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How does knowledge evolve using adaptive heuristics learning in an engineering game?

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ABSTRACT

In this paper, the primary focus is on the performers whose learning process originate by solving simple or complex problems and perceiving the performers interest in solving advanced problems from the knowledge obtained. An open-source puzzle like a game UNTANGLED is used in our study. The game is developed to unravel the mapping/placement problems in electrical engineering by using human instincts. Telemetry data for the two groups of performers who solved simple and complex puzzles in the first attempt is considered to investigate the Kolb's Experiential Learning Theory (KELT) and fathom the adaptive heuristics for building knowledge from experience. From analysis performed it is evident that a similar learning process is followed by both performers who played initial and complex puzzles in the first attempt. Also, results illustrate that the players who first played initial level puzzles are more interested in playing next level puzzles than the one who first played complex puzzles. Results illustrate that 18% of players who solved easy in first attempt played advanced puzzles in consecutive attempts. Apparently, conclusions advocate that to develop an indelible appetite to deal with advanced/complex problems, STEM education teachers need to structure the lab experiments or teach the complex concepts by starting from simple projects/concepts to complex one. By making learners to try a greater number of low-level abstraction problems will engage learners' interest in solving high-level abstraction problems. Similarly, educational game designers can develop a game environment introducing more intermediate levels, which gives enough experience to deal with difficult levels.

INTRODUCTION

Learning is the accretion of knowledge from experience and study. Kolb proposed a theory in 1984, which completely focuses on learning with experience. Different learning theories are proposed based on the behaviorism, constructivism, cognitivism and humanism [12]. Bi & Yang [3] studies shows the significance of modern learning era on different theories. Learning with experience plays a key role in the process of constructing knowledge. The four features of the process of learning are: (1) redesign process, (2) persistent conversion process, (3) depends on aim and individual, and (4) to master learning, know the sort of knowledge and vice versa. Kolb learning theory based on perception, experience, cognition and behavior and the theory is used to examine the learning process of the performers from experience [9].

Experiential Learning Theory

In the study on experiential learning, Kolb says that learning process is changed over years from repetitive to understanding, and learners need to involve in the learning process to enhance their performance in the higher education [12]. Piaget's cognitive development theory, Lewin's three stage model and Dewey's theory of Pragmatism are the base for Kolb's experiential theory. The theory is strongly embedded with studying, reflecting, thinking and doing. KELT is the constructivist model, which helps to grasp the knowledge and transform or experiment it to acquire new results. The theory is categorized into two levels: four stages of learning cycle and four types of learning styles. The learning styles assist learners to enhance the efficacy in different states of learning [14].

Kolb study [9-12] emphasizes that for efficient learning students should satisfy the four learning stages, as each stage is termed as human potential for optimal learning. The four stages of learning cycle are: Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC) and Active Experimentation (AE). In the first stage CE, learners will do new things without any prior experience/knowledge. Strictly speaking, in this stage learners experience something for the first time with the feel of doing it. In the second stage (RO), learners try to understand the procedure/rules and able to review the observations. In the third stage in the KELT is AC, in this stage learners make conclusions from the observations they made in the previous stage, and in the final stage (AE) learners try to experiment the knowledge obtained to advanced situations. There may be a change in the order of experiencing each stage based on field of study. In CE and AC stages learners apprehend knowledge, whereas in RO and AE stages learners transform knowledge.

Related Work

From previous studies on experiential theory, it is apparent that 30 years old theory is assumed as a productive pedagogical model. The theory is applied for learning difficult subjects in the field of science and engineering. Studies of Abdulwahed et.al [1], Hofstein & Lunetta [7] reviews the importance of satisfying the four dimensions of ELT for laboratory education, to motivate and improve the efficiency of the students in engineering. ELT is incorporated in learning various concepts of engineering field to deal with new competencies of modern era. Santos et al [20, 21] proposed a method by adding reality to learning context. Ebersohn et al [5] postulate that working as a group/team is an approach for learning with experience. Chen et al [4] developed a Ubiquitous Open Structured Neo-tech Edutainment (u-ONE) prototype for children based on experience, joyful and construct learning. Robot and Radio Frequency Identification (RFID) are used by children for learning. u-ONE system designed is composed of software and hardware, which defends instruction, self and collaborative learning.

In addition, games/interactive environment for learning, play a vital role in experiential learning process and considered as the holistic approach to learn with experience. ELT based models like Action Learning and Living Lab developed by MIT (Massachusetts Institute of Technology), LINDE (Learning in Doing Environmental) developed to improve the learning abilities and problem-solving skills of learners [8, 22]. Digital games assimilated with the Kolb's theory is designed to teach the concepts of Quantum mechanics [2], Fuzzy interference mechanism [16], and business process flow, for the undergraduate level students [13, 15]. Several models built based on constructing knowledge with experience model used to motivate learners and improve decision making skills. A gaming framework is used as the learning mechanism for modeling the complex systems [23]. Fraser [6] study on education of testing software using gaming framework, helps to develop the high-quality future generation software applications. Games developed on teaching software testing concepts can assist in learning software testing, helps in long term involvement of learners in testing and solving the complex testing challenges by crowdsourcing.

Proposition

The purpose of the study is to perceive whether the performers are building knowledge to solve complex puzzles/problems from previous experience obtained. The analysis is performed to answer the questions relating to four stages of the learning cycle. First, which puzzles are preferred by the players to play for the first time? Second, do performers use different features available in the game environment while solving the puzzle? Third, do performers gradually improve the thinking process to produce feasible solutions? The last question does performers show interest to play complex levels in the next attempts. To answer these questions, analysis is performed on the players who solved more than one puzzle. The required data is extracted from the gaming framework database, which is designed to solve electrical engineering problems.

BACKGROUND

Mehta et.al [17-19] developed a game to unravel the mapping strategies of the players to develop effective mapping algorithms from human instincts. UNTANGLED has received the *People's Choice Award* in the games & apps category of the International Science and Engineering Visualization Challenge conducted by the National Science Foundation and Science in the year 2012. The game consists of subgames, which are developed based on the connectivity and design constraints. For our analysis, we have considered the ten subgames G1-G10. And, each subgame has seven puzzles based on level of difficulty. Initial levels are named as E1, E2 and E3, and medium levels are named as M1 and M2, and next complex levels are named as H1 and H2. The seven levels in each subgame represents the benchmarks of the digital signal processing applications. The benchmarks are: Sobel (E1), Laplace (E2), GSM (E3), ADPCM decoder (M1), ADPCM encoder (M2), IDCT row (H1), and IDCT col (H2). After registering in *www.untangled.unt.edu* site for free, players can choose to play any puzzle of their choice and there are no restrictions applied. The score, badges, and leaderboard display are some of the features available to check the progress of the players and motivate them to produce feasible solutions. In-depth tutorials for each subgame are available in framework to introduce players to the game and provides details on rules of the game. For instance, connectivity for the game G3 is like the connectivity mentioned in figure 1. Table 1 shows the connectivity for three subgames G1, G3 and G5.

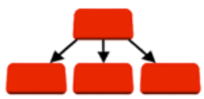
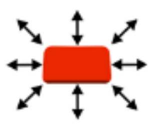
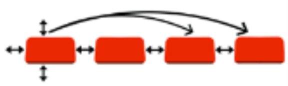
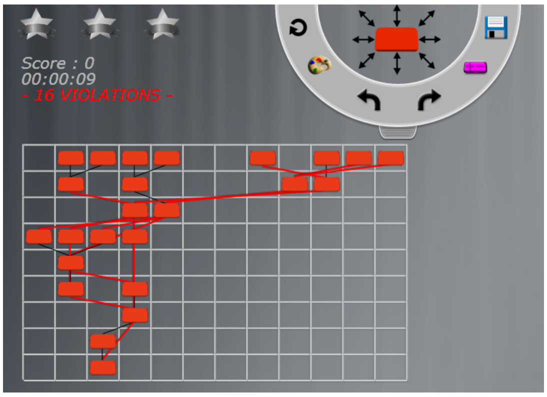
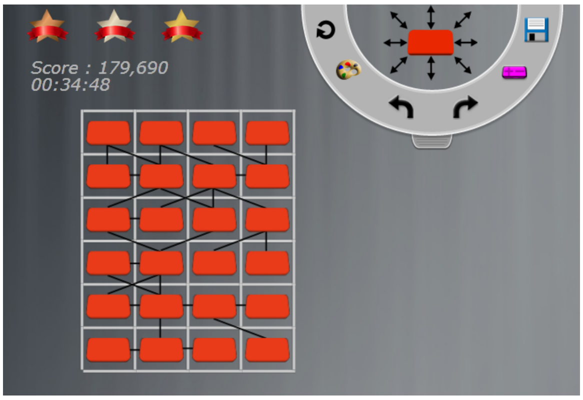
Subgame	Connectivity	Description
G1		The nodes are arranged horizontally and can be connected to below nodes.
G3		Eight-way connectivity, where a node can be connected to eight of its immediate neighbors.
G5		G5 connectivity is like G3, but instead of diagonal connection we can connect to the node by skipping two nodes.

Table 1: Connectivity of G1, G2 and G3 subgames (retrieved from *www.untangled.unt.edu*)





(a) **(b)**

Figure 1: G1-Easy level (a) Unsolved puzzle with 16 violations and zero score (b) Solved puzzle with zero violations and highest score of 179,690 (retrieved from *www.untangled.unt.edu*)

Figure 1 illustrates the G3-easy puzzle and environment of UNTANGLED, whereas figure 1(a) is the initial view of the puzzle and figure 1(b) is the solved puzzle with zero violations. The performers need to arrange the red blocks in the most compact way by reducing violations. The score depends on number of violations and efficient way of placing the red blocks. To move the red blocks, players can use different type of moves available in the game environment. Irrespective of the puzzle the most common moves are: single, multi and swap. Single move helps players to take one immediate step, multi move is used to select group of blocks together to move from one position to another, and swap move is used to interchange the position of two nodes.

EXPERIENTIAL ENVIRONMENT

UNTANGLED is an experimental setup used in this paper. Telemetry data of the players who solved two or more puzzles with a positive score and zero violations is extracted from the database. The data is elicited for the ten subgames G1-G10. In figure 2, degree of difficulty of the level is represented as the level complexity. On the x-axis subgame and level of difficulty are mentioned and the number of players is depicted on the y-axis. From figure 2, it is evident that the most preferred puzzle in the first attempt is G1 (easy, medium and hard), G3 (easy), G10 (easy) and G6 (easy).

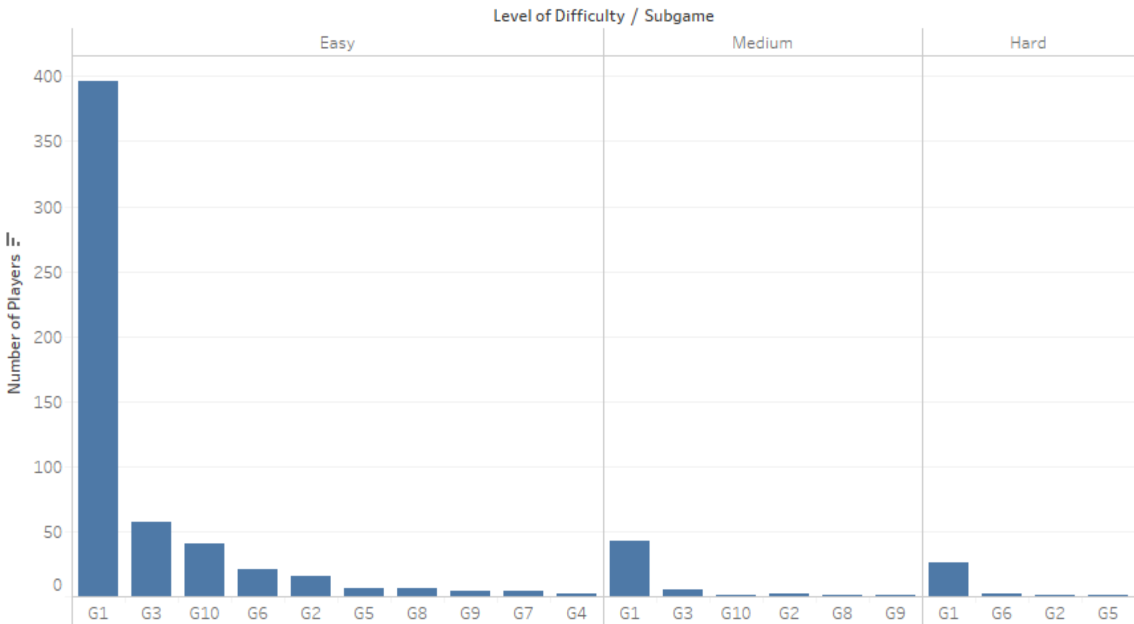


Figure 2: Players preferred architecture/level in the first attempt

Among the 636 players, more than 86% of players solved initial levels and more than 70% of them solved subgame G1 in the first attempt. Surprisingly, all the 636 players tried to solve different puzzle in their second attempt. As maximum number of players played G1 puzzles, the next section describes the performance of the players whose first attempt is G1.

ANALYSIS AND INTERPRETATIONS

In this section, analysis is performed on the players' performance in the first attempt and their interest to solve complex levels from previous knowledge obtained. Among the performers who played G1, almost 88% played easy levels and 12% played next complex levels. The analysis performed explores how performers gained knowledge after solving first puzzle and showed interest to solve the next complex puzzles. The puzzle solving period is divided into four equal parts: Q1, Q2, Q3, and Q4. The dependent variables are type of moves, score improvement, violations, and total score obtained. The independent variables are Quarters (categorized as Q1, Q2, Q3, and Q4), puzzle/graph played (G1, initial/easy and next/hard levels). These variables signify the players' performance in solving the puzzle.

The reason for considering the type of moves (single, swap and multi) as one of the metrics is, as these moves helps the players to solve the puzzle. It is not necessary all the players use same type of moves to solve the same puzzle, hence moves used by the player defines the player strategy to solve the puzzle. Score improvement is another metrics used in analysis, which says the improvement of the score for each quarter. Score improves as number of violations reduces. In this game, player can have multiple solutions for the same puzzle, hence we can say obtaining zero violation count mean player achieved a feasible solution. The total score is another metrics, which explains the final score obtained by the players after solving the puzzle with zero violations. As the extracted data is not satisfying normalization, the data is analyzed using suitable statistical tests. To know the effect of each quarter on dependent variable, non-parametric test called Mann-Whitney U is performed on the given data. The significant level or p-value is also called asymptotic significant value. P-value specifies whether all the groups are performing in the same way or if there is any difference in their performance. And, mean ranks obtained after performing Mann-Whitney test describe which group is having more impact on the dependent variable. In this section, we run the test for Q1 and Q4 quarters, which describes the players' performance while solving the puzzle during start and end phases.

Type of Moves

Tables 2 and 3 shows mean ranks of different moves for easy and hard puzzles, and significance value between the Q1 and Q4. Asymptotic Significance (mentioned as Asymp. Sig in Table 2 and 3) value helps to check whether there is the significance difference between the two groups (Q1 and Q4). The type of moves used in each quarter indicates that players are strategically using the moves available in the game to produce feasible solutions. There is a statistically significant difference in the number of moves used if $p \leq 0.05$. The test is conducted on the G1 easy players' data considering number of moves as continuous dependent variable.

Puzzle Moves	Type of	Quarters	N	Mean Rank	Sum of Ranks
G1-Easy	Single Move	Q1	391	401.12	156839.50
		Q4	389	379.82	147750.50
		Total	780		
	Swap Move	Q1	263	244.25	64238.00
		Q4	256	276.18	70702.00
		Total	519		
	Multi Move	Q1	252	237.84	59935.50
		Q4	245	260.48	63817.50
		Total	497		
G1- Hard	Single Move	Q1	26	33.08	860.00
		Q4	26	19.92	518.00
		Total	52		
	Swap Move	Q1	17	14.21	241.50
		Q4	23	25.15	578.50
		Total	40		
	Multi Move	Q1	21	23.21	487.50
		Q4	24	22.81	547.50
		Total	45		

Table 2: Mean ranks of type of moves used in each Q1 and Q4 for initial and complex levels

Test Statistics[a]

Puzzle		Single Move	Swap Move	Multi Move
G1-Easy	Mann-Whitney U	71895.500	29522.000	28057.500
	Wilcoxon W	147750.500	64238.000	59935.500
	Z	-1.321	-2.443	-1.774
	Asymp. Sig. (2-tailed)	.187	.015	.076
G1-Hard	Mann-Whitney U	167.000	88.500	247.500
	Wilcoxon W	518.000	241.500	547.500
	Z	-3.132	-2.932	-.103
	Asymp. Sig. (2-tailed)	.002	.003	.918

a. Grouping Variable: Quarters

Table 3: Significance of dependent variable between Q1 and Q4 for initial and complex levels

The p-value of single moves (0.187), swap move is (0.015) and multi moves (0.076) describes that different number of swap and multi moves are used in Q1 and Q4, and there is no significant difference in the number of single moves used. The p-value (single= 0.02, swap =0.003 and multi=0.918) for hard level data also indicates that the number of moves used in initial period (Q1) is different from the end period (Q4) of the game. Single moves mean rank is higher in first quarter compared to fourth quarter, which says that a greater number of moves are used in initial period of solving game compared to end period. Finally, we can conclude that players are using different number of moves during the puzzle solving period and most frequently used moves are single moves.

Violations and Score Improvement

Tables 4 and 5 shows mean ranks of violations and score for easy and hard puzzle, and significance value between the Q1 and Q4. The test is performed on the G1-easy and hard levels. A p-value obtained for easy level shows that there is a significant difference in the number of violations and in score improved for each quarter. The significance level (p= 0.013) and mean rank (Q1 =1046 and Q4= 1106.72) obtained for the violation variable depicts that there is statistically significant difference between Q1 and Q4 quarters. Similarly, there is statistically significant difference in score improvement (p=0.00) between Q1 (mean rank=1200) and Q4 (mean rank=970.19) quarters.

Puzzle Dependent Variables		Quarter	N	Mean Rank	Sum of Ranks
G1-Easy	Violations	Q1	1012	1046.60	1059155.00
		Q4	1144	1106.72	1266091.00
		Total	2156		
	Score Improvement	Q1	1012	1200.94	1215353.00
		Q4	1144	970.19	1109893.00
		Total	2156		
G1-Hard	Violations	Q1	71	69.14	4909.00
		Q4	90	90.36	8132.00
		Total	161		
	Score Improvement	Q1	71	100.54	7138.00
		Q4	90	65.59	5903.00
		Total	161		

Table 4: Mean ranks for the Q1 and Q4 for dependent variables violations and score

Test Statistics[a]

Puzzle		Violations	Score Improvement
G1-Easy	Mann-Whitney U	546577.000	454953.000
	Wilcoxon W	1059155.000	1109893.000
	Z	-2.471	-8.591
	Asymp. Sig. (2-tailed)	.013	.000
G1-Hard	Mann-Whitney U	2353.000	1808.000
	Wilcoxon W	4909.000	5903.000
	Z	-3.125	-4.722
	Asymp. Sig. (2-tailed)	.002	.000

a. Grouping Variable: Quarters

Table 5: Significance between Q1 and Q4 in initial and complex level played in first attempt

The p-value obtained for the hard level is ≤ 0.05, which says the significant difference in violations and score improvement in between Q1 and Q4. Finally, the results conclude that there is difference in the number of violations and score obtained from the initial period of game to the end.

Effect on Total Score

Tables 6-9 depict mean ranks and significant difference between the first and second attempts made by the players in easy and hard levels. This result shows whether there is any effect on score with the attempts made. Analysis performed shows how the score differs when players played in the order of easy first and then easy/hard in later attempts. The same analysis is performed on the players who performed hard first and then easy/hard in the next attempts. The significance level and mean rank (p= 0.00, mean rank=248.73 and 418.80) shows there is statistically significant difference in the total score obtained by the players who played easy in first and hard in second attempts. The mean ranks obtained illustrates that players are obtaining the maximum scores in second attempts than in first attempt.

	Attempts	N	Mean Rank	Sum of Ranks
Total Score	G1- Easy in first attempt and then G1-easy in later attempts			
	First (G1-Easy)	396	362.74	143647.00
	Later (G1-Easy)	522	532.90	278174.00
	Total	918		
	G1- Easy in first attempt and then G1-Hard in later attempts			
	First (G1-Easy)	396	248.73	98496.50
	Later (G1-Hard)	223	418.80	93393.50
	Total	619		

Table 6: Mean ranks when first attempt is G1-Easy Puzzle

Test Statistics[a]

	Total Score
G1-Easy in later attempts	
Mann-Whitney U	19890.500
Wilcoxon W	98496.500
Z	-11.359
Asymp. Sig. (2-tailed)	.000
G1-Hard in later attempts	
Mann-Whitney U	65041.000
Wilcoxon W	143647.000
Z	-9.630
Asymp. Sig. (2-tailed)	.000

a. Grouping Variable: Attempts

Table 7: Significance Level when first attempt is G1-Easy Puzzle

	Attempts	N	Mean Rank	Sum of Ranks
Total Score	G1- Hard in first attempt and then G1-easy in later attempts			
	First (G1-Hard)	26	42.12	1095.00
	Later (G1-Easy)	40	27.90	1116.00
	Total	66		
	G1- Hard in first attempt and then G1-Hard in later attempts			
	First (G1-Hard)	26	23.50	611.00
	Later (G1-Hard)	18	21.06	379.00
	Total	44		

Table 8: Mean ranks when first attempt is G1-Hard Puzzle

Test Statistics[a]

	Total Score
G1-Easy in later attempts	
Mann-Whitney U	296.000
Wilcoxon W	1116.000
Z	-2.940
Asymp. Sig. (2- tailed)	.003
G1-Hard in later attempts	
Mann-Whitney U	208.000
Wilcoxon W	379.000
Z	-.621
Asymp. Sig. (2-tailed)	.535

a. Grouping Variable: Attempts

Table 9: Significance Level when first attempt is G1-Hard Puzzle

The p-value (.003) considering first attempt as hard and second attempt is easy. Mean ranks (first=42.12 and second=27.90) explains that the high scores are obtained in the first attempt made by the player. Similar observations can be made from the players whose first attempt hard and second attempt easy. The results conclude that playing the easy levels first may produce better results than playing hard levels in first attempt. Also, we can say that most of the players are showing more interest to solve hard levels in later attempts than in first attempt.

DISCUSSION AND ASSOCIATION TO EDUCATION FIELD

The type of moves, score improvement, violations and total score obtained in the puzzle solving period portrays the learning process. The performers' conscious or unconscious process of constructing knowledge while solving puzzles aid to produce feasible solutions for the complex problems. By dividing the puzzle played period into quarters, we can see how the players are learning to solve the puzzle in the first attempt. Type of moves used, score improvement, violations and total score obtained shows impact on learning theory. The previous section shows significantly evident results of the players who followed four stages of learning process.

CE and RO Stages

Performers' sense of initiating the new puzzle without any proper training is considered as the *Concrete experience.* The difference in the number of moves used in each quarter shows that players are making the next move based on the observations made from the previous move. That is, performers are making observations in the previous quarters and acting accordingly in the succeeding quarters to produce better results. This kind of learning from the observations made depicts the *reflective* stage of the learning stage.

AC and AE Stages

While moves indicates efficient utilization of features available in game, the violations and score improvement shows that players thinking process while solving the puzzle. Either the puzzle is easy or complex, players tried to reduce the violations and improve the score while solving puzzle. Players positive scores and zero violations explain that they understood the concepts of the game to produce sensible solutions. This stage of experience is called *abstract conceptualization*. The interest shown by the 636 players to solve second puzzle after they solved their first puzzle illustrates that players are using the knowledge gained from the previous experience to solve the second puzzle. This kind of learning is mentioned by Kolb's as *active experience*. There are less than 18% players solved next level complex puzzles, which clearly discloses the fact that most of the players showed interest to solve easy puzzles and very few used their previous experience to solve the complex puzzles.

IMPLICATIONS

Instructors and educational game designers face a great challenge in developing interest among students to solve new and advanced problems from the previous experience obtained. We can see some students performing best while doing simple experiments and lose their interest as the complexity increases. Instructors can implement an alternative approach for students who face difficulty in completing complicated experiments. Instructors can assist students to practice simple projects first and then increase the level of difficulty gradually to motivate and engage their interest to perform well in complex/advanced projects. Based on the complexity of the concept instructors need to provide more introductory level projects to ease the process of learning and create long term interest. Even educators can provide the collaborative environment in the classroom, where students interact with better performed students, and share views and ideas to overcome hurdles for progressing skills from the previous experience. Similarly, educational game designers need to build with initial levels, which make players to walk through the game rules, and then gradually increase the complexity of levels to serve the purpose of designing the game. Game designers can create the interactive environment, where clues are provided to players to facilitate the next step in a game. Also, a gaming framework where players can work collaboratively to solve puzzles can help develop their interest to solve complex levels.

CONCLUSION

From analysis performed it is evident that performers showed interest to solve simple puzzles than the complex puzzles. First two stages (AC and RO) of experiential cycle obtained by playing the simple/complex puzzle for the first time and understanding the rules/options available. Performers thinking process of solving a puzzle till they obtain zero violations and trying to play new/complex puzzle in the next attempt depicts the next two stages (AC and AE) in learning theory. Finally, the learning process of the two group of performers is the same but less than 18% of players showed interest in solving complex problems in their consecutive attempts. To engage participants in solving complex problems instructors can help them with basics, fundamentals, solve easier problems that would improve their learning experience solving advanced problems. Instructors can also open discussion forums, where participants can have the chance to share their thoughts/ideas that can help them solve complex problems. Educational game designers can improve players game play experience by gradually increasing the level of difficulty and providing clues for more advanced puzzles. They can also consider providing multi-player gaming environment where players can collaborate and solve complex problems as a team.

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