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Evaluating the Adoption of the Physical Board Game Ludo for Automated Assessments of Cognitive Abilities

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Abstract. Serious games present a valuable tool for continuous cognitive assessments especially in the case of elderly, where there is a lack of cognitive tools to continuously assess the transitory conditions that occur between normal cognition and cognitive failure. However, designing games for elderly poses distinctive challenges since one has to take into account the limited experience of today's elderly with digital gameplay interfaces like touch screens that are second-nature to younger players. In this paper we present an initial user study with young and healthy subjects where we evaluate a computer-vision based digitalization process that is necessary to turn a physical version of the board game "Ludo" into an automated assessment tool. We further evaluate to which extend this tool presents a valid alternative to assess the strategic cognitive capabilities of a person. We have chosen Ludo in its physical form after careful consideration together with elderly and caregivers since many elderlies know this game from their childhood and thus do not need to learn new game rules or to adapt to digital environment.

Keywords: Serious games · Cognitive assessment · Evaluation
Board game · Ludo

1 Introduction

In many countries around the world the relative number of people aged 65 or older is increasing [1, 2]. As a consequence, the capacities for elderly care are predicted to get sparser. The European Union is trying to dampen the effects of such shortcomings by investing in research fields, such as Ambient Assisted Living (AAL) and Serious Games for Health [3, 4]. When Clark Abt first coined the term of Serious Games (SG) in 1970, he described it as a game that is "not intended to be played primarily for amusement." [5]. Overviews of the research field of SG by Susi et al. [6] and Djaouti et al. [7] show the diversity of use cases, ranging from the American military to educational classrooms and from role-play to video games. In the subfield of Healthcare Games a similar diversity can be found, ranging from exercise games to train the physical condition, to ones that focus on the mental abilities [8]. Michael and Chen indicate that Serious Games are a combination of learning and assessment [8].

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Moreover, Bellotti et al. highlight that in-game assessment provides the opportunity to take advantage of the medium itself and employ alternative, less intrusive and less obvious forms of assessment [9]. Yet, it may provide more detailed and reliable information about the test subject [10]. Shute further mentions the benefits of stealth assessment, an assessment method which is seemingly woven into the game and unobtrusive to the player, which might prove beneficial in the case of elderly [11].

But there are two inherent problems with regards to using SG in elderly care. Firstly, much of the research focus on SG is based on digital games, using computers or tablets as input method [12]. As a result, it requires the elderly to learn technology. This creates a barrier of entrance and leads to the fact that digital SG often assesses in the first place the ability of the elderly to learn new games rules, a new game environment, and how to use a new technology [13, 14] – not necessarily what should be assessed from a caregivers point of view: the ability to remember rules and their strategic abilities. In contrast, many digital SG are meant to teach a certain new objective, and are therefore designed from scratch with these objectives in mind. In elderly care this might overburden the elderly, cause disinterest, and distract the elderly from the assessment objective of the game [14].

To overcome these barriers we propose to study cognitive abilities (1) using a board game that is well-known to elderly from their childhood (2) not in a digital but in its physical form. As a result, elderly do not have to learn new rules or get acquainted with a new technology. Since the game is used in its physical form, elderly can play the way they are used to since their childhood by moving physical pawns on the physical game board. After careful consultations with elderly, caregivers, and experts from social care, together we decided to evaluate the game 'Ludo' which is very popular in Germany under the name "*Mensch ärgere dich nicht*" and in the Netherlands under the name "*Mens erger je niet*". There are only a couple of scientific publications concerning the game, Ludo. The first one uses Ludo as an exemplary game to present the ease of use of some GUI framework [15]. The second publication presents solutions to the AGTIVE 2007 Tool Contest, which required the participants to create and implement a deterministic version of the game [16, 17]. Cujzek and Vranic studied the use of a computerized version of Ludo as a training device for cognitive abilities of elderly [18]. To the best of our knowledge we are the first to study the application of Ludo as an assessment for cognitive abilities.

The study documented in this paper serves two purposes: (1) We explore the required effort to turn the physical board game into an assessment device allowing for continuous and automated assessments. Although digital game devices for serious games pose a barrier for elderly, they come with much comfort for the experimenters since the entire game state can be continuously documented in an automated way with little effort. Using a physical version of the game, we first have to digitize the entire game state, before we can hope to automate the assessment process. (2) We evaluate whether the game Ludo can be used to assess cognitive abilities of players. This question becomes important since the game uses dice to determine the possible moves of a player and thus incorporates a strong element of luck. We explore three key features of game playing:

- To evaluate if the game still can be influenced by the strategic abilities of the players we compare the distribution of the number of moves of human players with the distribution of a gameplay generated by a computer program that plays according to the rule but chooses randomly whenever confronted with a strategic choice.
- To evaluate if players simply follow a strict game policy or if they vary their approach, we evaluate if players familiar with the game of Ludo always choose to kick their opponents' pawn whenever possible.
- Furthermore, we evaluate if players that are expected to possess full cognitive capabilities play the game without making any mistakes with regard to the game rules.

In this paper we present test results from participants with an age in the range of 20 to 28. We explicitly chose to test first with healthy young subjects that are expected to have full cognitive capabilities to reduce the effect of cognitive capabilities on the initial test results and because for ethical reasons we found it important to test only with elderly when the setup is confirmed to work effectively.

2 Methods

2.1 Game Rules of Ludo and Experimental Setup

Figure 1(a) illustrates the board layout. The different shapes in Fig. 1(b) indicate the types of fields. We use a simplified version of the game for elderly where each player plays with 2 pawns (instead of 4 as it is typically the case) of one color (red, green, blue or yellow). The players take turns rolling a die and moving the own pawns by the count of the die. At the beginning, all pawns are placed in their corresponding home fields. The goal of the game is to move all pawns to their target fields of the same color. When a six is rolled, the player has the obligation to place one of its pawns from the home on the start field. On the next die roll this pawn has to be moved along the path of intermediate fields in clockwise direction according to the count shown by the die. An exception is the case, where a six is rolled but the start field is still occupied by a player's own pawn. When this happens, the pawn occupying the start field is moved by the die count. Every field can only be occupied by one pawn at a time. If a player's pawn moves onto a field being occupied by an opponent's pawn, the opponent's pawn has to return to its home field forcing the opponent to start over. Once a pawn has circled the entire board, it can enter the target fields, where it is safe.

The physical board of length 50 cm was placed under a stand (see Fig. 1(c)). A webcam was mounted to the stand at a height of 70 cm, filming the board from the bird's-eye perspective. For the experiments a Logitech C525 webcam was used with a resolution of 720p (1280px $\times$ 720px) and the RGB color profile. The video was recorded with 30 frames per second (FPS). However, the algorithm, described in the following used only 3 FPS, which ensured a stable frame rate for online processing of the game state.

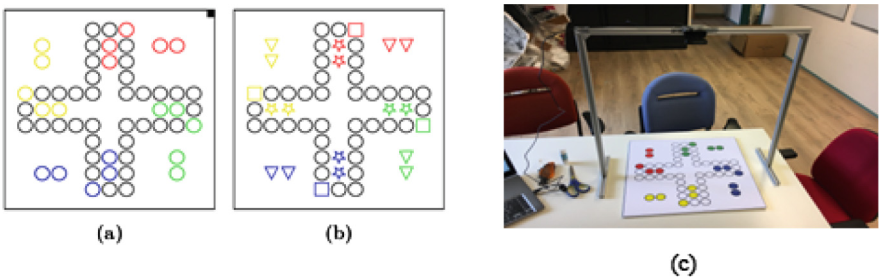


Fig. 1. (a) shows the final layout of the board used for experiments. The different shapes in (b) indicate the types of fields. Triangles: home fields, stars: target fields, squares start fields. (c) Experimental Setup. (Color figure online)

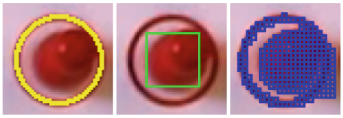
2.2 Digitization of Board Game

The analysis of the game state was performed through computer vision for autonomous detection of the physical game board, its game fields, and the placements of the pawns. Our approach was chosen to enable an assessment tool that could run autonomously and continuously in the background without affecting the players in their natural game play. The detection algorithm was implemented using Python 2.7 and the wrapper for the OpenCV library. The algorithm was designed to be sufficiently light-weight to run online on a standard computer so that we would be able in the future to provide feedback to users during the game. All images were recorded in form of a video file for careful offline analysis.

Our software continuously detects the black boundary of the physical game board by using the Canny edge detection algorithm [19]. From the binary image with detected edges, the largest contour is found using an algorithm first described by Suzuki [20]. The contour's area is then compared to the area of the largest four-sided approximation. If the areas do not differ by more than 2%, the four-sided approximation is used for a perspective transformation to square the edges and cut the image, such that only the board remains. Comparing the contour against a four-sided approximation is done to ensure that no hand is possibly obstructing the image of the board, in which case the contour would have more corners. Circles in the board representing the game fields are detected in the image using the 2-1 Hough Transform [21, 22]. Detected circles are matched up with the closest circles in the theoretical model of Fig. 1(a). A perspective transformation is applied using the homograph from a least squares fit. The fit is computed between detected circles and the expected circles from the model, if more than two circles are detected.

Before a game starts we run a calibration procedure to detect the correct RGB values of all pawns. It was decided to use the RGB color space rather than a more common color detection alternative such as HSV, since the red and yellow pawns used during the experiments had relatively similar hue values and a small change in the lighting situation would cause false detections. We could have used more distinctive colors that are easier to detect. However, after consultations with caregivers and elderly we decided to stay with the colors that are well-known and do not represent a distraction to the elderly.

Once calibrated during game play, game fields being occupied by pawns are automatically detected by finding those circles that are filled with non-white color. This is accomplished by using a threshold that discriminates white empty fields from fields that have other color. To avoid being influenced by the border of the circle, the algorithm only checks the largest square fitting inside the circular field, (see Fig. 2). Furthermore, the algorithm checks whether the number of non-white circles is equal to the total number of pawns. If this is not the case, it is assumed that the board is in an intermediate state where pawns were moved.



(a) (b) (c)

Fig. 2. (a) shows a detected circle, (b) shows the largest square inside the circle used for occupancy detection and (c) shows the circles split in small patches used for color detection. (Color figure online)

For the circles that are detected as non-white, the color is determined (Fig. 2). For this, a majority voting scheme, as described by Molla and Lepetit [23], is deployed. The smallest square encompassing the circle is, therefore, split in 196 patches. Each of the non-white patches determines its color by computing the smallest Euclidean distance to the calibrated colors. Afterwards, the color with the most votes is determined to be the color of the pawn on the field. By using this majority vote system, it is ensured that the color of the pawn is more important than the color of the field. If a red pawn is placed on a field with a green circle, this system will be able to detect the red pawn since it has considerably more votes.

2.3 Data Collection and User Study

We collected data of 15 participants playing in total 12 games in 4 rounds. Testing larger numbers of participants would have been logistically challenging since as part of the validation process of the digitalization approach we had to examine each game play situation by comparing the results from the automated digitalization with the observations that could be derived by a human from the taken video material. This required watching, pausing, and replaying all games of all participants several times and led to several days of work even with only 15 participants. The final digitalization technique simplifies the assessments but its verification that is presented here is very work intensive. One participant (ID = 1 and 16) participated twice. In each game 4 players participated at the same time. Each player played the game three times consecutively always against the same opponents in order to allow the players to adapt to the rules, to reduce the element of chance, and to be able to observe some trends in play behavior.

After playing three times, the players were asked to fill in a questionnaire, reflecting on their game play abilities and emotions. Our questionnaire was developed by adopting questionnaires for assessing technology acceptance of elderly [24, 25] and assesses emotions including stress, comfort, confidence, and excitement on a 5-level Likert scale.

All participants were enrolled students at Maastricht University in the age range of 20 to 28. Only two participants indicated that they had never played the game before. We recorded six female and nine male participants. From the recordings we stored (1) the position of all pawns on the board before a move, (2) the ID of the current player who was in turn to move, (3) the time between the last player finished a move and when the current player rolled the die, (4) the die count, and (5) the position of all pawns after the move of the current player. Invalid moves by players were not prevented during game play but accepted and manually checked against the video file to confirm them.

3 Results on Robustness of Game Board and Game State Detection

We first tested if an automation of the game board detection could be done reliably under real game situations to understand if testing elderly in the future could be reliably automated with the current setup. For each of the four experimental rounds with participants, the first game was used as a reference for testing the robustness of the board detection with varying lightning conditions. The first experimental round was indirectly lit with large windows on two sides of the board. The second and third rounds were in the same environment with a fluorescent light tube at the ceiling and a small window on one side of the board. However, during the third round there was no light coming through the window. Both rounds with fluorescent light show flickering in the video. The last setup was lit indirectly through two windows from one side of the board. During the test games, each frame from the video input was classified as either “board detected” if the contours of the board have been successfully detected or “board not detected” purely based on the detected contours of the game board. Each automatic classification was checked manually for validity and then counted, which resulted in the false positive and false negative rate shown in Table 1.

Table 1 show that round 3 has the lowest false negative rate and round 1 the lowest false positive rate. Furthermore, it shows that the last round has the highest false negative and false positive rate.

We found that once the board contour is detected, finding the circles of the game field is done with a success rate of at least 96%. Despite the fact that the board contour detection shows the aforementioned error rates, misdetections of an overall game state occurred only twice during all experiments when players covered the board with their hands during the entire change of game state.

Table 1. Detection of the board in different scenarios.

Round	1	2	3	4
Scenario	2 windows (2 sides)	1 window & fluorescent tube	Fluorescent tube only	2 windows (1 side)
Total # frames	3330	3401	2699	4581
Total # negative (no board)	1451	686	489	1802
False negative rate	32.80%	9.77%	5.52%	47.84%
Total # positive (board found)	1879	2715	2210	2779
False positive rate	7.24%	8.62%	24.93%	25.84%

4 Results on Ludo as an Assessment Tool for Cognitive Capabilities

In the following we evaluate how much influence players can have on the game of Ludo and if the game is suited as an assessment tool for cognitive abilities.

4.1 Effect by Reduction of Pawns

Based on the advice of caregivers and elderly we had reduced the number of pawns per player from 4 to 2. This was done to reduce the time of a single game and thus the time elderly players have to concentrate continuously. To quantify the effect of the reduction of pawns, 20000 simulations with random strategies were executed. The simulations ran for the original version, as well as the reduced version with 10000 iterations. The results were compared with regards to the average number of moves per player, as well as the percentage of moves in which the player had more than one choice. The reduced version has a decrease by more than 300% to a mean of 48.3 (for 2 pawns) from 207.5 (4 pawns) average moves per player per game. Furthermore, the percentage of choices has reduced to a mean of 39.0% (2 pawns) from 65.1% (4 pawns). This shows that despite the fact that the movement possibilities are partially controlled through a die, a player is still confronted with choices for which of the own pawns should be moved.

4.2 Do Human Players Play Randomly?

During games with human players we found that in the 2-pawn version players on average had to make 42.56 moves with a standard deviation of 5.96 (minimum number of moves: 31, maximum number of moves: 54). Figure 3 shows a comparison of the distribution of the number of moves gained from the human players, against those retrieved from a computer simulation using a random strategy. The Anderson-Darling test clearly rejects the null-hypothesis of an equal distribution ($p < 0{:}01$) indicating that human players do not play randomly but might follow a strategy.

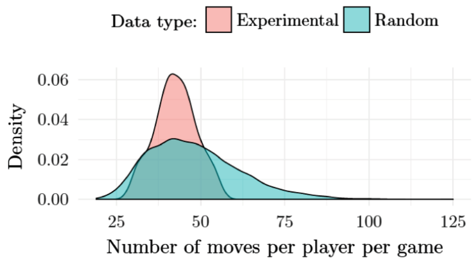


Fig. 3. Histogram comparing the distributions of the number of moves per player per game in the experiments from human players vs the simulation making purely random decisions.

4.3 Rule Conformity

Next we checked the participants' conformity to the game rules. Figure 4 shows those results, where each color represents the participant's ID and the different shapes highlight which game iteration the measurement originates from. Figure 4 shows an approximately equal distribution between participants that did not make any mistakes and those that made at least one mistake. This result rejects the hypothesis that healthy young participants would play the game without making any mistakes. Furthermore, all participants of the second experimental round, participants 5 to 8, have made mistakes in two or more games. However, there is no consistent trend over all participants of this experimental round: one can see a consistent improvement in the game of participant 7, while participant 8 has decreasing rule conformity.

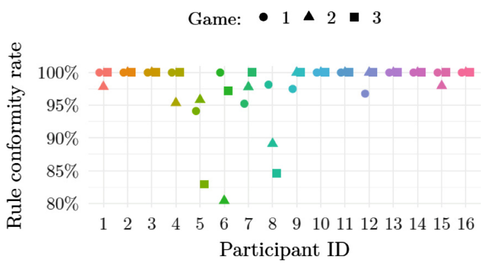


Fig. 4. The plot shows each participant's percentage of valid moves for the three consecutively played games. A rule conformity rate of 100% means that a participant always followed the rules. The data points were colored to better discriminate between participants.

4.4 Strategies

A main strategic decision offered to a player in Ludo is to either move a pawn to the safe target location as quickly as possible or to keep the available pawns close to each other in order to improve the chance of kicking opponents' pawns. Figure 5(a) shows that there is variance between the different participant's strategies, with individuals at either extreme of the scale. However, from the presented data a comparison of the consistency of a particular player's strategy is not possible without obtaining substantially more data since during the recordings several participants had too few active choices: different participants encountered a large variance of choices to decide on this strategy, ranging from 0 to 22 per participant and game.

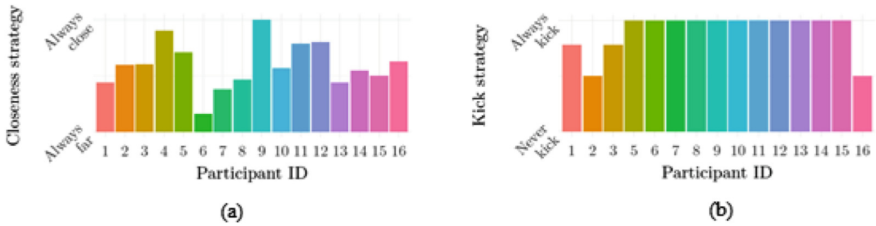


Fig. 5. (a) Bar diagram for each participant showing how often they decided to keep their pawns close to each other, when they had the opportunity. (b) Bar diagram for each participant showing how often they decided to kick an opponent out, when they had the choice. No data is available for participant 4.

One of the key elements of Ludo is to kick opponents' pawns out to force them to start over again from their home, causing the opponent to reset some of his/her progress. Figure 5(b) shows the percentage in which the participants decided to kick out one of their opponents whenever they had the opportunity to do so. It is clearly visible that twelve out of 16 participants decided to always kick. As far as the four participants who did not always kick are concerned, we found that all players have reached their lowest percentage in the third game. Moreover, three-quarters of the participants that did not always kick were members of the first experimental round, hinting towards a possible common reason.

4.5 Effect of Confidence and Emotions

Figure 6(a) shows the relationship of the mean total time per move per participant and the excitement, as assessed by the questionnaire. Firstly, it shows that there was a wide variance of excitement levels (min = 2, max = 5, standard deviation = 0.95) across the participants. The second experimental round had the highest diversity. Experimental round 4 contains an outlier, with an excitement level of 2, indicating little excitement, and a mean total time of more than 14 s. Apart from this outlier, a positive trend was detected, suggesting an increase in needed time with increasing excitement. However, testing the slope of a linear regression against 0 does not prove significant at the 5% level.

The relationship between a participant's conformity to the rules and the reflected confidence is displayed in Fig. 6(b). Rather than showing a lower confidence for those participants with a less accurate gameplay, Fig. 6(b) shows no trend. There are two outliers with high confidence and a low conformity. Furthermore, the plot shows that participants of the same experiment have similar confidence levels. The only exception is one member of Experiment 3 who indicates a confidence level of 5 rather than 3.

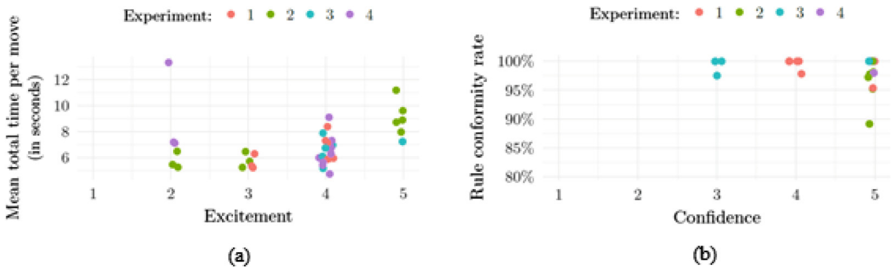


Fig. 6. (a) The average time needed per move with regards to the excitement level of each participant. The color discriminates between the experimental round the player participated in. (b) Relationship between confidence, where a higher number indicates a higher confidence level, and the percentage of valid moves over all games of a certain participant. Colors highlight the experimental round the participant joined.

Data indicates that this trend and clustering do not translate to other emotions, such as excitement.

5 Discussion

5.1 Robustness of Game State Detection

A robust detection of the game states is an essential precondition for using the physical version of the game for automated continuous assessments. When purely looking at the detection of the game board from its contours, the data from Sect. 3 indicates an expected strong dependency of the false and true negative detection rates on the light conditions. A high false negative rate is especially problematic since it could prevent the detection of a new game state. Game board and state detection is further problematic since human players can partially occlude the board with their hands when moving pawns. However, despite the fact that the game board contour detection by itself turned out to be problematic under challenging light conditions, the overall algorithm proved to provide satisfying results: Misdetections of a game state occurred only twice during all experiments when players covered the board with their hands during the entire change of game state. We believe that the robustness of the game state recognition comes from three features: (1) We can compare the digitized game with its known structure; (2) The detection of pawns based on their color is very robust after calibration if light conditions are not changed drastically during the game; (3) Most importantly, human players play at a relatively low speed that allows taking and analyzing many images in between game state changes. We found that players on average use 7.3 s to change the game state with a standard deviation of 4.36. So even for the scenario with the most challenging light conditions (Table 1) where no board contours have been detected in 43.5% of the images taken from the game board, given a frame rate of 3 frames per second, for each game move on average 21.9 images have been taken and the board contour has been detected and could be automatically analyzed about 14 times per change of game state.

5.2 Ludo as Assessment for Cognitive Abilities

The results of Sect. 4 show that human players indeed apply some strategies and do not make random moves (Fig. 3). Figure 5(b) indicates that players familiar with the game decide to always kick out opponents. Yet, some players did not always apply the kicking strategy. This could be caused by less awareness of the rules and game-flow. Furthermore, it could also be assumed that players who do not always kick have a tendency to become more "aggressive" over the course of the three experiments. The decrease in "aggressiveness" in the last game of participants 1 to 3, who were all members of the first experimental round, indicates a possible agreement in kicking strategy. During the game the experimenter observed that players lost interest in the game and stopped kicking opponents to force the game to be shorter. In particular, the closeness strategy of a player's pawns did show a lot of variation between participants (see Fig. 5(a)). However, the large variance of scenarios in which players had to act on this strategy did cause this study to not be able to determine clear strategies for participants with regards to their decision of keeping pawns close to each other on the field. The significance of the results of this strategy might be increased by playing more games per participant or using more pawns per player in the future.

Interestingly, our assumption of participants with lower confidence making more mistakes was not supported (see Fig. 6(b)). Rather, Fig. 6(b) shows a clustering of confidence between the different experimental groups. Whether this clustering was caused by grouping similar players or assimilation within the group is unknown. Yet, it might have influences on the performance and is worthwhile investigating further. In addition, it is worth mentioning that manually logging the die roll, which required the players to state the number of their roll, might have caused an increased awareness for an opponent's move. Future research should explore these open issues.

In any case our experiments indicate that even young healthy participants make mistakes during the game (see Fig. 4) – despite the relatively simple game rules. Since there seems to be no correlation between making mistakes and self-reflection on confidence in the game rules as being assessed by the questionnaire (Fig. 6(b)), human players seem not aware of their mistakes in applying game rules. Following our results and after discussions with experts from social care we decided to use rule conformity as key indicator of cognitive abilities for further studies with elderly.

6 Conclusion

In this paper we study if the board game Ludo can be transformed into a tool for continuous automated assessment of cognitive abilities by recording and analyzing movements and positions of pawns on the physical game board. To the best of our knowledge we are the first to study the application of Ludo as assessment for cognitive abilities. We presented a computer vision algorithm to transform a video recording of the game into a digital representation resulting in only two game state detection errors in 12 games. Overall, the results presented in this paper show that Ludo in its physical form is suitable for assessing automatically and continuously cognitive abilities including reaction times, rule conformity, and strategic game decision of players and they encourage a study with the demographic target group.

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