Dynamic Adaptive Gamification Framework to Improve User Gamification Experience for Online Training

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***Abstract*—In recent years, there has been a notable increase in the utilization of gamification for online training. Following the "one-fits-all" approach to designing a gamification experience for all participating users can be a significant disadvantage as all users are given the same experience. Previous approaches commonly used the static player profile that was obtained at the very beginning or initial stage of the user experience and presented the user with the gamification experience according to the fixed player type. This motivates the need for an adaptive gamification environment in online training. A dynamic adaptive gamification framework is proposed to introduce a gamification framework consisting of a method to correlate player types and game elements. The correlation is aimed at identifying the evolvement of players through interaction with game elements and observing how these player profiles are motivated to change over time. The study also presents an evaluation method to measure motivation in adoption and engagement in online training to reduce boredom and improve the overall user experience of the player.**

***Keywords*—adaptive gamification, game elements, player type, user experience**

I. Introduction

The emergence and evolution of technologies have brought many significant changes to the work industry. As careers become busier, learning becomes difficult due to time constraints for employees. Today, employees are digitally natives, and as such, online training modules are discerned as the best option to learn and keep skills updated on-the-job continuously. However, employees face challenges in the adoption and engagement of online training as they are perceived to have various needs, preferences, learning styles, and requirements for learning [1]. As a result, organizations are deemed to consider using various learning methods that may encourage their employees to be active participants with strong motivation and engagement [2].

Recently, online training concepts have been emphasized in techniques, such as Gamification, Hybrid Learning, Adaptive and Self-Directed Learning strategies [1, 3]. Gamification is defined as the utilization of various game mechanics in a non-gaming environment [4]. It has ensued to promote encouragement and inspire user behaviors [5]. A user is commonly addressed as a player in a gamification context when participating in a gamification environment. It is worth mentioning that a sustainable gamification design should provide an understandable and comprehensible objective to reduce boredom [6].

However, the "one fits all" approach of the gamified experiences following the implementation of applying the same and commonly "used-for-all" game elements for everyone participating in the gamification experience may result in poor user experience due to boredom and lack in motivation [4, 7]. Thus, adaptive gamification seems to be an alternative, considering that each user may have a different playing inspiration [8]. Adaptive gamification is based merely on adaptive criteria such as player type, gaming element and learning strategies. Player type categorization and identification of suitable game element in a gamification experience is expected to motivate the users [8, 9]. The player profile is identified at the initial stage of the experience, following the suggestions of game elements that may suitably fit the static profile [6]. Apparently, the recognition of the initial player profile may be inaccurate as not all users will reveal real information about themselves. This leads to difficulty in designing the gamification to suit user preferences which results in poor user experience [10].

For an effective user gamification experience, gamification should be adapted and aligned to user's preferences and expectations which includes user behavior and the motivation drive. Tailoring game elements to suit each user's behavior with the aim to motivate the user requires an improvised approach. Dynamic Adaptive Gamification (DAG) framework that considers adaptation based on user interaction and behavior is proposed. The DAG framework that will be incorporated in a gamification architecture is expected to exhibit player evolvement when in interaction in the gamification system. It is assumed that a rigid player type throughout the gamification experience demotivates the user. Thus, to reduce boredom and to motivate the user, the gamification experience has to be refined to a dynamic adaptation [11], where the user is allowed to customize the user experience based on their preferences. This requires utilizing the customized game elements based on the evolvement of the user as well.

II. Related Works

A. Gamification

In corporate training, the gamification process begins with the goal of learning to acquire content [12], and the accomplishment of learning is measured through various gamification elements, including points, badges, levels, certificates, leader boards, score boards and other game features [5, 7, 13]. Gamification is beneficial in creating interactivity in learning, sustaining user motivation in learning activities, giving users time to think deeper, reflecting on their actions faster, giving positive changes to users, and simulating the environment related to learning content [14]. Gamification is simply the application of game playing elements to a non-game context with an objective while also increasing user engagement and motivation [8, 15]. Depending on the context, the objective may vary. However, the application of gamification has been widely explored to stimulate user behavior through gamified experiences [16].

The gamification design adopts the "one-fits-all" approach which may lead to boredom as it considers that all users ought to have a similar profile, i.e., game elements are adapted to the users once based on a static user profile [9, 17]. Other than the profile, users are driven by different factors, such as motivation, time constraints and the willingness to learn when participating in the gamification. Thus, considering user diversity, an improvised gamification approach is expected. Alternatively, adaptive gamification is an approach used to cater to users who have various expectations and respond differently to specific game elements. An important goal is to automatically adapt game elements to player types [18]. Player types classification was found to be the basis of adaptive gamification [8, 10, 19]. It is worth mentioning that in most studies, the adaptation approach is based on player type which is determined using user profile. But most user profile seems to be a static profile [11, 20]. To obtain the user profile, users usually need to answer a player type questionnaire, as commonly mentioned in the gamification context [8, 9, 11]. Based on the answers given, the gamified system is expected to propose the game elements (e.g., badges and challenges) that are customized to their profile accordingly.

The process of establishing a user profile and presenting game elements according to the profile seems to be stagnant. This is due to the common approach of most gamified environments where it adopts to the "one size fits all" approach in its design, which does not take into account the individual user needs and preferences [21, 22]. It is notable that while interacting within a learning environment, users tend to have different learning expectations and are influenced by various factors such as learner's motivation, learners' performance and learners' engagement [2, 12, 23]. This leads to an apparent change in user preferences along the experience compared to the initial preferences when the user started participation in the learning experience. Therefore, gamification design is expected to be adaptable and customizable for each user with the goal of motivating the user and improving overall user experience [13, 24].

B. Adaptive Gamification

Adaptive Gamification is best mentioned as an approach that seeks to amplify the anticipated objectives for individuals by prioritizing their needs, preferences and requirements in a gamified environment [14, 25]. The exclusive characteristic of adaptive gamification, which is the prioritization of user needs, focuses on the ability to customize dynamic elements for each user to further encourage distinctive interactions in the environment [15, 26]. The adaptive gamification approach for each user contributes to many positive factors, such as enabling user engagement, provoking problem-solving skills on specific topics, and assisting users in achieving their goals in the most efficient manner [16, 27]. These studies necessitate work on adaptation ranging from adaptation engine architecture, gamification architecture, and evaluation of the effectiveness of the implementation.

The common requirements of adaptive gamification systems based on the literature includes exploring various adaptation methods and strategies, enhancing user models, and dynamic adaptation to evaluate the effect of gamification from perspective of user's motivation and performance [13, 17, 28]. There are various methods to adapt gamified systems, including difficulty adaptation, which is based on the player's behavior or performance, adaptive curriculum and content adaptation, which is based on the contents to adapt to the presentation of gamified systems, and motivational interventions when participating in the environment [14, 18, 29]. This research study relates to the content adaptation approach in which the user is presented with game elements that best fit their profile, which was generated at the very beginning. The content adaptation approach is expected to motivate the user to continue striving to complete learning activities while unfolding game elements [19, 24, 30].

In the past studies, dynamic adaptation has been explored with various adaptive gamification components and methods such as content adaptation, difficulty adaption and learners model adaptation [8, 10, 11, 14]. Lavoue *et al.* [31] in their research on learner's model adaptation, proposed the matrix factorization model that is alike to those used in recommender systems. Two matrices were used: (i) to characterize the player types for all users, and (ii) to depict the correlation of game elements to player types. These matrices are then combined to procure the scoring of the game elements for each user, followed by the process of selecting the element with the highest score. In another study, the researcher transcribed an algorithm called The-Q-Learning to generate a learning path that promotes user adaptation when in interaction with game element. The researchers proposed two tables, namely Table-S and Table-Q [32]. Table-S is designated to specify the adaptive state when each adaptation takes place, while Table-Q denotes the values assigned for each action of the adaptive state. These tables were designated for all participating profiles. The author also included Table-R, which specifies the reward assigned to each adaptive state in Table-S. The algorithm was developed to depict the adaptation for each user and the reward that possibly can be achieved by each user in the adaptive system. However, the research only considered game element adaptation to the initial player profile, while keeping a static player type throughout the experience [32].

In conclusion, most of the studies considered game element adaptation to the initial profile generated for the player, while preserving the player type in a static position throughout the entire experience [17, 33]. Therefore, this study aims to provide a customization of game element to create better user gamification experience. A correlation method based on player type and game element emphasizing the dynamic adaptation was developed. The dynamic adaptation focuses on the user interaction with the game element and refines the static adaptation of the gamification system within the proposed framework. The proposed method was developed based on model-matrix factorization. The adaptive algorithm (method) is expected to recalculate the player type based on the user interaction focusing on player scorings during the experience of adapting the game element to the respective user model at a given instance [19, 34]. A suitable game element is activated based on the recalculation of player type scores each time. The recalculation of player type exhibits player evolvement and thus, the identification of new player type. The correlation method is assumed to identify new player through evolvement and this supports the elimination of the static player profile which may result in boredom and demotivation.

C. Player Modelling

Various different strategies have been proposed to relate game elements to dissimilar user profiles. The techniques mainly focus on distinct user characterization, which includes player types, learning styles, personality traits, motivation, and various interactions with various other activities [35]. Many other researchers merged different characteristics into player type, followed by learning styles, to determine the learning activities and associated game elements in a learning process [14, 15, 36]. In contrast, Hallifax *et al.* [37] suggested utilizing a few different factors such as player type, player gender, player interactions, and content through various rule implementations. This was done mainly to determine the presentation of the game element followed by the displacement of the subsequent game elements to the player. Other studies concentrated on the emotion factor to predict the user's accomplishment and performance in the gamified assignments, which is possibly information that could be used in adaption to the characteristic corresponding to the game [20, 38].

The commonly used taxonomies of player types in current adaptive gamification approaches are BrainHex [39], Bartle [40] and HEXAD [41]. These taxonomies allow the effortless identification of player types from questionnaires and initiate the correlation between game elements and player types. In a recent study conducted by Sienel *et al*. [42], the researcher proposed a MoMo (Motivational Value Model). The proposed model is a combination of the four famous categories of models: Bartle, Hexad, BrainHex and Big Five. MoMo was validated across BrainHex, followed by Bartle in the application of a health-related environment. The outcome showed that MoMo could predict players' preferences much better than each of the individual models mentioned above. Questionnaires were then used to categorize the player types with a set of predefined scores. This was determined in preparation for experience. For instance, the HEXAD model [41] is expected to distinguish between six player types: philanthropist, disruptor, achiever, player, free spirit and socializer. The outcome of the questionnaire was presented to the user with the following ratings: philanthropist (21%), disruptor (8%), achiever (25%), player (18%), free spirit (5%), and socializer (10%). The decision to identify the final player type and the most appropriate game element generally relies significantly on the predominant ratings [23].

Another common technique used in most studies is the questionnaire [38, 43]. This is used to obtain information to identify the player profile. However, the results do not seem promising, as these questionnaires cannot be entirely reliable and require validation. In some circumstances, if the questionnaire is somewhat reliable, the answers given may be inaccurate or randomized or the results obtained in the beginning may not be persistent throughout the user experience [44]. In addition to questionnaires, other work proposed gathering user feedback on the learning activities or scores on other game elements amid the experience [25].

Gamification is expected to foster motivation and increase user engagement to complete the learning activities. The objective of this research is a) to propose a dynamic adaptive gamification framework which consists of a correlation method to exhibit player evolvement through interactions with game element and b) to evaluate the accuracy of the proposed method to motivate and increase user engagement in online training to reduce boredom and improve overall user experience. In this research, the adaptation is based on user interaction with game elements. The interaction focuses on the user's response towards the game element after completion of learning activity, e.g., if the user would like to unlock a gift, share the points with other users, strive for another challenge, try the lottery to achieve more points and so on. Based on the user's response, the gamification system will adjust the adaptation for the next game element to be activated followed by the recalculation of player type. Player types are constantly refined after recalculation throughout the experience. It is assumed that interactions with game elements; can increase motivation and performance, thus improving user experience. However, the user interaction in relation to gamification elements that suit the player type seems encouraging and worth investigating.

III. Method

A. Player Type

The player type is an important element of this research. The HEXAD [41] player model and its corresponding questionnaire to determine player type were used in this study. The Hexad model has become one of the most used models in gamified systems [35–37]. Furthermore, it is shown to be the most appropriate user typology to reflect on user preferences [37]. However, it is worth mentioning that in all recent studies, players in the models are assumed to have player characteristics and the "non player" type was not taken into consideration [33]. "Non player type" is referred to a user who dislikes playing games. As everyone has different preferences, it is worth considering the individuals who dislikes gamification but is required to participate in the gamification environment. Considering this scenario, it is worth investigating the outcome of a "non player" type's participation in a gamification environment. In this research, the user who dislikes to play is identified as "Detest" player. Apart from the existing Hexad player types [41], the "Accomplisher" player type and "Timer" player type are added to the existing Hexad taxonomy. The "Accomplisher" player type is motivated by the ability to be highly trained or skilled in a particular activity, whereas the "Timer" player type is defined as a user who challenges the timing to complete a given activity. Both these player types are taken from the BrainHex [39] and Bartle [40] models to further investigate the player characteristics when correlated to game elements.

Previous study proposed the combination of various player models such as Bartle, Brainhex and Big Five and resulted in better prediction of player's preferences [22, 42]. Therefore, in this research, specific player type from the Brainhex and Bartle models are selected for further investigation. In this DAG framework, the player type of a specific user of the system is constituted in a vector in the method developed using the factorization algorithm. Each player type is represented by scorings that vary with one another.

The Player Type (PT) is defined as

$$PT = \{pt1, pt2, \ldots, pt9\}$$

Player Type Scoring (PR) is defined as

$$PR(t) = (r1(t), r2(t), \ldots, r9(t)$$

The player types are briefly described in the Table 1.

Table 1. Player type taxonomy

Player Type (PT)	Description
1. Disruptor:	Has the ability to alter a system
2. Free Spirit	Has the ability to traverse the system freely
3. Achiever	Has the ability to attain challenges
4. Player	Prompted by the game or gamified system itself
5. Philanthropist	Has the potential to share knowledge and render help to other users
6. Socializer	Has the ability to highly socialise
7. Accomplisher	Has the ability of a highly trained or skilled in a particular activity
8. Timer	Users who challenge timings
9. Detest	Users who dislike to play

B. Game Element

The selection of game element is based on the correlation analysis of the HEXAD player types with 52 game design elements performed by Tondello *et al.* [43]. The 52 game designs were grouped by player type based on the correlation value of player type corresponding to the game element. In this research, nine types of game elements were selected considering the fact that all game element has the ability to motivate each player. Each of the game elements are not expected to serve only a specific type of player, but to motivate dissimilar types of players in the system. This justifies the selection of the nine game elements in this study. The game element is presented as a vector, and is then associated with the player type vector to establish a correlation. Each player is presented with a game element upon completion of learning activity. It is assumed that the user interaction with game element reveals the real player type. The player rating after each evolvement at the time of interaction is calculated based on the interactions made towards different game element and how the player rated the game element.

The Game Element (GE) is defined as

$$GE = (ge1, ge2, \ldots, ge9)$$

The Game Element (GE) is associated with an interaction and motivation vector *Mn(i),* where the component *i* indicates the percentage of motivation the game element can reflect on each player.

The motivation vector is defined as

$$Mn(i) = (mn1, mn2, mn3, \ldots, mn9)$$

The game elements used for the correlation are briefly described in Table 2.

Table 2. Game elements

Game element (GE)	Description
1. Progress	Permits the creation of gamification mechanics
2. Challenges	Player has to overcome challenges
3. Unlockable	A hidden content is unlocked when the player defeats a challenge
4. Badge	Awarded for a completion of hurdle task
5. Levels	Display progress that is subdivided into levels for task completion
6. Pointers	Gain of score and experience
7. Leader board	Present rank of scoring
8. Lottery	Opportunity for player to increase score
9. Social network	Permit to create, view profile and add friends in social network.

C. The Dynamic Adaptation

The static player profile and presentation of game element that is designed to suit the initial player profile is unable to motivate the user due to the "one fit all" approach [4, 7, 11]. The dynamic adaptation considers that the user's preference and expectation may change while in a gamification environment [44]. The adaptation must be customizable while allowing the user to create an experience uniquely suited to their preferences [45].

The dynamic adaptation in this study is in accordance with the correlation using matrix factorization algorithm method [46]. This correlation is based on subset elements of the player type and game element. The interaction and motivation vectors are associated to the correlation to measure the player evolvement when interacting with the system. Through evolvement, it is expected that a player can have more than one player profile at the end of the experience. Thus, any player (within the player type taxonomy can be correlated with any game element) to identify the real player profile. The adaptive method is assumed to invoke each player's inner player type through evolvement when interacting with the game element.

Assuming that this inner profile, can be approximated at an initial player type, using the HEXAD questionnaires at the beginning of the experience, it is assumed that the users' behavior and interactions with the game elements will eventually disclose their real player type. Once the initial player type is defined, the proposed method iteratively updates the player profile of the user and calculates the efficacy of displaying random game elements to the user. As the player profile keeps changing according to interactions with the game element, it is assumed that the player type will constantly evolve. Therefore, the initial player type, defined using the questionnaire, may differ after the player interacts with the system.

IV. The Proposed DAG Framework

In this research, a DAG framework was proposed. The proposed DAG framework consisting of a correlation method aims to identify the evolvement of player through interaction with the game elements and to observe how these player profiles are motivated to transpose over time. The method relies on the interaction of user within the gamification system and is defined as interaction index. The correlation method is developed using the factorization algorithm. This method is expected to present a dynamic adaptation that relies on the activation of the game element according to the scoring achieved by each player type upon completion of an activity. The evolvement of player type following the interaction is expected to motivate the user to further participate in the gamification system. The user is presented with game element and scoring based on the activity completion. The user is expected to respond towards the game element to unlock any gift or reward or to activate any other given game element. The gamification system adaptation is based on the user's interaction and presents the next game element to the user. The gamification system is expected to continuously update the player profile after every interaction. The user interaction is assumed to motivate the user and to unlock more game elements from different player profiles. The framework allows customization of game elements based on the user's interaction and preferences while enhancing the overall user gamification experience.

In the proposed DAG framework as shown in Fig. 1, two system components are expected to correspond to each other: (1) The Content & Game system and (2) The DAG system. The adaptive system is deployed in an architecture in which the gamification system inhabits the external server. In the Content & Game system, the learning management system Coursera host the Nanomoocs course. The gamification service is utilized through the XBlock Application Programming Interface (API) Architecture. The Coursera platform uses the Content/Activity XBlock from the Content & Game system component to define the activities, whereas the Gamification XBlock is intended to capture the calls to the external XBlock API architecture to request for the next game element. Game element is subsequently exhibited once the user completes the learning activity. XBlock was designed to display the game element and monitor the user's interaction with the game element. This process captures the user's interactivity and the time taken to activate the next game element. Game element activation occurs only when the user completes any learning activity. Interaction is measured in terms of scoring, where every 20 s is given for the player to unfold the game element based on activity completion. These interactivities are then sent to the proposed adaptive method, which is administered in an external XBlock gamification API to update the player's profile. The reiteration frequency of the method was 20 s. This duration is assumed to have sufficient time to obtain information on the constant user interaction and updates on the player profile.

The entire process begins when the user is required to fill in the information needed for the player type questionnaire as part of the first activity integrated into the system. Upon completion of the questionnaire, the initial player type and scoring are sent to the gamification API that resides within the architecture. The user will then perform learning activities within the Content/ Activity Xblock and upon completion of the activity, an event calls out the gamification using the designated gamification XBlocks and the game element is presented according to player scoring obtained previously upon completion of the learning activity. The dynamic adaptation occurs when the user is able to interact and unfold any game element based on their preferences. The gamification system will calculate the scoring associated to the game element and exhibit the player type. The game element is exhibited on the Coursera platform via an HTML file. The HTML file holds the JavaScript calls to the API to track the interactions of each user, and the amount of time spent unfolding the game element. Finally, the activated game element and the corresponding scoring is made available in the user's dashboard panel for viewing. In addition, the user will be able to review the activated game elements to identify the real player type. And as the process repeats, the player type continues to evolve.

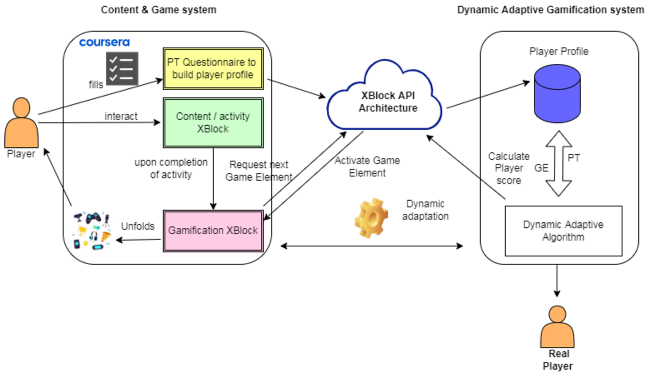

Fig. 1. The adaptation process using dynamic adaptive method in DAG framework.

The proposed method is assumed to exhibit player evolvement through interaction within the gamification system. The user is continuously motivated to further attempt the learning activity to unfold the next game element. The scoring is presented to the user when the game element is activated. The activation of game element is based on the interaction of each user and this allows the customization of game elements. The customization of game elements is achieved through continuous interaction by means of giving the user control over their experience in the gamification system. The continuous interaction and the customization of game elements are expected to constantly motivate the user and reduce boredom. This leads to a better user gamification experience.

V. The Proposed DAG Evaluation

The adaptive gamification strategy is expected to work as intended if the proposed game element fits the real player profile of the user and it is assumed that the user's real player type will not change while in the gamification environment. This assumption necessitates to measure the concurrence of the proposed method to a specific player type. It is worth mentioning that most studies used questionnaires [15, 18, 19] to identify the player type that results in a static profile Thus, the user experience cannot be measured [27, 38]. The proposed study is expected to validate the assumption made where the evolvement of player type in a gamification environment is expected to constantly motivate the user, thereby improving the overall user experience.

The effectiveness of the DAG framework is measured using simulation system with real users in a university environment. The simulation system will be integrated to the gamification system to capture the user's interaction and scoring. The participants of the evaluation will be the lecturers from various departments of the university consisting of about 50 lecturers. The lecturers are required to attend at least 10 hours of training annually as part of the university requirement.

The simulation system is expected to simulate the users considering the real player profile and its player scoring established at the beginning of the experience. The values of the player scoring will be extracted from the gamification system where 50 player profiles will be captured. The 50 player profiles will be categorized into nine modalities according to the player type defined in this study. Each modality is represented with its score (% of player type). Keeping in mind that a user may either reliably or unreliably answer the questionnaire at the beginning of the gamification experience, the gamification system will simulate the user's response accurately. The simulation system will recall the interaction index obtained during the interaction of user with the game element. The interaction index will be used to support the findings if the proposed method were able to simulate the users to participate in the gamification to exhibit player evolvement considering: a) The player scoring on interaction or response to the gamification system to unfold or activate the next game element, b) The player did not respond to the gamification system and the system has cancelled the dynamic adaptation for the player.

In the event where the gamification system has cancelled the adaptation for the player, the system will continue to present random game elements until the completion of the learning activity. There will be no interaction captured by the system. In another scenario, the player can choose to discontinue participation in the gamification once the adaptation is cancelled. This will lead to player not completing the learning activity and this can be assumed that the discontinuation is due to lack of motivation or the player dislikes playing games. The parameter to measure the effectiveness of the method will be defined as 'accuracy'. The player type scoring (% of player type) obtained after the interaction index computation will be compared with player type scoring (% of player type) obtained at the beginning of the gamification experience. In the simulation system, the initial setup of player will consist of real player type defining the results of its player type questionnaire. The method will be analyzed based on 2 scenarios (accurate or inaccurate answers from the questionnaire). The results will be presented as 'low accuracy', 'high accuracy' and 'average accuracy' of the proposed method. This is depending on the ability of the proposed method to yield outcome based on the method's accuracy to exhibit player evolvement in the gamification system. Apparently, the proposed method is expected to improve motivation and overall user gamification experience.

VI. Conclusion

The depiction of gamification is expected to further pursue the comprehensible objective of reducing boredom, thus improving user experience. However, the common "one fits all" approach of gamification experiences following the utilization of the same game elements for all users may result in poor user experience. Hence, a possible substitute could be adaptive gamification, which contemplates that each user has different motivations while playing and interacting in a gamified environment. Generally, the implementation of adaptive gamification is based on player type model. However, most adaptive approaches commonly use static player profiles. The player profile is gathered at the very beginning of the experience; thus, the user experience that best fits the intended player profile is mostly uncovered through the use of an actual player type questionnaire.

This research aims to present a DAG framework that consists of a correlation method that is expected to take the players' profiles as initial information and eventually consider how these profiles evolve over time with reference to the users' interactions in the gamification environment. Users interact with the system and depending on their activity completion, the game element is activated and the player type constantly evolves. As the system is adaptive to the user's interaction, this encourages the user to continue striving to complete the activities. The system provides a customizable preferences based on their interaction with the system. This further motivates the user to interact and hence, improves the user gamification experience. Apparently, in other words, the evolvement of players through interaction with game elements is expected to improve user experience. The evaluation of the approach by way of simulation with a real user participating in the gamified system will be carried out at a university.

However, this research compromises some limitations with future work. There are other player models such as Bartle and BrainHex which can be collaborated into a single model to further investigate the effect of player evolvement using different characterization of players. Additionally, this research is limited to only specific game elements incorporated in the adaptive approach. Other game elements such as points, timers, ranks and social status were not included. Therefore, different outcomes can be expected by integrating these game elements. The framework is specifically designed for the implementation in online training for employees, and results may differ in other domains.

As future work, the framework can be extended for the implementation in school classroom considering other user characteristics such as age and gender differences. To compare the accuracy of the adaptive approach, the method will be tested with bot simulated environment. The result will then be compared with the real user simulation approach carried out in this research. Additionally, new inputs such as sentiment and behavior will be incorporated in the method.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Yogeswari Shabadurai is the principal researcher of this study and wrote the initial manuscript. Fang-Fang Chua and Tek-Yong Lim provide the overall guidance of the research, reviewed and finalized the manuscript. All authors had approved the final version.

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