

Empirical Study of Adaptive Serious Games in Enhancing Learning Outcome

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Abstract

Use of serious games to teach concepts of various important topics including Cybersecurity is growing. With enhanced learning outcome and user experience, the player is likely to gain from engaging in game play. We report an empirical comparison of two cybersecurity games namely ; Use of Firewalls for network protection and concepts of Structured Query Language (SQL) injections to get unauthorised access to online databases. We have designed these games in two versions. The version without using adaptive features provide a baseline to compare efficacy of the machine learning based adaptive game while comparing the learning outcomes and user experience (UX). The efficacy of the Machine Learning (ML) agent in providing the adaptability to the game play is based on classification of player to two categories viz. Beginner and Expert using historical player data on three relevant attributes. The game dynamics is changed based on the player classification to ensure that game challenge is optimally suited to player type and the player continues to experience playful flow in different stages of the game. The analysis of the results in terms of objective evaluation of learning outcomes and subjective feedback from players for UX tend to show a marginal improvement by introduction of adaptive behaviour in both games.

Keywords: Adaptive Serious games, Machine Learning, Cybersecurity, Learning Outcome, User Experience (UX), LM-GM framework.

1 Introduction

In the online world, hackers are using sophisticated tools for performing the cyber-attacks on the online data. The most common way to perform the cyber-attacks on the online data is done with the social engineering methods. As a result of cyber-attacks, the online data is accessed by the hacker in an unauthorized way via the web applications. Hence, some methods must be adopted to create awareness/training of professionals related to the Cybersecurity. The motive of creating awareness among people is to reduce the impact of cyber-attacks on the online data. The methods like classroom-based teaching, security competitions, etc., [1, 2] are used for training professionals in traditional approaches. The cost of using the traditional methods for getting professionals trained appears to be higher. Therefore, there is a need of some innovative and effective way for training/educating professionals about cyber-attacks. Web based Serious Games (SGs) can fulfil this gap and can be used for training professionals at a lower cost.

There are many domains including cybersecurity where training on live systems is not possible in view of inadvertent and unintended consequences of a mistake by the learner. Use of simulators for training pilots in aviation sector both civil and military, before flying a real aircraft, is well known. Similarly driving lessons seem to benefit from use of simulators by the young aspirants before sitting on the driving seat of a car. Even medical professionals find use of serious games to teach emergency handling of patients a very useful adjunct to practical training under a qualified and experienced senior. Use of serious games to teach cybersecurity concepts has found favour because of similar reasons. While working on a Cyber range to learn appropriate responses to a cyber attack is a more pragmatic approach than letting the young cybersecurity professional to learn by doing on a live system. As reported in [3, 4], authors had used the CyberCIEGE game to create awareness on "Information Security" among the Thai students. To train professionals on web-sites related security, author had used the Anti Phishing Phil game [5]. One of the best way to reduce the risk of cybercrimes is to educate people and make them aware about the latest tools/prevention methods. The latest tools like Hydra [6, 7] etc., helps professionals to prevent cyber-attacks from occurring [8]. Use of serious games in teaching cybersecurity concepts is also reported by [9–11]. Hence, the combination of SGs with cybersecurity tends to be an effective solution for future directions.

SGs are, essentially, computer-based games that are used for purposes other than entertainment [12]. The advantage of using SGs are that by suitable design we can bring an element of fun, and thus enhance the user engagement via the virtual learning environment. The utilization of SGs in the educational domain to train/educate professionals is drawing increasing attention and will be more focal in near future [13]. The traditional system of education fails to provide the engagement and fun to the learner. Whereas in SGs we can easily provide engagement and fun by suitable use of gaming elements. The SGs are used for learning and education in various domains like health care, military etc., where learning content are customized in the game and instantaneous feedback is provided. The instantaneous feedback tracks the progress and level of understanding of players in the game. To engage/motivate the players in the game, various features are illustrated in [14].

However, fixed trajectory SGs possess a demerit of not adapting the gaming environment as per the player needs. Adaptation during game play better engages the player in the game while player is facing the challenges [15]. Such SGs are coined as "Adaptive SGs" [16, 17]. To make the SGs adaptive, the Machine Learning (ML) [18] agent is used. The ML agent provides an immediate suggestions to the player based on each step taken. In literature, the Artificial Intelligence (AI) [19] is used for mimicking human intelligence as well as generating levels/scenarios as per the players' ability [20–25]. In [26] authors discuss about the adaptive version of the Gidget programming game, i.e., GidgetML. In this game, autobot provides the tutorials to the players. The tutorials helps the players in modifying the written script if written incorrect. Michael [27] discussed about the MAXMIN Ant System (MMAS) algorithm which helps in deciding the best path for the ML agent. Manuel Ninaus [28] detected the facial emotions of the players that were engaged throughout the game. To maximize the learning objectives of the adaptive SGs, the author had proposed an innovative method for sand box serious games (SBSGs). This new technique also highlights the requirements that are needed for agent based decision [29]. In [30], author had used the Narrative Game-based Learning objects (NGLOBs) in an adaptive SGs. This helps to compose the story in an automated way in the game.

In some of these papers in literature of adaptive SGs, prediction models were also developed by the authors for predicting the performance of players. In our research, we have focused only on classifying the players into two classes, i.e., Beginner, and Expert using ML approach and adapt the future trajectory of game based on user type.

However, in designing Adaptive SGs one needs to pay attention to avoid any mismatch

between the Learning Mechanics (LM) and Game Mechanics (GM), which serves to be an important component for a successful game-based learning solution [31]. An effective SG is required to maintain a correct balance between pedagogical and game theories to make the game more immersive [32]. In this perspective, one possible method is to use the Learning Mechanics-Game Mechanics (LM-GM) framework [33, 34]. To design the main pedagogical and gaming features in a game all linkages between LM and GM should be analyzed to ensure an optimum balance between the two.

The major contributions of our paper are:

1. We have attempted an empirical study to ascertain the efficacy of an adaptive game over a fixed trajectory game.
2. We make use of three of the player attributes to classify a player as Beginner or Expert and combine these three attributes based player data while computing the learning outcomes. Earlier studies on computation of learning outcomes have only used one of the player attributes namely; time taken [35] or number of attempts [36].

The organization of our paper is as follows. Section II describes the game design for an Adaptive SGs. Section III describes the design considerations. Section IV discusses the methodology for the two games and the results of this research. Section V discusses the steps taken to assess the Learning Outcome (LO) of the two games. Section VI highlights the limitations of our research. Finally, the concluding remarks and future directions are placed in Section VII.

2 Game Design

The game design consists of three stages: input, process and output based on the works in [37] that illustrate game-based learning as an input-process-output system. The input domain provides the instructional content and game features based on the target audience. The instructional content is presented in the form of a tutorial in the game. The game features may include rewarding the badges after level completion, providing a certificate for Master players, etc. The process domain explains the game design phase of Adaptive SGs. The game design

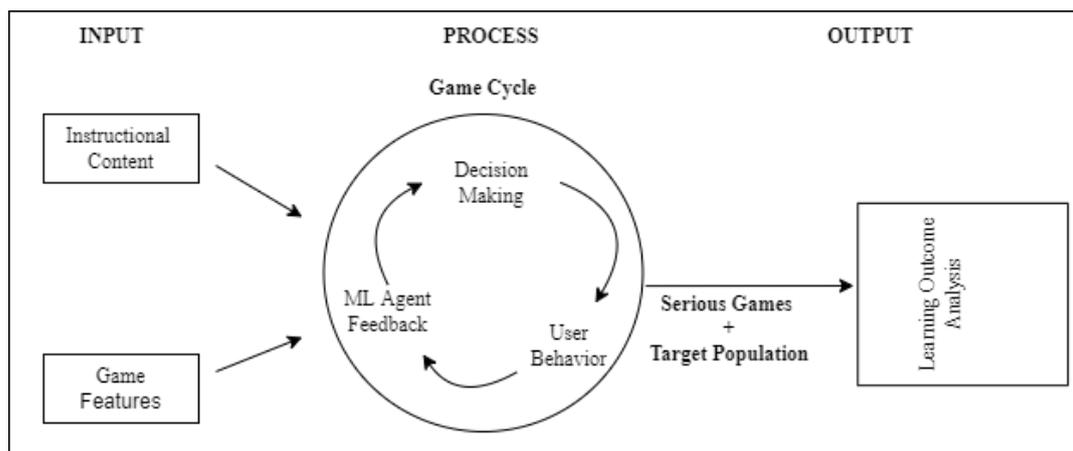


Figure 1: Game Design for an Adaptive SGs

phase proceeds in a cyclic way where the ML Agent takes the decision based on the players' behavior. To establish a connection between learning mechanics and gaming mechanics, the LM-GM framework is detailed in Section 3. The LM-GM framework help in analyzing the

effectiveness of our Adaptive SGs. The result of the input and process domain is the Adaptive SGs which are played by the players. At the end of the game, feedback displays the players' progress w.r.t. the game task specific to the Learning outcomes in the output domain. The game design is shown in Figure 1.

3 Design Considerations

The two web-based games, *i.e.*, SQL Injection with ML and Firewall with ML are developed using Unity platform [38]. Unity acts as a development platform/test bed for eliciting objective player data using its 'Unity analytics' feature. Unity is a cross-platform game engine that deploys easily on several platforms. The two web-based games are accessible on IIT Delhi website¹.

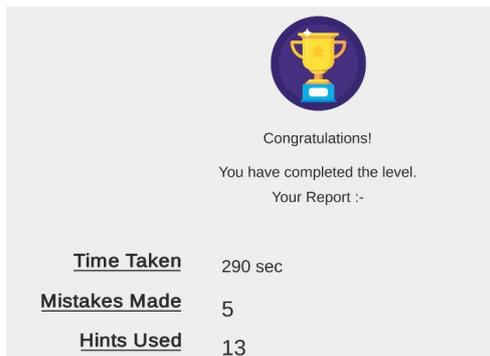
The two web-based games are designed with a purpose to teach the players about one of the Open Web Application Security Project (OWASP) top 10 vulnerabilities, *i.e.*, SQL Injection and a network security, *i.e.*, Firewall. Earlier we had designed two games to teach these concepts using fixed trajectory for all type of players. These earlier designed web-based games provide a baseline to compare performance of our new games with ML agents and this comparison results are being reported by this paper. The system administrators/entry-level IT users are considered as the target audience for the two web-based games. The two playable games are accessible online. While designing the SGs, the main challenge is to maintain a balance between the learning and gaming mechanics. In this regard, the Learning Mechanics-Game Mechanics (LM-GM) framework is used. To design the SGs, designers generally chose common elements from the pool of LM-GM framework along with the learning mechanics. The LM-GM framework with a list of LM and GM mechanics are referenced from [34]. Furthermore, this tool is used as a reflection tool for existing games, it helps in identifying learning/gaming mechanics in an existing game and relation between them. Moreover, the designers also creates the dynamics of mechanics during the game flow to show how the two mechanics adapt themselves and support each other.

The foremost step in using the LM-GM framework is to identify/describe the actual gaming and learning mechanics. We started with an initial Adaptive SGs design with a few gaming and learning mechanics. The design of an Adaptive SGs started with defining the content for the game. To have a clear understanding of the pedagogical intent of the game mechanics, it is necessary to understand the Adaptive SGs' content with the intended learning outcome. We further identified which LM-GM mechanics are to be applied to the gaming scenarios as tabulated by LM-GM framework [34, 35].

At first, the context of the game is presented via an instructional backstory that defines the objectives of the player and rationale for subsequent actions. This is accomplished by utilizing cut scenes. After that, the core mechanics of the game is introduced to the player via a short tutorial. This makes the player comfortable with the user interface and main controls (cascading information). The core loop of the Adaptive SGs are to make the SGs adaptable in levels, where the tasks of the game are explored by the players (behavioral momentum), she tries to understand its structure and how effectively the game adapts to the player needs using a simulate/response method. At the end of each level, the feedback is provided that monitors the progress of the player (score accomplished). This method guarantees that students need to learn and completely comprehend to finish each stage.

To make the Firewall games (with/without ML) more challenging amongst players, we have created a system of rewards by way of badges and display of position of players in the Leaderboard. The badges are assigned to the players once the levels are completed success-

¹http://gost.iitd.ac.in/serious_games/pages/ser.html.



(a) SQL Injection game



(b) Firewall game with Leaderboard



(c) Firewall game with Rewards

Figure 2: Screenshots of the SQL Injection and Firewall Games

fully. Similarly, the players get higher rank if they excel in any more than two of the three metrics; else player gets lower rank. In case of SQL Injection games (with/without ML), the performance report of the players are displayed once the levels are completed successfully. The relevant screenshots are shown in Figure 2. Thus, we see that the game creates a win-loss condition for the players while playing the game.

4 Methodology

This section is divided into two sub sections: (a) Player Classification (b) Learning Outcome (LO). In the Player classification subsection, players are classified into two categories, i.e., Beginner and Expert using Machine Learning Agent. In the LO subsection, LO is analyzed for the adaptive SGs and LM-GM framework is highlighted.

4.1 Player Classification

In serious games [39] without Machine Learning (ML), SGs are constructed in a sequential manner, where on completion of Level 1, Level 2 follows and so on. The demerit of this approach to game design is that all players experience the game similarly and there is no consideration to adapt the game flow to suit the observed capability of the player. To provide this desirable feature of adaptation to the game, we propose to make use of the player data being stored in a database² by Unity analytics. We attempt to use ML to classify a player into two categories, i.e., Beginner and Expert by using the player data for three play attributes namely; number of mistakes made (nm), number of hints used (nh) and time taken to complete

²<https://firebase.google.com/>.

(t), the initial learning phase. We compare these values with median³ of historical data for players who have played this phase in past. We use data of past fifty player while computing the median from historical data. This design decision ensures that we are able to classify the player with reasonable confidence while limiting the data size to a practical limit of fifty. If the player data for any of the three attributes is larger than median of historical data the player is classified as Beginner and game trajectory is adapted to provide additional hints, tutorials and feedback. However, if the player data for all three attributes is lesser than median of historical data, the player is classified as Expert and game trajectory moves faster to suit this type of player. This adaptive approach is used in all levels of the game and has very useful outcome for the player. A Beginner is provided adequate hand holding so that he does not get overwhelmed by the game progress, since context sensitive help is provided to facilitate learning of new concepts, at the same time an Expert is provided opportunity to move forward in his learning journey without unnecessary hand holding which may have resulted in his getting bored with the game. This adaptability of game to ensure the game challenges are tailor made to the type of player is expected to improve learning outcome. A flowchart describing the classification process is shown in Figure 3.

From Figure 3, the equation is shown in Eq. 1:

$$\phi(M_1, M_2, M_3, nm, nh, t) = \begin{cases} B \text{ if } (((nm > M_1) \vee (nh > M_2) \vee (t > M_3)) = 1) \\ E \text{ if } (((nm < M_1) \vee (nh < M_2) \vee (t < M_3)) = 0) \end{cases} \quad (1)$$

where ϕ is the classification function; M_1 , M_2 and M_3 are the computed Median for number of mistakes (nm), number of hints (nh) and time taken (t) respectively. B stands for Beginner categories and E stands for Expert categories. To have a clear difference between two version of games, i.e., with and without ML, some screenshots are presented from Figure (4 to 5). In Figure 4(a), ML agent provides suggestions/hints to the players based on the ability in adaptive SQL Injection game against the SQL Injection game shown in Figure 4(b) is implemented without ML. In Adaptive SQL Injection game, expert players are allowed to skip the levels as shown in Figure 4(c).

Figure 5(a) shows the snapshot of an Adaptive Firewall game. In adaptive Firewall game, Bot appears to introduce the player with the elements of the level. In Adaptive Firewall game, if a player is classified as Beginner, hints are provided to the player when the syntax of command is incorrect (Figure (5(c) to 5(d))); however for expert players no hints are provided (Figure (5(e))). On successfully mastering the Firewall concept, a certificate is issued to the players as shown in Figure 5(f).

After these four games i.e. two with ML and two fixed trajectories are played by sample players to carry out a validation study, we have attempted empirical comparison of two types of games. The reason for carrying out the empirical study between two different approaches are to judge the players' knowledge in these games and get an idea about any observable difference between the two approaches.

4.2 Learning Outcome (LO)

From literature [40], it can be seen that LM-GM framework can't assist us with estimating the LO. The limitation of LM-GM is that it doesn't uncover the association between concrete mechanics and the educational objectives that the game should accomplish. In our research, the LO is measured by using player data which is captured during game play. We have tried to measure the LO of a player with the procedure recommended in [36]. LO is one of the critical

³<https://www.graduatetutor.com/statistics-tutor/measures-of-central-tendency-mean-median-mode/>.

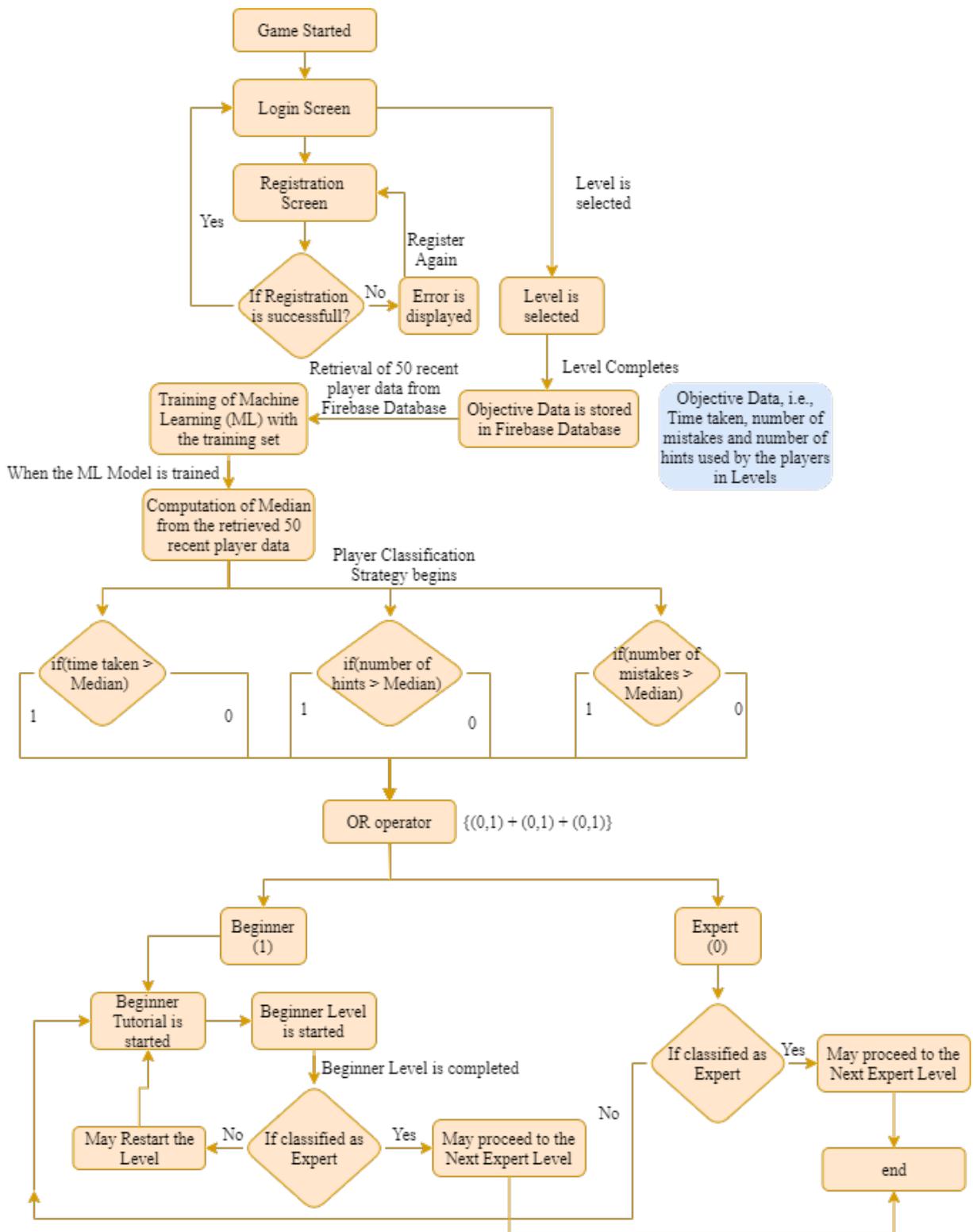
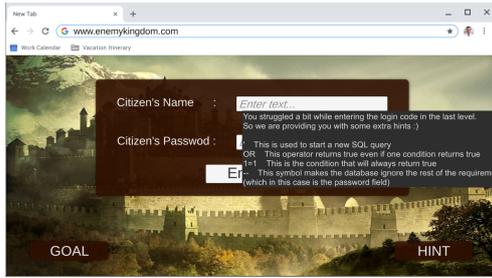


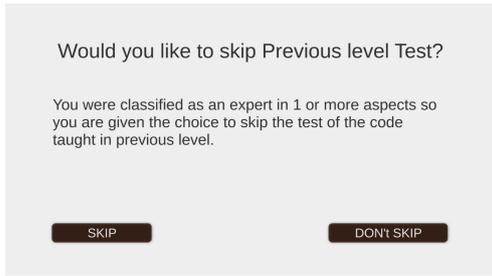
Figure 3: Illustrative Flowchart for classification of players



(a) Adaptive SQL Injection



(b) SQL Injection Without Machine Learning



(c) SQL Injection With Machine Learning

Figure 4: Screenshots of SQL Injection game

characteristics of a SGs and unless we accomplish it in a very clear manner, we might miss achieving our fundamental objective.

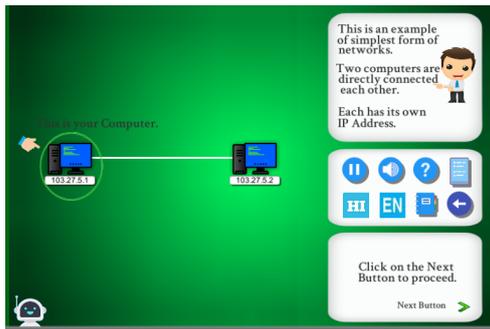
The phases of these games are divided into two phase: (a) Teaching Phase. (b) Testing Phase. Moreover, the teaching phase and testing phase are divided into five levels for Firewall game and three levels in the SQL Injection game respectively.

We assess the scores acquired in every one of the levels to categorize the players. Besides, to normalize the difficulty level across the levels, we take the weighted amount of scores acquired in each level. In [35], author had used only time taken as a metric for awarding the score. In our case, we use the number of mistakes, number of hints and time taken by players to complete level as a metric for awarding the score. Both phases have various learning goals. The Initial Assessment Score (IA) corresponds to the teaching phase and the Final Assessment Score (FA) corresponds to the testing phase [36]. The IA and FA are computed separately for each metric like number of mistakes, etc. Once the separate IA and FA are computed for each metric, the Geometric Mean (GM)⁴ is taken for both IA and FA. The reason behind choosing the GM is that GM provides more stable results in case of widely skewed data. The computation process of IA and FA is taken as a reference from [35, 36] which is shown in Eq. (2 to 3).

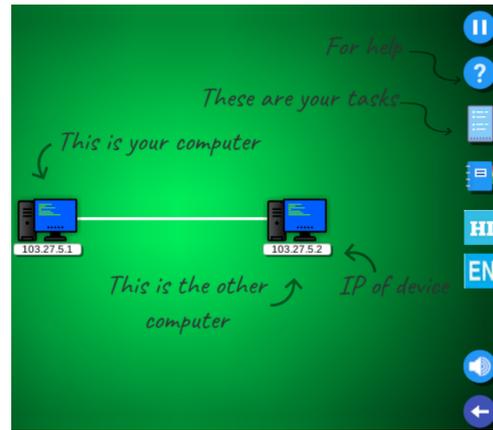
$$IA = G(IA_1, IA_2, IA_3) \quad (2) \qquad FA = G(FA_1, FA_2, FA_3) \quad (3)$$

where G is the function defined for computing the GM. The completion of each phase is determined with the change in values of IA and FA w.r.t. the Initial Threshold (IT) and Final

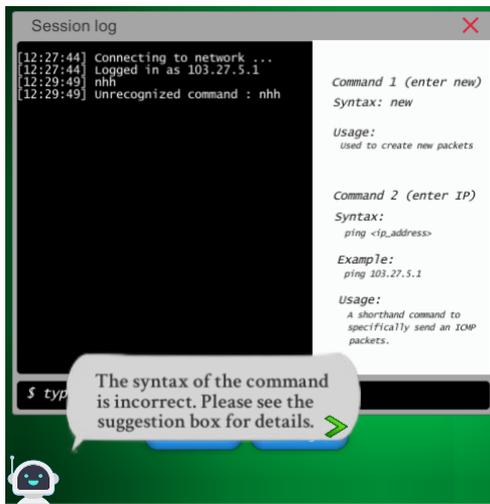
⁴<https://www.educba.com/geometric-mean-vs-arithmetic-mean/>.



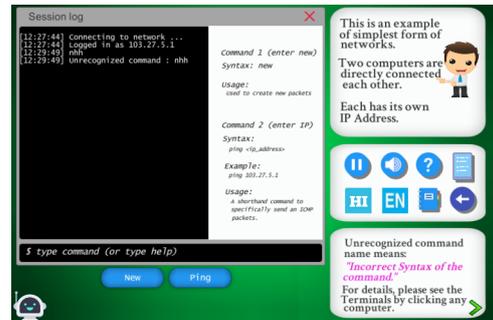
(a) Bot for Adaptive Firewall game



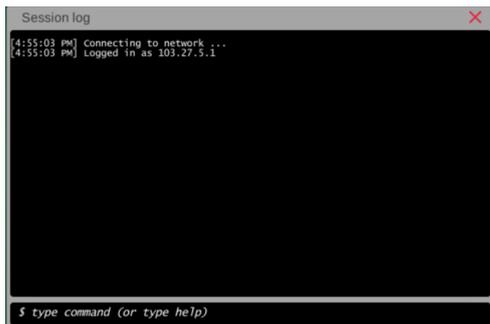
(b) Firewall game without Machine Learning



(c) Bot in Terminal of Adaptive Firewall game for Beginner players



(d) Bot explains the syntax of command in Adaptive Firewall game for Beginner players



(e) Terminal for Expert players in Adaptive Firewall game



(f) Certificate appears on completion of Challenge Level in Adaptive Firewall game

Figure 5: Screenshots of the Firewall Game

Threshold (FT). The IT is computed as mean of IA and FT is computed as mean of FA as taken from Eq. (2 to 3). The mean is taken to compute the threshold for final IA and FA. This

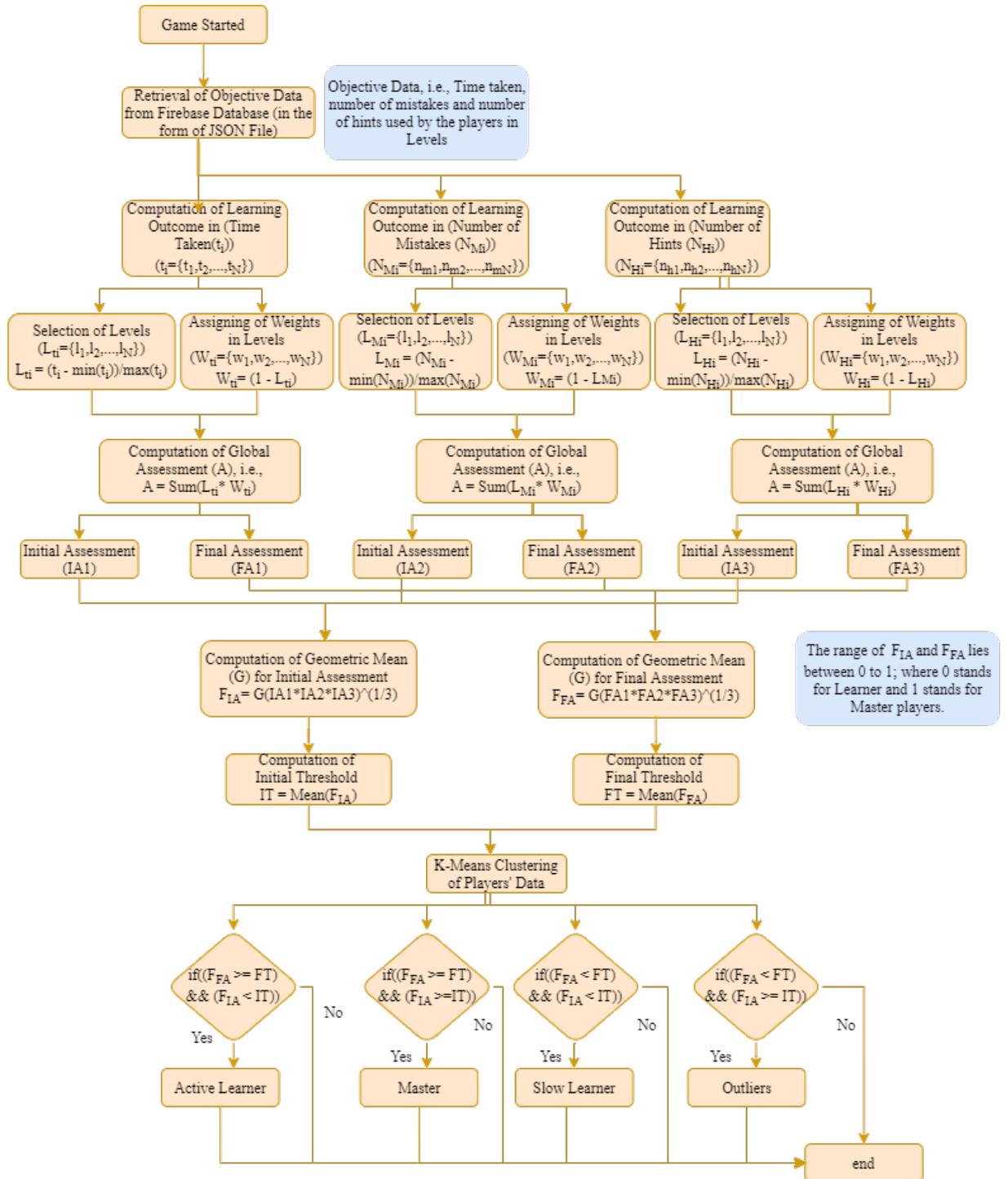


Figure 6: Illustrative Flowchart for Learning Outcome

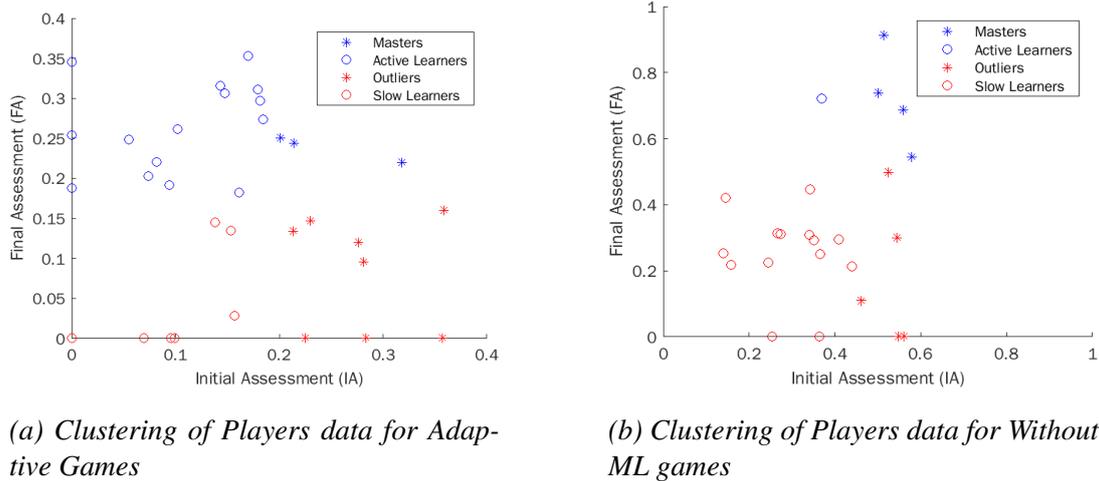


Figure 7: Clustering of Players data for both games

computation process is depicted in the form of a flowchart as shown in Figure 6.

Results

We additionally classify the player into four categories as; The Active Learners are those who perform very well during FA as against Slow Learners who perform low in both IA and FA. Masters are those who achieve high scores in IA and they appear to have sound knowledge during FA phase. Outliers are those players who score poorly in FA even getting great scores during the IA stage. By using k-means clustering [41], the players' data are clustered into four categories as referenced from [35].

Moreover, the clustering of players are done for Adaptive games and non-adaptive games. The focus of this clustering is to show the percentage increase in number of learners (N_L) in the Adaptive SGs as shown in Figure 7. The total data points in Adaptive SGs and SGs without ML are 38 and 30 respectively. This clustering would be more significant when the number of players is large, i.e., more than and subsequently, the clustering displayed in Figure 7 is just for illustration purposes. With the help of an embedded questionnaire, we are able to elicit subjective inputs from players based on their experience while playing these games. The experience of players is described on a five-point Likert scale as suggested in [42]. Subjective feedback from players are gathered in Table 1.

In addition to use of K-Mean Clustering for separating of players in four categories, viz., Active Learners, Slow Learners, Masters, and Outliers, we make use of two statistical approaches for ascertaining the efficacy of Adaptive games. These techniques are described below. The effectiveness of an adaptive game is decided with an assumption, i.e., more number of masters in the game means players have understood the underlying concept of the game very well and vice-versa. To further validate this assumption, the statistical analysis is performed. This is performed with the help of p-value⁵ and correlation coefficient⁶. For p-value analysis, we have assumed in the following ways:

1. Null Hypothesis(H_0): The non-adaptive games are effective.
2. Alternative Hypothesis(H_1): The adaptive games are effective.
3. Assumption: The significance level (α) is 0.10.

⁵<https://www.investopedia.com/terms/p/p-value.asp>.

⁶<https://www.statisticshowto.com/probability-and-statistics/correlation-coefficient-formula/>.

This is done using Student t-test⁷. Based on the analysis, we have obtained p-values as:

1. Case 1: In non-adaptive games, p-value for IA and FA are 0.12471 and 0.15824 respectively.
2. Case 2: In adaptive games, p-value for IA and FA are 0.08858 and 0.04825 respectively.

From the above two cases, we see that Case 2 seems to be stronger than Case 1. This is because p-value is smaller than α in Case 2 than Case 1. So, we reject H_0 and accept H_1 . Hence, we conclude that an adaptive game is more effective for learners than non-adaptive game. Similarly, to carry out the correlation between learners and non-learners players across the game, the correlation coefficient is needed. The formula for correlation coefficient is given in Eq. 4:

$$R_{XY} = \frac{N \times \sum_{j=1}^n xy - (\sum_{j=1}^n x \times \sum_{j=1}^n y)}{\sqrt{[N \times \sum_{j=1}^n x^2 - (\sum_{j=1}^n x)^2][N \times \sum_{j=1}^n y^2 - (\sum_{j=1}^n y)^2]}} \quad (4)$$

where X is set of IA values, Y is set of FA values, x is set of active learners' data, y is set of slow learners' data such that $x \in X$ and $y \in Y$ respectively. After using the correlation formula, the percentage of learners (both slow and active) in adaptive and non-adaptive games are 16.03% and 50.24% respectively. From the correlation coefficient, we conclude that an adaptive game contains more number of Masters against non-adaptive games.

5 Discussion

The analysis of the results in terms of objective evaluation of learning outcome and subjective feedback from players for user experience (UX) tend to show a marginal improvement by introduction of adaptive behaviour in both games. However, this research has used only limited player data and we hope to generate more meaningful data by collecting player data for more than 100 samples. There is also a need to calibrate the criteria being used in learning outcome assessment. This would be possible after a larger set of data samples are available. Our research in evaluating the efficacy of using ML based approach over fixed trajectory games has shown a template for such future studies

6 Limitations

Although our games capture the objective player data using Unity analytics and subjective feedback via a game-based questionnaire, as in Table 1, our dataset is pertaining to only 15 to 18 players because of physical availability of players under ongoing pandemic. We plan to overcome this limitation in near future when more realistic testing under controlled condition becomes feasible.

7 Conclusions and Future Directions

Our paper has focused on describing the design of SGs to show one of the Open Web Application Security Project (OWASP) top 10 weaknesses namely; SQL Injection and network security by utilizing a Firewall. The purpose of designing SGs is to have a focus on UI and UX with regular interaction with an expert in the design aspects. The user interface has been

⁷<https://www.statology.org/how-to-calculate-a-p-value-from-a-t-test-by-hand/>.

Table 1: Subjective feedback Mean Score for two games[35]

Dimension	Attribute	Survey Item	Mean Score of Adaptive SQL Injection	Mean Score of Adaptive Firewall	Mean Score of SQL Injection	Mean Score of Firewall
Gaming Experience	Challenge	The experience was challenging. I found the game stimulating.	3.47	3.15	3	2.8
	Flow	I was able to achieve the goals set in the game.	3.52	3.63	2.93	2.6
	Immersion	I remained focused on the game throughout.	3.36	3.73	3.26	3.4
	Affect	The overall experience was positive.	3.21	3	3.33	3.46
Learning Experience	Learning Goal	The learning goals of the game were clear.	3.05	3.10	3.4	3.2
	Content Appropriateness	The game scenario had relevance to the subject.	2.78	2.94	3	3.46
	Integration	The game required me to use skills being taught.	3.68	2.89	2.8	3.26
	Feedback	The game provided opportunities to receive feedback.	3.84	3.36	3.4	2.53
Usability	Interface Interaction	The user interface was easy to use.	3.36	3.68	3.06	3.2
		It was easy to get started with the game.	3.26	3.52	2.73	3.13
		I learnt how to play the game quickly.	3.42	3.47	2.8	3.53
Fidelity	Visual Appeal Identification Verisimilitude	The playing environment was visually appealing.	3.31	3.78	3	3.46
		I can identify with the components used in the game.	2.89	3.68	2.8	3.2
		I can identify with the story/scenario in the game. The experience felt real.	2.73	2.78	2.86	3.33

modified several times to guarantee that essential fundamental of design are used in these games. We have used embedded questionnaire for viewing the subjective feedback from the players besides using objective data to arrive at a construct of learning outcome. This hybrid view would help in improving next versions of our games. We further have a plan for estimating LO by including sufficient number of players, in near future. We hope to muster students' participation under control group settings when physical participation becomes feasible. Further improvements in terms of content and UI/UX would be attempted based on structured objective analytics and subjective feedback.

Acknowledgement

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