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Learners Engaged: Visualizing Analytics through an Integrated Model for Learning Analytics in Adaptive Gamified E-Learning

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ABSTRACT During the Coronavirus pandemic, e-learning systems have proven to be an essential pillar for education. This raises to surface what many studies have addressed earlier; creating a platform that completes the traditional classroom work and maximizes the effectiveness of learning outcomes. Striving to achieve such platform, studies have considered gamifying and personalizing the educational resources for the adaptation of educational systems as per the intended learners through intensive learning analytics. But was the learner really a part of the adaptation process taking place? Learning analytics are usually designed to the course's adaptation and solely for the teachers. Thus, learning analytics in gamified adaptive educational systems involving the course, teachers and learners together are still under investigation. In this study, the Personalized Adaptive Gamified E-learning (PAGE) model is introduced to extend MOOCs by providing new satisfactory levels of learning analytics and visualization in the rich e-learning process that supports the learner's intervention in the resultant learning analytics. The proposed Learning analytics have been developed to make the necessary adaptation to the course and learner's learning flow, as well as visualizing the process and adaptation decisions to the learners. Results show a positive potential towards learning adaptation and visualization, and a necessity to provide an additional focus for the gamification concept.

INDEX TERMS adaptation, e-learning, gamification, learning analytics, learning behavior, visualization

I. INTRODUCTION

As a part of the social distancing regulations stated after the global pandemic of the Coronavirus, e-learning systems have become the saviour for all educational institutions, depending on them to continue their educational studies [1]. This raises many issues regarding the current systems, which were auxiliary side-by-side tools with the on-ground process. Such issues are due to the stress resulted from this sudden heavy dependence on these technologies and no face to face interaction, increasing the urge to boost e-learning systems to better engagement experiences.

The recent major leap on e-learning systems was MOOCs that provide learners with an open access to various courses [2]. However, studies have shown that even after MOOCs, their theoretical benefits to the e-learning experience did not meet the expectations, as there exist high dropout rates [2]. As today's incident does not tolerate dropping out, learners are at even greater risk to continue a course without any interest or attention [3]. Other factors affecting e-learning across web eras were reviewed for all intended stakeholders, providing a comprehensive view on e-learning advances.

According to the learners, one main e-learning advantage was having control over the learning process, promoting self-regulated learning in moving with individual's pace. While for the course designers, the main advantage was the reusability of course materials [4]. Learners also found it effective to have a constructive feedback from their teachers, in addition to a clear course goal [5]. On the other hand, the challenges faced by the learners include the lack of learner's motivation, support, proper content, low possibility of communication with a teacher /counsellor, and the unreliable assurance of learning progress and knowledge gain [4][6][2]. The ability to design a proper instructional design was the main challenge facing the course designers [4].

Continuing with the aspects influencing the e-learning process, the success factors from the teacher's perspective are the proper instructional design, considering learning preferences, sustainable content, and the assessment technique [4]. With respect to the standard instructional design process, three major fundamentals have been emphasized; designing the course, tutoring, knowledge assessment, and analyzing then adapting the learning process [7][8]. As the adaptation seeks to meet the learner's learning needs, then utilizing adaptation with the learner's preferences can be a way of creating a successful learning environment. Additionally, the sustainable content factor can be achieved in MOOCs by designing the courses as open educational resources (OERs) to facilitate reusability, assessment, and adaptation that support having sustainable content [9] [10] [11] [12][13]. As the OER is made up of assets, such as video, audio, etc., the adaptation would try selecting the most suitable assets of that OER whose learning preferences best match those of the learner [9]. Other factors associated with the success of e-learning are the learner's engagement and learner's motivation from the learner's and teacher's perspectives respectively [4], which can be tolerated by gamification. Gamification presents the application of game design elements into a non-game context, differentiating it from other related concepts, such as serious games and gaming that have a game-context [14].

Gamification concept has been lately considered to motivate and engage learners to maximize the learning outcomes [15][16][8][17]. Thus, gamifying adaptive educational systems can further help engaging the learners in the learning process on their own pace, so they can learn through the game while they are enjoying and developing skills as per their learning preferences [15][18][19][20][21]. On the other hand, learning analytics allow extracting meaningful insights, such as the learner's anticipated status, to enhance the overall learning process [22][23]. For instance, the prediction analysis can anticipate the learner's next move through predicting his/her performance, learning preferences, risk detection, behavior detection, etc. [24][25]. The expected action after performing analytics is to reflect the results into the process afterwards, which is the aim behind applying the data analysis. Therefore, in order to employ the required enhancements on the interacting environment, it is assumed that there exists a strong reliable model that considers adaptation on each component of the gamified educational system.

However, current e-learning systems and MOOCs platforms are still unable to find the ideal combination between adaptation, gamification, learning preferences and OERs consideration. Studies that addressed adaptation lacked the tracking of the learner's preference, which is a direct differentiation method for distinguishing learners in order to present them with their suitable content [16][8][17]. Adaptation involves many dimensions that were not entirely adopted in many previous studies [26]. Even though some studies addressed adaptation, they ignored the gamification concept, and vice versa. Moreover, most of the research studies have not handled the educational game as a set of dependent OERs/LOs, making them difficult to be reused, shared, modified, or adapted [12]. Additionally, studies mainly perform learning analytics targeted to the teachers, or for the learning process itself, keeping the learners out of the equation.

In this paper, we propose the Personalized Adaptive Gamified E-learning (PAGE) model to provide an infrastructure for a new generation of adaptive gamified educational systems. Analytical techniques are performed for decision making on the adaptation of the course and learner's preferences intended for both the teachers and learners. Since gamifying the learning process alone is not the solution for fostering the learner's performance, in fact, designing the content and rearranging the process contribute to the success of gamification. Therefore, the PAGE model organizes the course content in such a way that focuses on each individual learner, including both adaptation and gamification to assist and guide a unique, personalized and motivating learning process. The proposed model is domain-independent to fit any type of course for any learner. Teacher can build a dynamic course plan or/and exercises, with ordered prerequisites and flexible gamifying settings, as well as the OERs that form the reusable gamified LOs. Such flexibility helps the commission of a wide range of courses/MOOCs and builds a system for any learning preferences. In addition, the PAGE model allows learners' supervision when needed to overcome the challenges of miscommunication caused by distance learning.

The rest of the paper is organized as follows. The main previous studies addressing the adaptation and gamification concerns in the e-learning process are expounded with their limitations in section II, discussing the research gap and the main contributions of this study in section III. Section IV demonstrates the proposed PAGE model, describing its main components and their interactions. The evaluation approach for PAGE model is illustrated in section V, with a detailed discussion of the evaluation results. Finally, section VI concludes the research study and highlights the future work.

II. Background

As MOOC is a platform where learners are self-driven to enrol [27], the online educational experience should be attractive for each learner to ensure persistency, especially when there is no other option during this current global pandemic [3]. Many studies have proposed different approaches that ought to influence the learner's completeness in e-learning systems as presented in the following sub-sections.

A. ANALYTICS WITHOUT ADAPTATION

Several studies have focused on analyzing the data resulted from the interactions taken place in e-learning systems. Regardless of that gamification concept was out of scope, the common limitation of these analytics is that these were performed mostly for the teachers, as well as the lack of utilizing these data by the system for any adaptation purposes.

Another focus in the last few years regarding e-learning systems was on learning analytics techniques, such as performance prediction for risk identification. Visualized recommendations were developed in [28], where a learning analytics extension model for Khan Academy educational system was created using Google Charts API over four courses. These were presented to the teachers for decision making support and to learners for self-feedback. Nonetheless, there was no addressing for any sort of modification in the learner's preferences to reflect generated recommendations. Two generic tutorials were put on LMS to study the interaction with learners in [29]. The objective was to predict the learners' performance through timely collected set of data sources for timely feedback to the learners and teachers. However, this feedback was not further utilized for modifying the process.

Authors in [30] predicted the academic performance through social network analysis that tracked the interactions of teachers and learners over the communication area for a financial course. The social network parameters included replies, sent messages, etc. But still, the analytics results did not provide information about how to utilize the results in the learning process. Unlike [31], which developed a model to standardize the variables of data collected in gamification and then converted them to sequential streams to be analyzed. Yet, the developed API was concerned only with the interaction data. Therefore, it was not mentioned neither how a course designer could take a part in adapting the gamified presented content, nor how the learning process could be adapted for each learner for a personalized learning experience.

B. GAMIFICATION LACKING ADAPTATION

Many studies have addressed gamification but suffered from shortages in critical instructional process steps, such as adaptation. A problem-solving game-based learning was presented in [32], as an experiment for raising motivation, developing problem solving skills and achievements for students during a full semester. However, the gamified course assumed that learners had already knowledge about the course. There was no discussion whether the game had a hierarchical structure for sequencing according to prerequisites, or any difficulty and skill levels. In addition, many game mechanics and dynamics, like leader boards showing the learner's status compared to others in the same course, were also neglected.

In [33], specific problem-posing gamified courses were addressed, claiming that they could assist in raising the flow experience and engagement for better learning outcomes. The game assumed a learner's pre-knowledge of the course. In addition, the game mechanics, in terms of presenting progressive challenging levels or leader board for learners were not covered. Authors in [34] created a learning design for games using LOs, adopting the game mechanics concepts like fictional story and rewarding mechanism, in addition to the instructional feedback. Though, there was no mention if the learning process was adaptive. Thus, the resultant game had a static content structure, with a fixed rewarding mechanism, game presentation, and process flow.

[14] proposed a framework integrating the success factors of information systems categorized broadly as information, system quality and user satisfaction with the gamification concept in MOOC. Similarly, that framework's success factors did not include the feedback concept, which in turn removed adaptation from the equation. In [35], the authors focused on an online gamified quizzes platform that supported game mechanics and dynamics like achievements, rewarding, leaderboard, etc., providing a way to inform the learners' parents about their children's scores through e-mails to follow up. However, the study neither considered adaptation, nor that teachers are able to design different courses or not.

C. ADAPTATION LIMITED FOR ADAPTATION TYPES

In [36], the authors discussed preferences-based adaptations to present the learner with the suitable content. However, the adaptation types and the content structure were not considered. [37] developed an adaptive game, based on the learner's learning preferences. However, the adopted preferences were limited to the preferred structural dimension of the course (depth-first or breadth-first). In addition, the gamified course did not address course structure adaptation. Although the game contained a database for the learning material, there was no mention about how the course structure was developed. Therefore, the game did not fully support feedback, as a main step in the educational process. Another adaptive gamification model based on a linear model was presented in [38]. The model crossed the learner's preferences in general with the gamification mechanisms to select the most suitable gamification feature for each individual learner. Focusing mainly on the gamification adaptation, the model did not involve any course designer intervention, nor address the content structure building.

III. RESEARCH GAP AND MAIN CONTRIBUTIONS

Previous studies have arisen the eager demand to fulfil an expanding gap in current MOOC's structure. Some studies have performed learning analytics, without reflecting the resultant analysis into the system adaptation. Some have focused on gamification, but lacked a good instructional process, including adaptation. Others have considered adaptation but were limited to cover adaptation types only. This gap can be summarized as follows:

- The oversight of the learner's role as a key contributing factor, where the learner should be able to view his/her learning outcome for self-motivation, evaluation, and decision making. In addition, the learner should have

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the right to contribute his/her opinion on any adaptation affecting his/her educational path before being applied by a system.

- Shortages in learning analytics, including the lack of utilizing the results in the instructional process adaptation, considering that gamification was not a part of the performed analysis.
- Gamification shortages, including some unaddressed game elements and instructional process adaptation.
- Adaptation shortages, due to not considering the adaptation of all the aspects of instructional process.
- Instructional process shortages, including poor application of course structure design, in opposite to that of the traditional classroom, and domain-specific systems with no reusable course content or any sort of modification by teachers or course designers.

Hence, the Personalized Adaptive Gamified E-learning (PAGE) model is proposed to provide a wide infrastructure that can be adopted to create domain-independent, learning based adaptable gamified educational systems. The main contributions in this study can be summarized as follows:

(1) It supports building an instructional design process regardless of the course scientific domain.
(2) It organizes the course developed as a set of OERs, allowing more flexibility in the storage, usage, rating, and modification.
(3) It considers the adaptability of the course plan at several levels; adapting the OERs presented and their sequence based on the learner's learning preferences, modifying poor OERs and the course structure itself by the course designer, to be reflected with the new enrolment. Thus, overcoming any repeated flaws in the course.
(4) It analyzes the data returned from both the learner's learning behavior, by tracking his/her performance during an LO accomplishment, and the learner's performance and feedback on the course's OERs.
(5) It adapts/recommends adaptation for the course designer with the appropriate required modification.
(6) It combines the gamification concept with adaptation in terms of considering all known game mechanics. The course designer can customize the game settings while developing the course plan and its OERs.
(7) It presents a dashboard to the learners to keep them informed of their status, as well as a leaderboard that presents their status compared to other learners enrolled in the same course.
(8) It presents the learner with the suggested modification to apply, after analyzing his/her performance, to be reviewed and edited by the learner.

IV. THE PROPOSED PAGE MODEL

In this section, a detailed description of the proposed Personalized Adaptive Gamified E-learning (PAGE) model is presented. The PAGE model is alleged to provide an auxiliary learning environment to traditional ones that allows a structured learning analytics. The model addresses mechanisms that provide learners with a more personalized educational experience and an accurately assessed and analyzed performance, in addition to the game mechanics extension. This results in a comprehensive model for a generic adaptive gamified education. As shown in Fig. 1, the proposed PAGE model consists of three main modules. A thorough explanation is discussed in the following sub-sections.

FIGURE 1. The Personalized Adaptive Gamified E-learning (PAGE) model architecture

A. THE MAIN INTERACTING ROLES

The proposed PAGE model interacts with three roles: The *Course Designer*, representing the expert responsible for building the course. The *Learner*, representing the person who learns through the course's OERs presented in a gamified context, in which the learner's behavior is monitored and stored for analysis and evaluation. The *Supervisor*, who can be a teacher, consultant, academic advisor, social advisor, parent, or the *Course Designer*. The difference is that the *Supervisor* is directly related to the *Learner*(s) and is interested to regularly observe their performance and status. Moreover, the *Supervisor* can cooperate in building the Learner's portfolio on behalf of the *Learner*, which is advisable in some cases, such as young learners.

B. THE REPOSITORIES

The PAGE model has four repositories, in which the data are constantly updated; The *Course* repository stores the course information, such as the name, author, and its tree-like structure that includes topics, practices, etc., with flags to the associated OERs for each course element. The actual built OERs are stored as individual objects in the *OER* repository to allow their reusability in any other course. The *Learner Portfolio* repository stores the Learner's data. The Learner's data consist of some basic data, like the name, age, gender, etc., as well as some dynamic data that are constantly modified due to the regular interactions with the model, such as the Learner's learning preferences, achievements level, etc. The duty of the *Learning Behavior History* repository comes when the learner has started the learning process. It acts as a Learner's log, recording his/her learning behavior through an OER, together with his/her feedback on it, which in turn, are used to collect feedback about the learning process.

C. THE COURSE DESIGN MODULE

The contribution of the *course designer* is required for a detailed planning and designing of the course before the learner can enrol into the gamified course. To illustrate the proposed model throughout this study, an arithmetic course is used as an example, having the main topics: addition, subtraction, multiplication, and division. Thus, this arithmetic course structure and its OERs are built through the *course designer*'s inputs. A detailed description follows for the sub-modules of this module.

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1) THE COURSE STRUCTURE BUILDER

In this sub-module, the *course designer* sets out the general aims of the course and builds its initial structure. He/she communicates first with the (a) *Elements Specifications Associate* to define the topics/subtopics of the course for both explanatory and exercising materials. The *course designer* defines the elements, associated with their specifications, learning objectives, and prerequisites. After having a well-defined course structure, (b) *Achievements Locator* defines the set of course elements that can be treated as an accomplished milestone. This sub-module compels the *course designer* to follow the game mechanics, as having achievements located after a set of course elements allows the learner to feel accomplishment victory on a regular basis, keeping him/her motivated enough to continue with the process [39].

Example I: The course designer can flag the topics "Addition", "Multiplication", "Subtraction", and "Division" as the four main achievements in the arithmetic course named "understanding arithmetic operations". This will allow the model to visualize the path to the learner in the form of achievements to be accomplished rather than course content.

Moreover, the *course designer* can use the (c) *Fictional Course Setting*, to build a fictional story for the course, which is also an additional contributing factor for the flow as mentioned in the Game Dynamics and Mechanics [40] [39]. The fictional story consists of adding a background story, story characters, themed points and rewards, associating themed achievements related to that background story, which can correspond to a small success in the story, etc.

Example II: If the course designer chooses a kingdom theme for the course, then the achievement "Addition" would rather be "First War Victory: Addition" which could be rewarded by "3 coins" instead of "3 marks", having the game characters as knights and a king instead of learners and a teacher.

2) THE OER BUILDER

As the OERs are reusable, the *course designer* may reuse an existing one as long as it is tagged with the same learning objective(s) or may create a new OER. In this sub-module, the *course designer* develops the OERs, which include: (a) *OER Assets Combiner*, where the *course designer* builds the OER by associating all applicable assets for it, as video, audio, etc. [41]. The (b) *Rewarding and Evaluation Mechanism Designer* allows the *course designer* to define what action(s) would offer points to the learner, (i.e.) the action could be a click, a word, … etc., or a set of ordered consequence actions.

Example III: The course designer has created an explanatory OER for the sub-topic "Addition of two numbers", explaining the rule, then provided examples in audio, text, and animation video. The model would choose the appropriate format matching the learner's learning preferences to display.

3) THE DATA MODELS

Let $course_c$ represents the course c as shown in (1):

$$course_c = < ACH_c, FS_c, FB_c, TP_c > \quad (1)$$

Where ACH_c is the set of topics considered as achievements. FS_c is the selected fictional story settings (the story line, story characters images, reward name(s), reward icon(s), achievements names, etc.). FB_c is the accumulated feedback given by the learners to that course (1 as 'totally agree' and 5 as 'totally disagree'). TP_c is the list of all topics in the $course_c$, where each topic consists of a list of the associated OERs.

Let OER_j represent the open educational resource j as shown in (2):

$$OER_j = < LO_j, AST_j, PQ_j, FB_j, MN\_LB_j, MX\_LB_j, LP_j > \quad (2)$$

Where LO_j is a list of tag(s) identifying the learning objective of OER_j. AST_j is the set of assets associated with OER_j. Let PQ_j be the list of its prerequisite OERs as shown in (3):

$$PQ_j = < OER_{j-1}, OER_{j-2}, OER_{j-3}, \ldots > \quad (3)$$

Where $OER_{j-1}, OER_{j-2}, OER_{j-3}$ are the prerequisite OERs for OER_j. FB_j is a numerical value that represents the overall feedback by all learners exposed to OER_j (1 as 'totally agree' and 5 as 'totally disagree').

Let MX_LB_j be the maximum thresholds of the expected learner behavior parameters, defined by the *course designer* as shown in (4):

$$MX\_LB_j =< MX\_FA_j, MX\_TT_j, MX\_WA_j > \quad (4)$$

Where MX_FA_j is the maximum thresholds for the total failed attempts to solve LO_j, MX_TT_j is the maximum thresholds for the total time taken in minutes to pass LO_j, and, MX_WA_j is the maximum threshold for the total number of wrong actions done while progressing in LO_j before the right action(s) were performed. As the right action(s) are already specified, one click on a wrong choice is counted as one wrong action. These thresholds are predefined by the *course designer* to identify the extreme bounds for each OER, by which exceeding them means losing that OER.

Let LP_j be the learning preferences associated with OER_j as shown in (5), which is dependent on the developed assets. The learning preferences can be expressed in many ways. One way could be through the learner's learning style. Considering the FSLM list of four dimensions, named as perception (with poles sensitive or intuitive), input (with poles visual or verbal), processing (with poles active or reflective), and understanding (with poles sequential or global) [42]. Each dimension is defined by one of two categorical pole values as shown below:

$$LP_j = < P1_j, P2_j, P3_j, P4_j > \quad (5)$$

Where $P1_j$, $P2_j$, $P3_j$, and $P4_j$ are the pole values for the four dimensions of the LP_j respectively. As in [36], each dimension ranges from 0 to 1, where 0 and 1 are the two extreme poles. The PAGE model can adopt any other learning preference approach, as there will always be two extremes for any aspect describing the learner's preferred behavior. Fig. 2 summarizes the processing of the *Course Design* module.

FIGURE 2. The course design module flowchart

D. THE PERSONALIZED GAMIFIED LEARNING FLOW MODULE

This is where the gamified learning process takes place. This module interacts with the learner and/or *supervisor* in order to explicitly and implicitly gather data that include the learner's preferences and status, resulting in a learning experience that best suits the learner. Followed is a detailed description of the sub-modules included in this module.

1) THE LEARNER PORTFOLIO BUILDER

This sub-module gathers both the static and dynamic data of the learner to build his/her portfolio. The static data is the main general information about the learner, like name, gender, age, etc. The dynamic data is the learner's learning preferences and learner's level of achievement in each course. The PAGE model provides the flexibility for the *supervisor*'s cooperation, since it is considered as a better alternative in some cases, where the learners may not be able to take a full control of the learning process configuration, such as young, disabled, or home-schooled children, or instructors who prefer controlling the learning process for a group of classroom students. This sub-module is responsible to regularly update the learner's portfolio with any alteration done, to be then organized into the *Learner Portfolio* repository.

2) THE LEARNING PREFERENCES INITIATOR

It interacts with the learner to deduce his/her learning preferences through an initial activity, i.e. questionnaire, game, etc. with their evaluation mechanism. Through the learner's answers, his/her initial suggested learning preferences are implicitly deduced and initially considered to build the personalized learning settings.

3) THE PERSONALIZED GAMIFIED LEARNING ADAPTOR

Relying on the learner's information and the course structure provided by the *Learner Portfolio* and the *Course* repositories respectively, this sub-module builds the personalized adaptive gamified learning settings for the learner. It starts by first passing through the *Gamified Learning Flow Aligner* to arrange the appearance sequence of the OERs to create the gamified learning game in respect to their prerequisites and the learner's portfolio. The course alignment is also used by the *OERs Customizer* to select the best matching OER from all that are tagged with the same learning objective(s). All made interactions are then sent to the *Learning Analytics and Personalized Adaptation* module to be analyzed, and later visualized to the learner in the *Learning Visualization*.

4) THE LEARNING BEHAVIOR AND FEEDBACK HISTORY BUILDER

This sub-module tracks the learner's learning behavior during his/her interaction with each OER and receives his/her feedback on each one, as well as his/her feedback on the course as a whole. It accumulates the learning behavior after each trial of solving an OER until its accomplishment, while storing its parameters in the *Learning Behavior History* repository. The learning behavior parameters are the number of failed attempts, the number of wrong actions made before the successful one(s) and the time taken to have the successful attempt. On the other hand, it receives the learner's opinion about the OER. Fig. 3 summarizes the processing of the *Personalized Gamified Learning Flow* module.

FIGURE 3. The Personalized Gamified Learning Flow module flowchart

5) THE DATA MODELS

Let $DDLearner_i$ represent the dynamic data of $learner_i$ as shown in (6):

$$DDLearner_i \ = \ < LP_i, ACH_{ic} > \tag{6}$$

Where LP_{ic} is the associated learning preferences of $learner_i$ deduced implicitly or explicitly as shown in (7):

$$LP_i \ = \ < P1_i, P2_i, P3_i, P4_i > \tag{7}$$

Where $P1_i$, $P2_i$, $P3_i$, and $P4_i$ are the pole values for the four dimensions of the LP_i respectively in $course_c$, similar to that of (6). ACH_{ic} is the achievement level percentage achieved by $learner_i$ in the $course_c$.

For the *OER Customizer* to determine the similarity between the learner's learning behavior LP_{ic} and that of the OER's LP_j, let $J(LP_i, LP_j)$ represent the Jaccard similarity coefficient [43] as shown in (8):

$$J(LP_i, LP_j) = |LP_i \cap LP_j| / |LP_i \cup LP_j| \tag{8}$$

Where LP_i is the learning preferences of $learner_i$ presented in (9), and LP_j is the learner preferences of OER_j presented in (2). The resultant coefficient varies from 0 (totally different) to 1 (completely similar). Therefore, *OER Customizer* selects the assets combination that maximizes the similarity between LP_j and LP_i. In this way, the learner would be only engaged with those OERs that best meet his/her learning preferences.

Let LB_{ij} be the learning behavior of $learner_i$ through OER_j as presented in (9):

$$LB_{ij} \ = \ < FA_{ij}, TT_{ij}, WA_{ij} > \tag{9}$$

Where FA_{ij} is the total number of failed attempts, TT_{ij} is the total time taken in minutes, and WA_{ij} is the total number of wrong actions done by $learner_i$ while progressing in OER_j before the right action(s) are performed.

Example IV: Assume that Sarah, $Learner_{0408}$, is presented with OER_{21} "Addition of two numbers", which is in the form of a multiple-choice question. The problem to be solved is followed by four choices, where only one choice is the right answer. $Learner_{0408}$ has solved this OER_{21}, generating $LB_{0408\ 21} =< 5,30,8 >$. This means that $Learner_{0408}$ has failed to pass this OER_{21} 5 times before the succeeded trial, passing it in the sixth trial, with overall time of 30 minutes and total 8 wrong actions before the right one.

Let FB_{ij} represent the feedback of $learner_i$ regarding OER_j on the three aspects as in (10):

$$FB_{ij} \ = \ < LA_{ij}, GA_{ij}, UA_{ij} > \tag{10}$$

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Where LA_{ij}, GA_{ij}, and UA_{ij} are the feedbacks of $learner_i$ on OER_j regarding its learning, gaming, and usability aspects respectively. On the other hand, let FB_{ic} represent the feedback of $learner_i$ regarding $course_c$ as shown in (11):

$$FB_{ic} = < LA_{ic}, GA_{ic}, UA_{ic} > \qquad (11)$$

Where LA_{ic}, GA_{ic}, and UA_{ic} are the feedbacks of $learner_i$ on $course_c$ regarding its learning aspect, gaming aspect, and usability aspect respectively.

E. THE LEARNING ANALYTICS AND PERSONALIZED ADAPTATION MODULE

This module utilizes the retrieved data from the repositories to evaluate both the learner's performance and the presented course quality to identify whether any necessary adaptation(s) or recommendation(s) are needed, as well as to visualize the learner's performance for the learner to track his progress. A detailed explanation is presented in the next subsections. Fig.4 summarizes the processing of the *Learning Analytics and Personalized Adaptation* module.

FIGURE 4. The learning analytics and personalized adaptation module flowchart

1) LEARNING PROCESS ANALYZER

All necessary acquired data as shown in Table I related to the learner, course and its OERs are analyzed in this sub-module regarding the quality of the course and the learner's performance. Detecting any abnormality in the learner's learning behavior after finishing an OER acts as a trigger to start analysis to avoid any upcoming drop out. Similarly, the trigger for analyzing the course or any of its OERs is typically a negative feedback or when no learners are currently active. The output from this sub-module includes various numerical scores or Boolean indicators about the learner and the course, which are sent to the *Learning Adaptor* and *Learning Recommender* respectively for further processing. Moreover, the results about the learner's performance are sent to the *Learning Behavior and Recommendations Visualizer* for the learner to interpret his progress visually.

Table I

THE PARAMETERS OF THE LEARNING PROCESS ANALYTICS

2) THE LEARNING ADAPTOR

Upon receiving the analytics results related to the learner, this sub-module makes the necessary adaptations needed so that the learner continues the learning process more smoothly. Adaptations made differ according to the received results, as shown in Table II. Abnormality occurs when one or more of the learner's LB parameters as in (9) exceeds the acceptable range MX_LB_j as in (4) for OER_j. Accordingly, the different variations of abnormality are each considered a case as shown in Algorithm I, indicating that the learner's abnormal behavior may be due to a distracted learner, a lot of time consumed in thinking through, badly created OER, or the presented OER does not match his/her learning preferences. Due to the various possible interpretations as shown in Fig. 4, the corresponding required adaptation may be either to add hints to assist the learner, add a timer to keep him/her focused, change his/her learning preferences, or recommend a required modification to that OER as shown in Table III. This reported action is sent to the *Learning Recommender* to be handled there.

TABLE II

VARIATIONS OF ABNORMALITY IN LEARNING BEHAVIOR

ALGORITHM 1 FOR LEARNING ADAPTATION

TABLE III

THE ADAPTATION TYPES COVERED BY THE PAGE MODEL

3) THE LEARNING RECOMMENDER

This sub-module acts as a decision supporter to the *course designer*, reporting back to the *Course Design* module some modification suggestions that are expected to enhance the course's overall quality. The analysis results correspond to the learner's feedback given on an OER or the course itself, mapping it to the suggested modification needed to be made. It is then the *course designer*'s responsibility to apply these suggestions if he confirms them as per his expertise. These changes reflect on one or more of the eight adaptation types proposed in [26]. Accordingly, Table III demonstrates the covered adaptation types against the entity responsible for that adaptation and the factor being analyzed. However, the user grouping adaptation is not addressed at this phase, since it requires unfolding further concepts, such as collaboration, which considers a group of learners rather than an individual learner. The recommended adaptations are on the course and OERs levels. The adaptation on the course level takes place in the *Course Structure Builder*, where the content itself may be adapted, as well as the achievements allocation and fictional story settings, which may adapt the game mechanics applied. At the OER level, the changes take place in the *OER Builder*, to be reflected on both newly enrolled and current learners. The usability adaptation refers to the user experience in the game, i.e. the controllers, sound quality, or game performance, etc. The rewarding mechanism adaptation is also applied to increase, add, remove, or modify point offered for each action.

4) THE LEARNING BEHAVIOR & RECOMMENDATIONS VISUALIZER

The resultant learning analytics and recommendations are interpreted in this sub-module in a way that helps the learner and the *course designer* to visualize and understand the current situation. Regarding the learner, there exists a visualized representation for his/her performance and status after each OER. Moreover, it shows the learner his overall status in the course, total time consumption, number of loses, accomplished achievements, etc., in addition to a unique leaderboard that is unlike the traditional ones ranking learners according to some rewarded points. This leaderboard ranks the learners with respect to three different aspects of the learning behavior as shown in (9), which means that there can be three different learners ranked first at the same OER, but each is in a different aspect. For instance, one learner may be the fastest to accomplish OER_1, another may achieve it with the least number of mistakes (i.e. wrong actions), while a third learner may be ranked the first since he/she has the least number of loses (failed attempts). Thus, increasing the potential for everyone to taste victory and success at some aspect. In addition, this helps the learners to discover their skills and what they really can master best. This sub-module acts as the learner's dashboard, giving him/her a space to monitor their own progress by themselves.

V. THE EVALUATION APPROACH

A. THE EVALUATION OBJECTIVE

The main objective of evaluating the proposed PAGE model is to investigate whether all adopted concepts have been properly addressed and efficiently integrated from the expected users' perspective. The model's assessment is carried in two directions; (i) a survey is created to evaluate the conceptual structure of the PAGE model, (ii) a system is developed for the *Learning Analytics and Personalized Adaptation* module for the learner's learning analytics, adaptation, and visualization, as detailed below.

B. ASSESSMENT 1: PAGE MODEL SURVEY

The PAGE model uniquely integrates concepts proposed in previous studies. Hence, the whole integration needs to be evaluated, as the previous studies did not handle all perspectives adopted in this proposed model altogether. A survey was constructed to evaluate the effectiveness of the unique integration adopted in the PAGE model.

1) THE PARTICIPANTS

A sample of 143 faculty staff and research assistants from different domains has participated in the evaluation. The elected participants are not only *course designers* who create their own courses, but also, they can be the *supervisors* as well as consultants in the field of computer science and software engineering for the development phase. As shown in Table IV, the sample is categorized by gender, years of experience, field of specialization, and the locations where they earned their postgraduate studies from, which is expected to impact their opinions and experiences exposure regarding education.

TABLE IV
THE DEMOGRAPHICS OF THE SURVEY'S PARTICIPANTS TO EVALUATE THE PROPOSED PAGE MODEL

2) THE PROCEDURE AND DATA ANALYSIS METHOD

The survey involved 15 close-ended questions. Each item is followed by three-point Likert scale [44]: 3= Well-integrated, 2= I'm not sure, and 1=Poorly integrated. As shown in Table V, the evaluation metrics are the parameters of the adopted concepts, to investigate their influence on the learning outcomes. The participants were invited to fill in the survey separately and anonymously, treated as ordinal responses. Before answering the survey, the PAGE model was presented in a printed format and explained orally to the participants. They were also informed about the intention of the survey, which is to evaluate whether the adopted concepts are correctly applied with positive effect on the learner's progress and achievement of the course's learning outcomes. Each participant had a maximum of two hours to complete it. The statistical analysis was performed using SPSS software V27.

TABLE V
THE EVALUATION METRICS ADOPTED TO BUILD THE SURVEY EVALUATING THE PROPOSED PAGE MODEL

3) THE SURVEY RESULTS AND DISCUSSION

The evaluation of the survey results is demonstrated with respect to three different perspectives: per item, per evaluation category, and per PAGE module. Per item, all 15 items are negatively skewed, indicating a positive agreement on the logic behind the integration proposed in the PAGE model as shown in Table VI. A deeper look is then considered for the next two perspectives, in which one sample t-test was conducted with null hypothesis for per evaluation category, and per PAGE module perspectives as shown in Tables VII and VIII respectively. The t-value measures the size of the difference relative to the variation in our sample data.

TABLE VI
THE RESULTS OF THE SURVEY USED TO EVALUATE THE PROPOSED PAGE MODEL

TABLE VII
THE RESULTS OF THE ONE SAMPLE T-TEST AND THE EVALUATION STATISTICS FOR THE FOUR EVALUATING CATEGORIES OF THE PAGE MODEL

TABLE VIII
THE RESULTS OF THE ONE SAMPLE T-TEST AND THE EVALUATION STATISTICS FOR THE THREE MODULES OF THE PAGE MODEL

For the four evaluating categories, the values shown in Table VII and illustrated in Fig. 5 indicate that the participants have mostly agreed on the positive effect of the PAGE model regarding the learning experience with an average of 86%. This includes raising the motivation, engagement, and productivity of the learner during the course. Therefore, the PAGE model serves its purpose in the enhancement of the learning process. The instructional design steps come next with almost equal overall mean values as adaptation as 81.5% and 80.4% respectively, indicating that the participants equally agree that integrating the instructional design steps and adaptation concepts positively impact the learning process. The gamification with all its concepts integrated in the PAGE model is the least agreed evaluating category of 73.9%, deducing that the gamification of learning materials as a concept, including the application of game mechanics, is still new in the traditional education environment with a weak practical judgement. Thus, the participants agreed that the gaming concepts, such as leaderboard and achievements, are well-integrated to help the motivation and progress of the learning process with 83.2%, yet it was not agreed upon when it came to how the *course designer* may apply them with 65.7%.

FIGURE 5. The evaluation statistics of PAGE model in terms of the evaluating categories

The aggregated evaluation of PAGE model, in terms of the three PAGE modules as shown in Table VIII and illustrated in Fig. 6, deduces that the *Personalized Gamified Learning Flow* module has the most applied concepts that the participants agreed on their effective well-integration with 84.3%. This module is responsible for analyzing the learner's preferences, updating his/her portfolio regularly, creating a personalized

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gaming experience with accurately selected OERs, while tracking the learning behavior. Therefore, it is considered as the linkage module between all concepts that directly interact with the learners. The least rated evaluated module was the *Course Design* module with 78.5%. Although this module describes the automation of the course building process, which is familiar to all participants, it has introduced few new concepts, which are mainly related to adding the game mechanics. Therefore, this module has the highest variance (σ^2 0.23) because of the lack of participants' related practical experience. Raising the same issue, the course building platform should be designed carefully to allow the *course designer*'s easy configuration of the course settings. Table IX determines the issues that need more focus due to their low rating, along with initial solutions to further think about.

FIGURE 6. The evaluation statistics of PAGE model in terms of the PAGE modules

TABLE IX
RATES IMPACT OF THE SURVEY RESULT FOR FURTHER INVESTIGATION

C. ASSESSMENT 2: DEVELOPMENT OF THE LEARNING ANALYTICS, ADAPTATION AND VISUALIZATION

1) THE EXPERIMENTAL METHODOLOGY

As the model focuses on the learner, a system is developed to handle the learning analytics, adaptation, and visualization from the learner's perspective. The objective of the system is to develop a visualized interpretation of the learner's performance after each passed /failed OER and throughout the whole course as per the proposed PAGE model. The system performs analytics for adapting the learner's learning path for future learning processes. Adaptation takes place upon any detected abnormality in $Learner_i$'s learning behavior LB_{ij} after each OER_{ij}. Therefore, the analytics are performed after each OER displayed to the learner, which are visualized for a continuous overview of the learner's performance through the course. The system is developed using C# and the experiments were held on Windows 10, 8GB RAM, Intel Core i7.

2) THE DATASETS

The learning behavior analytics dataset was used to test the developed system [45]. The dataset simulates the interactions taking place in the proposed PAGE model for 20 learners through 17 OERs, representing the main different learning behaviors that can be found in any group of learners at e-learning / educational systems. It consists of two files: (i) The 'OER Tracked Behavior' that is concerned with the learning analytics associated with the learning adaptation. It consists of a single OER's data for all possible learner's interactions. This includes the tracked learner's learning behavior in that OER for the failed and passed trials as in (9), as well as the learner's learning preferences as in (7). This file is used to compare it with the current learner's situation at the same OER to make the adaptation decision. (ii) The 'Course Tracked Behavior' consists of 20 learners' learning behaviors and preferences, OER ID, last accessed date for that OER, OER feedback, and the OER's maximum learning behavior as in (4).

3) THE EXPERIMENTAL RESULTS AND DISCUSSION

The main aim of the conducted executions is to evaluate the learning analytics regarding how would different learning behaviors affect the resultant adaptation by applying the cases in Table II. Each case has been examined using specific test cases with certain input test data. One OER was used as an example with ID=1 and a maximum learning behavior of $\{3,15,3\}$ as in (4). The learners' data in the experiments represent passed and failed learners, in which their learning preferences best match this OER. Different variations of learning behaviors and learners' feedback on this OER are included. Fig. 7 shows the different cases handled in PAGE learning analytics.

Testing learning analytics for adaptation, a learner is considered representing case 1, with a learning behavior of $\{5,18,5\}$ and a positive feedback on this OER. Fig. 7(a) shows the resultant learning analytics with the interpretation made for the learning performance and the decision to apply for the upcoming OERs. The learner has crossed the allowed maximum range for learning behavior of that OER, urging to make learning preferences adaptation. Fig. 7(b) shows the difference if the feedback is negative while keeping the same parameters, acknowledging the possibility of having a problem from the *course designer*'s side. Therefore, the analytics recommend a modification to the *course designer,* as well as adaptation to the OER selection made for this learner. Case 2 and 6 are tested as in Fig. 7(c) for a learner with a learning behavior of $\{5,19,2\}$. The results indicate an increase in the time taken to complete the OER, considering this as the main reason for failure. This is interpreted as a distracted learner, either by thinking too much, or by not paying attention to the OER. The decision made was to adapt the assets of the upcoming OERs to include a timer to help the learner focus. Fig. 7(d) considers case 3, for a learner having a learning behavior of $\{4,12,4\}$. The analytics indicate that the learner was stuck helpless, trying many wrong actions. Therefore, another asset adaptation may guide the learner's moves through this OER by adding the hints asset to help the learner. Fig. 7(e) evaluates case 8, for a learner with learning behavior of $\{1,10,1\}$, indicating an acceptable performance and no adaptation is needed.

FIGURE 7. The different cases handled in PAGE learning analytics

Fig. 8 shows an example of learning analytics visualized for a whole course to a learner. The visualization intends to keep the learner informed with his/her performance, where data are accumulated after each OER. An overall view of the learner's performance is illustrated in fig. 8(a) for the achievements made, minutes spent, etc. throughout the course, whereas fig. 8(b) displays the progress made, the course accomplishment and the changes in his/her behavior. This makes the learner have an insight of how he/she manipulates the OERs.

FIGURE 8. An example of learning analytics visualized for a whole course to a learner

An important part of the learning visualization is the leaderboard for all passed learners, which is designed to show the rankings of all learners engaged in that OER, ordered by the best performance with respect to three perspectives: (i) the failed attempts as shown in fig. 9(a) having the first learner with the least mistakes, (ii) the time taken as shown in fig. 9(b) having the first learner with the least time taken to complete an OER, (iii) the wrong actions as in fig. 9(c) having the first learner with the least wrong actions made during that OER.

FIGURE 9. An example of a leaderboard for a whole course

VI. CONCLUSION

In this paper, the Personalized Adaptive Gamified E-learning (PAGE) model is proposed to enrich learning analytics by uniquely integrating the e-learning and traditional educational processes. The PAGE model (1) flourishes the traditional instructional design steps by adopting OERs and applying the game mechanics. (2) personalizes courses to each individual learner and tracks the learner's learning behavior to help the regular adaptation process, and (3) analyzes the learner's performance to support decision making for better learning process. The model is evaluated through a conducted survey, and a developed system for the analytics, adaptation, and visualization intended for the learner. 143 participants provided their insights about the PAGE model integration in the survey. The results indicated a potential positive impact of the proposed model on the learning outcomes with an average of 86%, showing few uncertainties regarding gamification.

For the future work, the PAGE model opens the opportunity to emerge many future research directions. One direction is the automated mapping of the appropriate teaching strategies with game genres, the course and OER adaptation with the given learner's feedback. Further research on the personalization approaches and adaptation based on learning preferences, learner feedback and evaluation are expected, as well as addressing collaborative learning and fictional story handling.

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