: Prepare the ILOs questions' set for each learning style LS_x

For each question q_{xy}, $q_{xy} \in qb(LS_x)$, q_{xy} is nominated to be a member in $qb(ILO_g|\, LS_x)$ where similarity (($KT(ILO_g)$, $KT(q_{xy})$) > Min_Th, Min_Th is the minimum similarity threshold.

Formally, $qb(ILO_g|LS_x) = qb(ILO_g|\, LS_x) \bigcup \{q_{xy}\}|$ similarity (($KT(ILO_g)$, $KT(LS_x)$) > Min_Th, Min_Th, $Tag(KT(ILO_g))$ = VB

Step 3: select questions based on learning styles' weights w_{xi}

For each ILO_g, select the questions from each ILO_g questions' set following each learning style LS_x based on LS_x weight.

$\text{Sub\_Exam}(ILO_g|\ LS_x\ ) = \text{Select } QILO_{gx}$ random questions from $qb(ILO_g|\ LS_x)$

Step4: prepare sub_exam for each learning style (LS_x)

$\text{Sub\_Exam}(LS_x) = \bigcup_{i=1}^{g} \text{Sub\_Exam}(LS_x|ILO_i)$

Step5: prepare the student St exam

$\text{Exam (St} \mid \text{C)} = \bigcup_{i=1}^{h} \text{Sub\_Exam}(LS_x)$.

According to the presented steps, each student will conduct the exam in which questions are selected according to the student's learning style preferences. Section IV discusses the experimental study which describes how the proposed model is applied while section V presents the results of the students' exams to clarify the applicability of the proposed model.

IV. EXPERIMENTAL STUDY

The experiment is conducted in a course titled ''systems analysis and design'' in which 671 students registered in the course. As discussed in [46], raising the educational system quality is a vital aim for all educational institutions. Therefore, seeking quality accreditation has become one of the main objectives. Reaching this aim is performed through the assessment of the different aspects of the educational process including the students' performance. ABET accreditation is one of the main targets for educational institutions in all countries. As mentioned in [46], students' assessment with the target of continuous improvement is one of the main ABET requirements to grant accreditation. It is performed by evaluating their progress in the courses that participates in the continuous improvement plan. According to [46], this evaluation is performed through different methods including exams' questions which marks are transformed into assessment scores. Therefore, the current research follows the ABET assessment methods in the evaluation process by measuring the student's progress through the exams' method.

The proposed approach has been followed and the remaining of this section discusses all the details.

A. BASIC DATA

The set of students is distributed over three groups as presented in table 1. The aim of presenting the students into groups was for follow-up reasons. However, students were originally distributed in groups, each has a range from 60 to 80 students. The students' grades' history was collected based on the midterm and quizzes for the same course while the plan was to apply the proposed approach on a final quiz. On the other hand, as highlighted in formula 2 (VARK Questions' set), a total of 16 questions are included in the questionnaire. As the kinesthetic style is not applicable to the written exam, therefore, the experiment only included the remaining three styles (Visual, Aural, and Written). Moreover, table 2 presents each style with the corresponding questions' types. For example, the question for the ILO of systems analysis and design course ''Select appropriate methodologies and techniques for a given problem solution and setting out their limitations and errors'' satisfies the auditory learning style by multiple choice question while it could satisfy the writing style by amending the question with a justification query and the visual style by selecting the correct illustration of the suitable methodology.

TABLE 1. Statistics representing the experiment dataset.

	Total
Group 1	100
Group 2	423
Group 3	148
Total	671

TABLE 2. Mapping the learning styles with questions' types.

Kinesthetic	Visual	Auditory	Writing/Reading
-	Images	Short answers (images/text)	Long text answers

B. IDENTIFYING THE KEY TERMS (PREPARATORY PHASE)

Identifying the Key terms included three directions, the key terms for the learning styles, the course ILOs, and the Questions.

1) LEARNING STYLES' KEY TERMS IDENTIFICATION

The learning styles' key terms are identified from the Bloom Taxonomy verbs (VBs) [47]. A total of two hundred and seventy-one VBs are considered as key terms for the learning styles which are a total of 271 distributed along the four styles. Table 3 presents examples of these taxonomy key terms. It is worth clarifying that some of the VBs were active for more than one style such as ''design'' which is applicable to either design a figure which follows the visual style or design an algorithm that follows the writing/reading style, however, it is considered that it only follows one style to raise the output accuracy.

2) COURSES' KEY TERMS EXTRACTION

The course syllabus was the source for the ILOs. The tokenizing of each ILO is performed as a direct natural language processing process in addition to the part of speech tagging. Moreover, the tokenization process is extended to remove redundancy, stop words, numbers, symbols, and special characters such as (brackets, hyphen, etc). Other enhancements are performed such as replacing abbreviations with the original terms such as XP with Extreme Programming. This step has been performed under the supervision of the instructor to confirm the correct scientific terms. Moreover, while the research in [48] argued that extracting key terms could be conducted with no required resources, however, in the research of Othman and his colleagues [49], it is argued that the key terms extraction; which is the main target; requires executing part of speech tagging which was already

TABLE 3. A sample of the learning styles' Key terms.

Key Question Term	Learning Style
write	Writing/ Reading
state	Writing/Reading
outline	Auditory
classify	Auditory
define	Writing/Reading
discuss	Writing/Reading
describe	Writing/Reading
identify	Writing/Reading
explain	Writing/Reading
summarize	Writing/Reading
assess	Writing/Reading
criticize	Writing/Reading
differentiate	Writing/Reading
construct	Visual
design	Visual
compare	Writing/Reading
develop	Visual
draw	Visual
Sketch	Visual

TABLE 4. A sample of the ILOs' key terms.

ILO	Uni-gram Key terms	Bi-gram Key terms
Discuss specifications and strategic planning for a given project.	Discuss/VB, specification/NNS, strategic/JJ, planning/NN, project/NN	"Specification strategic", "strategic planning", "planning project"
Illustrate management process for software projects and productions.	Illustrate/VB, management/NN, process/NN, software/NN, project/NNS, production/NNS	"Management process", "process software ", "software project", "project production"

performed as well as lemmatization which confirms the tokens' unification. Therefore, and as this is not the scope of the research, a decision has been made to follow the approach in [49] to ensure the extraction process's accuracy. Moreover, developing the key terms is then performed following the n-gram heuristic-based approach by building uni-gram key terms as well as bi-gram key terms from each ILO. The bi-gram key term includes two tokens that successively exist in the original ILO. The proposed approach considered only the bi-gram key terms following the approach proposed in [45] which applicability is also confirmed in [50] and [51]. Extracting the key terms of the course followed the method proposed in [49]. According to followed approach, a total of 56 uni-gram key terms and 36 bi-gram key terms are identified. Table 4 illustrates a sample for extracting the Key terms results.

3) QUESTIONS' KEY TERMS EXTRACTION

The course test bank for the experiment included 300 questions, with 100 hundred questions for each learning style. It is worth highlighting that the question difficulty level is not considered an evaluation factor. Therefore, all questions had the same difficulty level. Moreover, the number of questions for each student is set to be thirty questions. Extracting the questions' tokens is applied targeting to match the questions with their associated ILOs. The extraction process followed the same approach as in section IV-B2. In this level, eliminating redundancy is only applied in the context of associating tokens for a single question. This means that the same token can be included in more than one question's token set. The key terms are developed by also following the n-gram heuristic-based approach.

C. EXAM SETUP (INTERMEDIATE PHASE)

As previously described, exploring the student learning style is performed using a two-step method. Conducting students' questionnaire and considering the previous exams' results.

As a first step, the questionnaire was distributed to the students. The total number of students who received the questionnaire is illustrated in table 5 (Total). The questionnaire was adopted from [52] Responding to the questionnaire was optional, the students answered the questionnaire voluntarily with no obligation to any further contact. Therefore, not all students responded, moreover, some responded without answering all the questionnaire questions. The experiment included only the students who wrote their names to be able to compare their grades. The count of students whose response is considered in the experiment was illustrated in table 5 (Considered). The final number of students who were applicable to participate was 563 students. The remaining students either did not fully or partially respond to the questionnaire or their previous grades' data were not available as they did not write their names in the questionnaire (see table 5).

TABLE 5. Statistics representing the experiment dataset.

	Total	Considered
Group 1	100	86
Group 2	423	392
Group 3	148	85
Total	671	563

According to the questionnaire results, each learning style is weighted for each student according to the student's response to the questionnaire. A sample for the learning styles weighting calculation based on the questionnaire response is presented in table 6 with noticing that the adapted percentage is calculated after excluding the Kinesthetic Style and re-calculating the remaining styles with the base of 100.

On the other hand, the second step focused on the student's grades of previous exams. These grades are collected from the previously conducted exams of the same course. For more

TABLE 6. A sample of a student's response.

circled	No	Percentage	Adapted percentage
V	4	25	31
A	3	18.75	23
R	6	37.5	46
K	3	18.75	--

explanation, the students had conducted different quizzes prepared using a set of questions without considering the student preferences. These exams are marked and the average mark was considered to be compared with the exam following the proposed approach. The questions of the previous exams followed the same approach in extracting the corresponding key terms for each question. In addition, the correspondence learning style is identified based on the keywords with an associated tag equal "VB". After identifying the learning style for each question, the student grades for each question represented a contribution to the learning style weight. The final student learning styles' weights is then determined by calculating the average weight for both steps. The weight is determined based on the students' grades history and the student's questionnaire responses.

D. APPLYING EXAM (TESTING PHASE)

Preparing the testing phase exam is conducted for each student with the required number of questions for each learning style based on the learning style weight for this defined student. The thirty questions are randomly selected from the test bank learning style sets according to the learning style weight with respect to the ILOs distribution as illustrated in the example in table 7.

It is worth mentioning that the exam questions in the testing phase were extracted from the same questions' bank. However, the discriminative aspect is that each student had the exam questions' type according to the explored personality. The difference between this phase and the previously conducted exams is that the questions in the previous exams were pure randomly selected for the students while in the testing phase exam, the questions' set could be considered a subset of the questions' bank according to the explored student' personalized questions' type. This strategy ensures exam fairness in the difficulty level between the previous exams and the test phase exam to ensure the results' applicability.

TABLE 7. A sample of a student's learning styles weighting.

	Visual	Auditory	Writing/Reading
Learning Style Weight Distribution	20	25	55
No of Questions for each learning style	6	7	17
No ILOS covered in each style (out of 9)	6	7	9

The experiment considered all ILOs with the same importance, therefore, regarding a defined learning style, in case the number of questions is less than the number of ILOs, then questions that refer to ILOs are selected randomly with considering one question to each ILO.

V. EXPERIMENTAL RESULTS

In order to prove the success of the proposed model, the conducted exam results have been compared with the student's average grade which is earned from the previously conducted exams (student's grades' history) as illustrated in table 8. The grades' history was collected from a set of conducted exams in the same course by the instructor with no consideration of the students' responses to the questionnaire. In the testing exam, with respect to the offered number of questions, the same question was provided in the test bank considering the type. For example, a question about the suitable software development methodology is offered in the exam by three different methods, a multiple choice question to select the suitable methodology for a certain situation, a justification for more elaboration, and an illustration. Each type was offered to the corresponding student with the same marking level to ensure as much equal evaluation as possible. A graphical representation of the students' results' distributions and the grades' distribution is presented in figure I where EX is for Excellent grade, V.G is for Very Good grades, G is for Good grade, P is for Pass grade, and F is for Fail grade. The grades percentages distribution in table 5 shows that the success percentage of the course by applying the proposed model is raised to 92.36% compared with the previously conducted exams which was 83.66%. Moreover, the grades distribution has also revealed an enhancement which proved that the following proposed model succeeded in raising student performance.

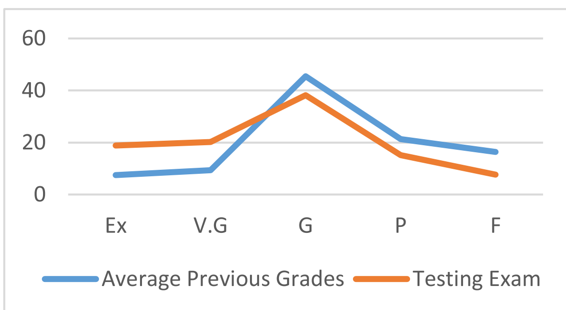

FIGURE 1. Comparison between the previously conducted exams' percentages distribution and the testing phase exam (%).

VI. DISCUSSION AND PRACTICAL IMPLICATIONS

The experimental results revealed the positive contribution of considering the students' preference in raising the successful percentage. The proposed model succeeded in reducing the fail percentage by 8.7% as well as contributing to the grades' distribution to raise the excellent grade by 11.35% and very good grade by 10.84%. The grades' distribution confirmed

TABLE 8. Comparison of the Two phases Statistics.

	Ex		V.G		G		P		F	
	No	%	No	%	No	%	No	%	No	%
Average Previous Grades	42	7.47	53	9.41	256	45.47	120	21.31	92	16.34
Testing Exam	106	18.82	114	20.25	215	38.19	85	15.1	43	7.64

that introducing the personalization approach into the exams preparation provides a positive impact on the education process.

To reveal more elaboration on the proposed model contribution, the following is a discussion that confirms that the current study is filling one of the research gaps in this research field. Although some researchers discussed the same direction, however, different approaches were followed. In [19], students' personalities were detected by the students' social media data, however, in the current research. A more direct methodology was adopted by offering the questionnaire. The research in [19] had successful percentages, however, following the current proposed approach for identifying the questions and formulating the exam, the current research reached a more uniform curve as illustrated in figures I and II which reveals more accurate results and more unbiased questions for the students. Another research in [7] also considered the same perspective of conducting a questionnaire for determining the students' preferences, however, the exam was set manually with no intelligent approach to construct which also provides an advancement of the current proposed approach.

According to the previous discussion, it is confirmed that the proposed approach is applicable to be applied. However, it could be more reliable if an approach for integration with other components such as in [29] for considering the suitable exam time, [30] for more reliable exam marking, and [37] for enhancing the learning engagement as well as adopting it for more intelligent exam preparation.

VII. CONCLUSION

This research focuses on the aspect of the student's evaluation. The research highlighted the positive contribution of engaging the student's personal characteristics in preparing exams. The research aimed to explore the variation in the students' learning styles. The proposed model also considered the uniform distribution of the exam to the course contents in order to satisfy the quality assessment. The proposed model utilized mining techniques as well as text analysis in order to reveal the acquired personality and ensure the highest available level of quality for the exam. The proposed model was applied to a total of 563 students which revealed the advancement of the proposed model in enhancing the success percentage to be 92.36% compared with the previously conducted exams which was 83.66%. Moreover, the grades' distribution has also revealed an enhancement which proved that the following the proposed model succeeded in raising student performance.

The proposed model raised confidence in the applicability of the educational process quality through the appropriate evaluation process. Future directions for enhancements include engaging other personalization criteria such as daily activities. Another direction is the need to apply the proposed model on different datasets with a variety in the courses' nature and the students' levels. Moreover, considering the teaching process to enhance the level of quality could be also considered a vital research point. Another future direction is considering the security issue while conducting the exams as well as securing the exams' results.

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