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The effect of different difficulty adaptation strategies on enjoyment and performance in a serious game for memory training

O efeito de diferentes adaptações de dificuldade em estratégias de diversão e performance em serious games para trieno de memória

El efecto de diferentes adaptaciones de dificultades en estrategias de diversion y performance en serious games para entrenamiento de memoria

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ABSTRACT

Keywords: Video games; Motivation; Psychology; Cognition disorders; Games experimental

Objective: The goal of this study was to evaluate two kinds of difficulty adaptation techniques in terms of enjoyment and performance in a simple memory training game: one based on difficulty-performance matching ("task-guided") and the other based on providing a high degree of control/choice ("user-guided"). **Methods:** Performance and enjoyment are both critical in making serious games effective. Therefore the adaptations were based on two different approaches that are used to sustain performance and enjoyment in serious games: 1) adapting task difficulty to match user performance by leveraging the theories of zone of proximal development and flow, thus maximizing performance that can then lead to increased enjoyment and 2) providing a high degree of control and choice by using constructs from self-determination theory, which maximizes enjoyment, that can potentially increase performance. 24 participants played a simple memory training serious game in a fully randomized, repeated measures design. The primary outcome measures were enjoyment and performance. **Results:** Enjoyment was significantly greater in user-guided ($p < 0.05$), whereas performance was significantly greater in task-guided ($p < 0.05$). **Conclusion:** The results suggest that a trade-off between maximizing performance and maximizing enjoyment could be achieved by combining the two approaches into a "hybrid" adaptation mode that gives users a high degree of control in setting difficulty, but also advises them about optimizing performance.

RESUMO

Descritores: Jogos de vídeo; Motivação; Psicologia; Transtornos cognitivos; Jogos experimentais

Objetivo: Consiste em avaliar dois tipos de adaptação de dificuldades em termos de ludicidade e desempenho num jogo simples de treino de memória: um dos métodos é baseado no relacionamento entre desempenho e dificuldade (guiado a tarefas) e o outro é baseado em prover um alto grau de controle e escolha (guiado a usuário). **Método:** Desempenho e ludicidade são ambos críticos ao fazer jogos sérios serem eficientes. Assim sendo, a adaptação foi baseada em dois aspectos diferentes que são usados para sustentar tanto o desempenho como a ludicidade: 1) adaptar as dificuldades das tarefas para corresponder o desempenho do usuário através de nivelamento das teorias da zona proximal, maximizando o desempenho que podem levar ao acréscimo do fator lúdico e 2) prover um alto grau de controle e escolha usando construtores da teoria da autodeterminação, que maximiza o lúdico e potencializa o aumento do desempenho. Foram selecionados 24 participantes para utilizar o jogo de treino da memória de uma forma totalmente aleatória. Os primeiros resultados medidos foram ludicidade e desempenho. **Resultados:** A ludicidade foi significativamente maior na abordagem guiada a usuário ($p<0.05$), enquanto o desempenho foi significativamente maior no modelo guiado a tarefas ($p<0.05$). **Conclusão:** Os resultados sugerem que haja uma combinação entre maximização de desempenho e maximização de ludicidade, criando um modelo adaptado híbrido, capaz de dar ao usuário um alto grau de controle na escolha da dificuldade, mas também sugerindo otimizações de desempenho.

RESUMEN

Descriptores: Juegos de video; Motivación; Psicologia; Trastornos del Conocimiento; Juegos experimentales

Objetivo: Estudio consiste en valuar dos tipos de adaptación de dificultades en respecto al lúdico y performance en un juego simple de entretenimiento para memoria: uno de los métodos es basado en el relacionamiento entre performance y dificultad (guiado a tareas) y el otro es basado en fornecer un alto grado de controle y elección (guiado a usuario). **Metodos:** Performance y lúdico son ambos críticos al hacer que juegos serios sean eficientes. Esto dicho, la adaptación fue basada en dos aspectos distintos que son usados para sostener tanto la performance como el lúdico: 1) adaptar las dificultades de las tareas para corresponder a la performance del usuario por el uso de las teorías de zona proximal, maximizando e la performance que pueden llevar al aumento del factor lúdico y 2) proveer un alto grado de control y elección usando constructores de la teoría de la autodeterminación, que maximiza el lúdico y potencializa el aumento de performance. Fueran seleccionados 24 participantes para utilizar el juego de manera totalmente aleatoria. Los primeros resultados medidos fueron el factor lúdico y performance. **Resultados:** El lúdico fue significativamente mayor en la abordaje guiada a usuario ($p<0.05$), mientras la performance fue significativamente mayor en el modelo guiado a tareas ($p<0.05$). **Conclusión:** Los resultados sugieren que haya una combinación entre maximización de performance y maximización del factor lúdico, creando un modelo adaptado hibrido, capaz de dar al usuario un alto grado de control en la elección de la dificultad, pero también sugiriendo optimizaciones de performance.

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INTRODUCTION

Computer-based games and learning environments are being increasingly used to facilitate learning, training and rehabilitation in an enjoyable way. Prominent examples are serious games[1] and intelligent tutoring systems[2]. The attraction of using games and learning environments for training is that they can be augmented with dynamic difficulty adaptation that is able to adapt tasks to users' requirements in a personalized manner[3], which can improve their functional effect[4].

The design of computer-based games and learning environments is driven by two, sometimes conflicting goals: to make the games performance-oriented, and also to make them enjoyable. The performance-oriented requirement is implicit: in order to enable the functional effect that they are designed for, serious games and learning environments must ensure that user performance, generally defined as how well users complete tasks, be of a certain, high degree[1]. On the other hand, enjoyment is also important because users are more likely to play serious games if they are enjoyable[5] and enjoyment also results in a more positive learning outcome[6-8]. The methods used to sustain performance and enjoyment in serious games can be broadly divided into two categories. One set of methods seeks to maximize performance, which can then lead to increased enjoyment. The second category includes methods which come from the other direction: they seek to maximize enjoyment, which can lead to increased performance.

The first category includes techniques based on two separate but related concepts in motivation theory, namely the zone of proximal development (ZPD) and the theory of flow. ZPD, originally proposed by Vygotsky[9], is the gap between what a learner has already mastered (actual level of development) and what he or she can achieve when provided with educational support (potential development)[10]. An operational definition, given by Murray *et al*[11], is that ZPD is the zone of instructional interaction wherein the material given to the learner is neither too difficult nor too easy, so that the learner is neither too bored nor too confused. The concept of flow, introduced by Csikszentmihalyi[12], postulates that motivation to do a task can be increased by matching the task difficulty to user performance, so that the user is neither overwhelmed nor bored. These two ideas have been used to adjust task difficulty of serious games and learning environments, so that the user remains in ZPD or the flow channel when performing the task. Examples include intelligent learning environments that keep track of learners' performance and provide guidance to keep the learners in ZPD[2, 13-14], and serious games that are augmented with adaptation mechanisms that match task difficulty to user performance[15-17].

The second category has been influenced by self-determination theory (SDT), which has been applied to enhancing motivation in serious games and learning environments. SDT postulates that the basic psychological needs that foster motivation for tasks are autonomy, competence and relatedness[18]. Perceived competence has been found to be positively related to the state of flow[19] and is thus affected by similar adaptation mechanisms as described before. In-game autonomy, on the other hand, is facilitated not by difficulty-performance matching, but by providing control/choice, which can lead to increased enjoyment[20]. Control/choice appear as a factor in other models of game enjoyment[21], in making serious games more enjoyable[22], in increasing motivation in computer-based educational activity[23] and as one of the elements that make instructional environments motivating[24].

While previous research has been able to leverage the constructs of motivation theories to make games and learning environments enjoyable, most of the work has focused on either difficulty-performance matching (keeping users in flow/ZPD, satisfying the competence need of SDT) or on providing control/choice (satisfying the autonomy need of SDT). However, it is not clear whether the two approaches lead to similar results or whether focusing on performance may lead to sub-optimal enjoyment. This is extremely relevant since, while serious games and learning environments naturally aim to increase performance, they also need to be enjoyable in order to be effective[25].

The present work seeks to address this issue by evaluating the effect of two kinds of difficulty adaptations in the same game: one adaptation based solely on difficulty-performance matching and the other based solely on providing a high degree of control/choice. The adaptation based on difficulty-performance matching was expected to keep users in the ZPD/flow channel and thus maximize their performance while potentially increasing enjoyment. An adaptation based solely on a high degree of control/choice, on the other hand, was expected to maximize enjoyment while potentially increasing performance. While exploratory in nature, the present study could provide clues to making games and learning environments both enjoyable and performance-oriented.

The paper is structured as follows. Section 2 describes the serious game used in the study, the adaptation modes and their implementation, the study design and the enjoyment and performance measures used to evaluate the modes. Section 3 reports the results for enjoyment and performance in the different modes. Finally, Section 4 concludes the paper with a discussion of the results and implications for serious game design.

METHODS

The Adaptation Modes

As previously mentioned, two important theoretical bases for dynamic difficulty adaptation have been difficulty-performance matching and providing control/choice. To evaluate their effects, two primary modes of adaptation were envisaged.The first mode was designed to provide a high degree of control/choice by giving users the control to set values of difficulty parameters *during* the game. This would enable the users to regard their performance and behavior in the game to be under their own personal control and potentially increase their enjoyment. This is in contrast to the pre-set difficulty levels that users can select before starting a game, typically described by subjective terms like "easy", "medium", "hard". Such subjective terms may not enable users to judge the actual task difficulty. In addition, users' skill level might change over the course of the gameplay, rendering pre-set difficulty level inadequate or overwhelming. Therefore, providing control at a high granularity could lead to sustained enjoyment in the game. This adaptation mode was termed *user-guided*.

As a comparison to user-guided, a second adaptation mode was designed that focused on difficulty-performance matching. This adaptation mode, termed *task-guided*, automatically adjusted difficulty parameters of the game task to match performance of the user. We note here that the difficulty parameters available for change in user-guided were exactly the same as those available to task-guided. Temporally, the points at which users could change the parameters were also the same as when task-guided could change them. In this way, user-guided was analogous to task-guided.

As a baseline against which to compare user-guided and task-guided, a third mode, termed *random*, was also included in the study, which set difficulty parameters to bounded, random values, at the same time points as the other two modes.

With these three adaptation modes designed, we postulated two research questions:

RQ1. Is enjoyment significantly greater in any one adaptation mode than the others?

RQ2. Is performance significantly greater in any one adaptation mode than the others?

Experiment Design

The experiment was conducted with 24 healthy participants (mean age = 27.5, SD = 2.74; 19 male, 5 female). Participants were recruited via the university flyer board and their participation in the experiment was voluntary.

The participants played a simple serious game in which they were placed in a virtual living room containing some objects lying on the floor and several numbered locations, where the objects could be placed (Fig. 1a). The game was played in first person perspective. Participants could move around the virtual living room using the keyboard (move front/back) and the mouse (turn left/right). Interaction with the objects was achieved by mouse click: an object was picked by moving the mouse cursor over the object and left clicking and it was released by right click. An object was placed at a location by picking it up, carrying it to the location, and clicking on the location. The memory task that the participants had to perform was to memorize a list of object names and location numbers, to find the objects and to place them in the appropriate location. Participants could view the list of object names and location numbers by pressing the 'L' key (Fig. 1b); however, this list could only be viewed a limited number of times.

The serious game was developed using the Unity game engine*. Unity is an intuitive, graphically programmable game engine that is especially suitable for rapid development of small games and thus finds widespread use in serious game development. The game was run on a 3.5 GHz Intel i7 computer running Windows 7 with 16 GB of RAM, coupled with NVidia GeForce GTX 670 graphics card, using a 24 inch LED monitor set to a resolution of 1920 x 1080. Participants were free to adjust the position of the monitor and the chair.

The task was to memorize a list of object names and location numbers, to find the objects and to place them in the appropriate location. Once participants finished putting all objects in their correct location, a round was completed, and participants won some virtual cash based on the number of objects (N), the number of times list was viewed (M), and the number of times list was viewable (L), as given by (1).

$$Cash = \frac{N^2}{M \times L} \qquad (1)$$

The way virtual cash was computed ensured that participants who viewed the list as few times as possible were awarded for it. Additionally, taking into account number of times list is viewable rewarded participants in user-guided who "bet" on their memory by setting a low value for this parameter. Once participants finished a round, they had the option of "buying" a bonus object using their virtual cash. The bonus objects included things like a massage chair, a mountain bike, guitar, amplifiers, which were thought to be desirable objects, and could act as a factor of motivation. Subsequently, a new round was started. At all times during a round, participants also had the option to restart the round.

A repeated measures design was used, in which each

Figure 1 - (a) The serious game used in the experiment, where participants were placed in a virtual living room containing some objects and numbered locations. (b) The list of object names and location numbers which had to be memorized.

* http://unity3d.com/

participant played the game in all the 3 adaptation modes: user-guided, task-guided, and random. The experiment was conducted in 3 sessions, over 3 consecutive days, 1 session per mode. Each session lasted 40 minutes and was held at the same time of day, +/- 1 hour. The order of the 3 modes was fully randomized, which resulted in 6 groups of combinations. The 24 participants were randomly divided into the 6 groups in single blind fashion.

Implementation of the adaptation modes

The adaptation modes described in section 2.1 worked on the following two difficulty parameters of the game task:

- Number of objects: The total number of objects in the current round.

- Number of times list is viewable: The total number of times participants could view the list of object names and location numbers.

The initial values for number of objects and number of times list is viewable were set to 5 and 2, respectively. These values were obtained from pilot tests which were conducted internally prior to the start of the experiment. The pilot subjects did not participate in the actual experiment.

In user-guided, after completing a round, the game presented a message to the participants, informing them of the formula that was used to compute how much cash they won, as given in (1). The game then asked participants if they wished to change the two parameters: number of objects and number of times list is viewable. At this stage, participants could either change one or both parameters, or choose to continue with the same parameters, after which a new round was started.

Task-guided increased the number of objects by 1 and decreased the number of times list is viewable by 1 if the participant successfully completed a round. On the other hand, if the participant restarted a round, the number of objects was decreased by 1 in case of 3 or more consecutive restarts, or the number of times list is viewable was increased by 1 for all other cases. Both the difficulty parameters were not changed upon round restart in order to give participants the opportunity to finish the round with the same number of objects. Task-guided was kept simple in order to focus only on performance. Automatic adaptation, by its very nature, cannot fit all users, and it was deemed better to have a minimalist technique that increases and decreases difficulty in steps of 1.

In random, after completing a round, number of objects and number of times list is viewable were set to random values. The random values were generated prior to the start of the experiment and stored in a file. The same values were used for all participants, ensuring that there would be no divergence in motivation and performance on account of different values. The random values were bounded within the same range as in user-guided and task-guided.

Measures

Subjective measures

Motivational measures typically consist of self-report by users, in which users answer a questionnaire with items that have to be rated on a Likert scale, often from "strongly disagree" to "strongly agree"[26-29] . One such questionnaire is the Intrinsic Motivation Inventory (IMI)[30-31], which has been used and validated in many motivation studies [32-35], and which was used in the present study.

After each session, participants were asked to fill in a questionnaire that consisted of the perceived enjoyment and perceived competence subscales of the Intrinsic Motivation Inventory[30-31] and the perceived challenge subscale of the Physical Education Learning Environment Scale (PELES)[33]. Each subscale consisted of 5 subjective questions, to be graded on a 7-point Likert scale, from 1 ("not at all true") to 7 ("very true"), giving a total of 15 questions. All the questions were adapted to be relevant to the present study.

At the end of the experiment, participants were asked to subjectively rank the three sessions in terms of perceived enjoyment, perceived competence and perceived challenge in 3 levels: most-, moderately- and least-. An example of a ranking would be: most enjoyed on Day 1, moderately enjoyed on Day 3, least enjoyed on Day 2. Since the group to which a participant belonged was known, the ranking of days was translated to a ranking of adaptation modes.

Performance

To evaluate the effect of the three modes on performance, game play was recorded in a log and

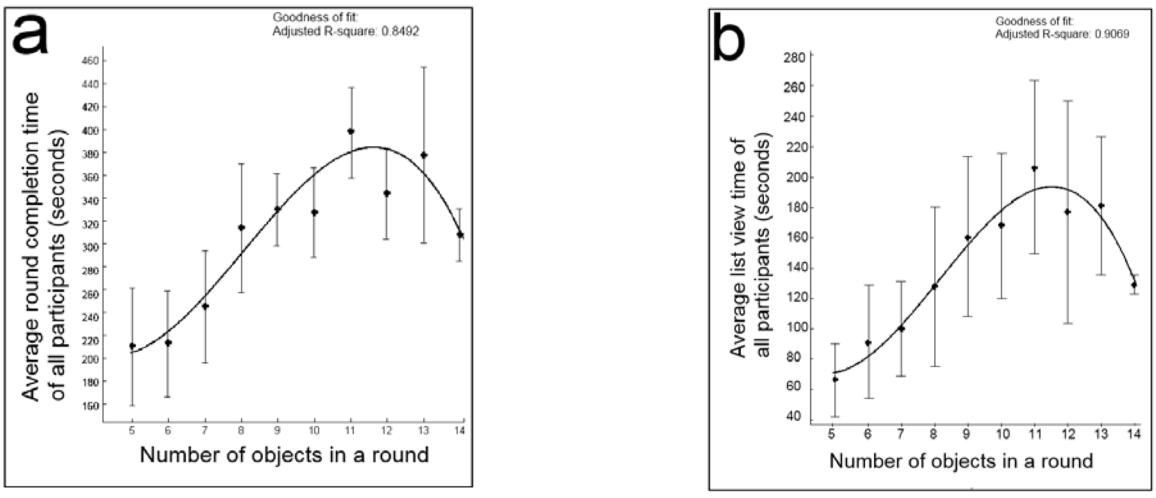


Figure 2 - (a) Round completion time and (b) list view time, both shown as a function of the number of objects in that round, in task-guided, averaged across all participants.

analyzed post-game to derive the following metrics:

1) Average List view time

This was computed as the total time spent looking at the list in all rounds in a session, averaged by the number of objects in all rounds.

2) Cash won

This was the total cash won in a session, which was computed according to the formula given in (1). The square term used in the formula was validated at the end of the experiment by relating number of objects in a round in task-guided with round completion time and list view time. Both were related to number of objects by a cubic polynomial (Fig. 2).Since round completion time and list view time were good indicators of the effort required to complete a round, the cubic relation with number of objects validated cash won as a performance metric.

Approach in user-guided mode

From pilot tests which were conducted prior to the experiment, it was found that participants in user-guided mainly used one of two approaches: either they were explicitly trying to maximize cash ("cash-seekers"), or they were trying to challenge themselves ("challenge-seekers"). Therefore, in the actual experiment, at the end of the user-guided session, participants were asked about the approach that they followed, and the amount of cash won by participants in the two groups was compared.

RESULTS

Subjective measures

The answers to the 5 questions on the three subscales of perceived enjoyment, perceived competence and perceived challenge that participants answered after each session were averaged to give one real number value for each subscale, for each adaptation mode. Differences in the subscales were analyzed with a one-way repeated-measures analysis of variances with adaptation mode as the factor of interest. The Sidak test was used for post-hoc comparisons. The threshold for significance was set at $p = 0.05$. Perceived enjoyment was found to be significantly greater in user-guided than both task-guided and random, thus answering **RQ1** (Fig. 3a). Perceived challenge, on the other hand, was found to be significantly greater in task-guided than both user-guided and random (Fig. 3b), which could be due to the fact that participants set lower number of objects for themselves in user-guided than what the game set for them in task-guided (Fig. 5a). Perceived competence did not exhibit any significant differences (Fig.3c). In order to visualize post-experiment rankings, numerical values were assigned to the answers, with a value 2 given to "most-", a value 1 given to "moderately-", and a value 0 given to "least-". These values were averaged over all participants and plotted for the three modes (Fig. 3d). The statistical findings of post-session questionnaire were reinforced here: enjoyment was greatest in user-guided and challenge was greatest in task-guided.

Group-wise, there were no significant differences in the motivation subscales between the six groups (Fig. 4a). Participants in the groups for which user-guided was on Day 1 (Groups 1 and 2) had, on average, a higher perceived enjoyment than other groups (Fig. 4a). In general, participants were motivated to play the game, and found the memory task to be interesting. Even though they were all healthy, several participants reported that it was

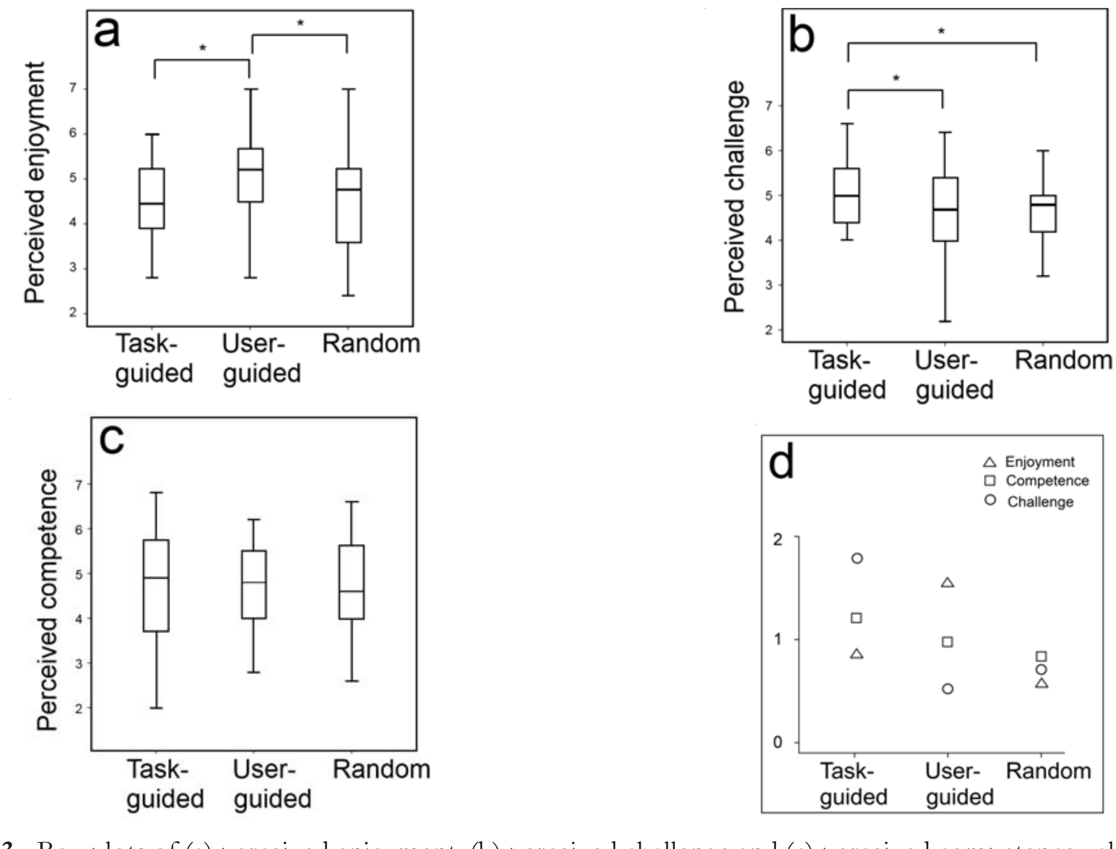


Figure 3 - Box plots of (a) perceived enjoyment, (b) perceived challenge and (c) perceived competence values for the three modes. Differences at the $p < 0.05$ level are marked with a *; (d) Post-experiment rankings in the three subscales of enjoyment, competence and challenge, averaged across all participants.

challenging to form memorizing strategies at higher difficulty levels, especially in task-guided. A few participants in user-guided found the session duration of 40 minutes to be too little, and wanted to play longer so that they could challenge themselves further.

Performance

Differences in performance metrics were analyzed with a one-way repeated-measures analysis of variances with adaptation mode as the factor of interest. The Sidak test was used for post-hoc comparisons. The threshold for significance was set at $p = 0.05$. Both cash won and list view time were significantly greater in task-guided than user-guided and random (Fig. 6). Cash won, being a function of the two difficulty parameters of number of objects and number of times list is viewable, was the objective performance metric. Therefore, cash won being greatest in task-guided answered **RQ2**.

Average list view time being greater in task-guided can be explained by the fact that since in task-guided, number of list views rapidly went down to 1, participants spent more time looking at the list. Intuitively, one can imagine that if you have one list view with 10 objects, and two list views with 5 objects each, the average list view time per object would be higher in the former case. Group-wise, there were no significant differences in any of the performance metrics, although participants in the groups for which user-guided was on Day 1 (Groups 1 and 2) won, on average, less cash than the other groups (Fig. 4b).

Approach in user-guided mode

In user-guided, in answer to the question "which approach did you use in this mode", 8 participants answered a variation of "was trying to win maximum cash" (categorized as cash-seekers) and 6 participants answered a variation of "was trying to challenge myself" (categorized as challenge-seekers). 10 participants could not definitely say if they were using either one approach or the other. Table 1 shows the cash won in user-guided for the different subsets of participants and also in task-guided, although the question of approach was explicitly asked only after user-guided.

Table 1 - Cash won for different subsets of participants.

Subset of participants	*N*	*M*	*SD*
User-guided, all participants	24	7079	1677
User-guided, cash-seekers	8	7353	1510
User-guided, challenge-seekers	6	8156	1723
Task-guided, all participants	24	9958	2168
Task-guided, cash-seekers	8	11211	2015
Task-guided, challenge seekers	6	9676	2357

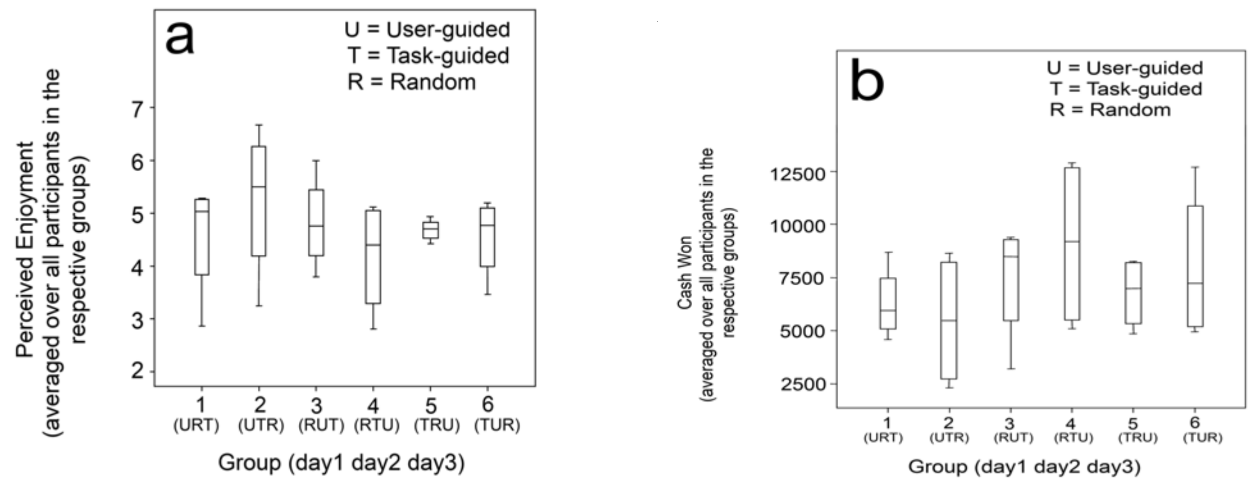


Figure 4 - (a) Box plot of perceived enjoyment values and (b) box plot of cash won values for the six groups of participants.

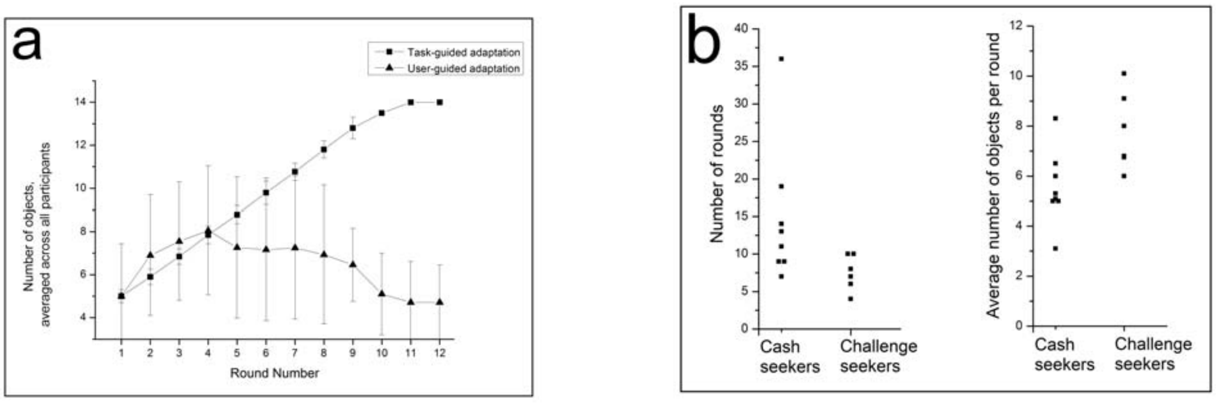
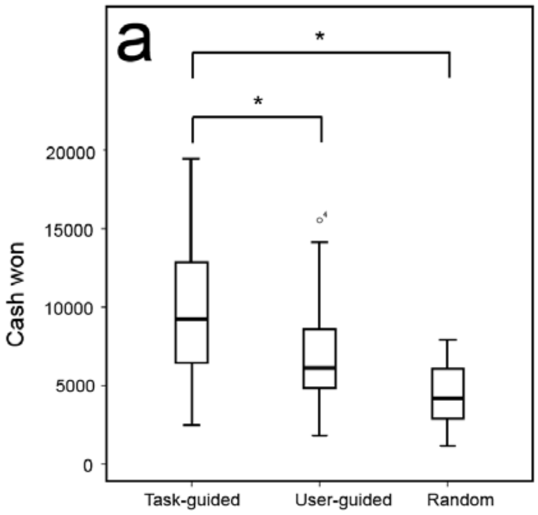


Figure 5 - (a) Number of objects in the first 12 rounds in task-guided and user-guided, averaged across all participants. (b) Number of rounds (left) and average number of objects per round (right) in user-guided mode for participants using different approaches.



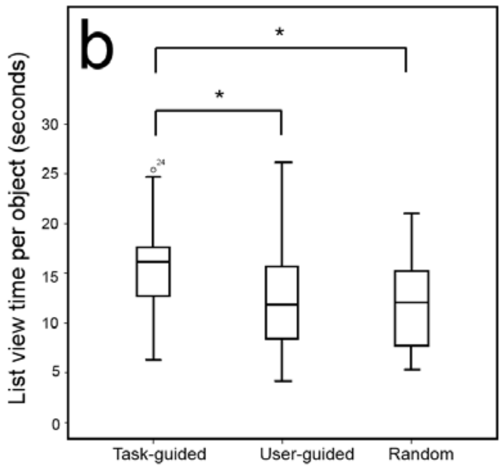


Figure 6: (a) Box plot of cash won and (b) box plot of list view time per object for the three modes. Differences at the $p < 0.05$ level are marked with a *.

DISCUSSION AND CONCLUSIONS

Discussion of the results

Various approaches have been used to make serious games both enjoyable and performance-oriented. The approaches that we considered in the introduction, flow/ZPD and SDT, broadly attempt to address the issue in two very different ways. Flow/ZPD tries to maximize performance by matching task difficulty to user performance, which can potentially lead to increased enjoyment. SDT begins in the other direction, by giving users the feeling of autonomy and competence, in order to maximize enjoyment, which can then potentially lead to increased performance. User-guided and task-guided, which were the two modes of adaptation based on SDT and flow/ZPD respectively, showed markedly different results for enjoyment and performance.

Enjoyment was found to be significantly greater in user-guided than both task-guided and random. Performance, on the other hand, as reflected in the primary objective measure of cash won, was significantly greater in task-guided than both user-guided and random. It is true that task-guided had been designed explicitly to maximize performance, and the way the cash metric was computed depended primarily on the number of objects (Equation 1). However, it was expected that increased enjoyment in user-guided would spur users to set higher difficulty levels for themselves. In fact, the cash won in user-guided and task-guided was dependent on the approach that the participants used (Table 1). The results in Table 1 present a rather mixed picture. On average, challenge-seekers won more cash in user-guided than cash-seekers. Cash-seekers played more rounds on average than challenge-seekers, but they also had fewer objects per round (Fig. 5b). This suggests that cash-seekers used a strategy of cramming in as many rounds as possible in the 40 minute session, hoping to finish each round quickly by having few objects. Although this strategy did not translate into more cash, it does point to the fact that participants consciously set out to play the user-guided mode with a specific purpose and actively shaped their adaptation to fulfill the purpose. On the other hand, in task-guided, cash-seekers did win more cash as compared to challenge-seekers (Table 1). Since only 14 of the 24 participants could definitely say that they were using a particular approach, the numbers in Table 1 must be interpreted with caution. Certain tentative conclusions, however, could be drawn. In user-guided, challenge-seekers used the flexibility of being able to set custom difficulty parameters to their advantage. Cash-seekers, too, tried to play the game with a certain strategy (more rounds, few objects per round). Had the game been able to *advise* participants about the cash they would win if they continued with their current strategy, there is a possibility that participants might have used the advice. In task-guided, a possible reason for challenge-seekers winning less cash than cash-seekers could be because they were not comfortable with the game setting parameters for them. While these conclusions are tentative, it can be argued that providing the control to set difficulty parameters worked for some participants, and the game setting the parameters worked for others.

No significant group-wise differences were found in enjoyment and performance measures, although cash won was less in the groups who had user-guided on Day 1 (Groups 1 and 2; Fig. 4b). Since participants in user-guided set a lower difficulty level (Fig. 5a), winning less cash on Day 1 could be attributed to participants not forming strategies to memorize locations of a large number of objects on Day 1, and thus not being "ready" for the higher difficulty levels that awaited them on Days 2 and 3. Enjoyment, on the other hand, showed the opposite trend, being higher in Groups 1 and 2 than the other groups (Fig. 4a), which could be due to participants enjoying all the sessions more once they had the chance to set difficulty parameters for themselves on Day 1. This highlights, to some degree, the dichotomy that exists between enjoyment and performance in serious games.

Implications for serious game design

In the introduction, we described difficulty-performance matching and providing control/choice as two approaches to maximize enjoyment and performance in serious games. Our results indicate that different in-game actions are needed for the two approaches, and that neither of them is optimal: players enjoyed themselves the most in user-guided mode, but performed the best in task-guided. This supports previous suggestions, for example by[36-37], that fun and learning might not be compatible and that players' desire for fun might detract them from learning. An important related consideration is the short-term vs. long-term learning effect of a serious game. While we did not expect and thus did not directly measure a learning effect in our study, the cash won could be considered as an approximation of the game's short-term learning effect (similarly to Jarvis *et al*[38]), which would suggest that maximizing performance would also maximize learning. However, the relative lack of enjoyment with such an approach could hamper long-term learning[25].

It is our opinion that a "trade-off" between maximizing performance and maximizing enjoyment is needed to ensure both short-term and long-term learning in serious games. In our simple memory training game, one potential strategy could be a "hybrid" mode where users would have the control to set values of difficulty parameters, similar to user-guided. However, the game would *advise* users about the resulting performance, and consequently the learning effect, of the current combination of difficulty parameters. In this hybrid mode, short-term learning could be effected by advising users on ways to improve their performance, and long-term learning could be sustained by letting users retain the control to adjust difficulty parameters so that they enjoy playing the game. Additionally, by advising users, the game could help users form a strategy to improve their performance. Assuming that performance does indeed reflect learning effect of the game, such helpfulness could foster enjoyment in users[39].

This study is limited by some factors: the simple nature of the serious game, the small sample size, and the fact that participants were healthy young adults, as opposed to elderly and cognitively impaired people who are the target population of memory training games. Despite its limitations, the present study emphasizes the different approaches required to achieve performance and enjoyment in a serious game, and a possible way to bridge the gap between the two. Although the proposed hybrid adaptation mode requires long-term studies with the target population, it has the potential to make serious games both performance-oriented and enjoyable.

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