# Inducing and Detecting Anchoring Bias via Game-Play in Time-extended Decision-Making Tasks

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***Abstract*—We consider the problem of detecting anchoring bias in problems where a decision maker has to make multiple, correlated decisions over time. The main research question we investigate is whether the problem's solution from working on the problem multiple times has an anchoring effect on the decisions made to solve the problem in the future. To address this question, we propose a computer-based navigation game where an autonomous agent dynamically adapts initially hidden information that is required by human players to solve the game, in successive iterations of the game. We use the navigation decisions made by human players while playing the game, as the game information gets incrementally revealed, to infer the presence of anchoring bias in the player's decisions. Our results with game-playing data collected from 74 human subjects comprising Navy and Marine trainee personnel show a strong evidence of anchoring bias, although the bias diminishes rapidly after the player is exposed to information that contradicts the information in the anchor. We have also validated our results using an anchoring bias model from literature to show that our results conform to the model in 77-80 percent of game-play instances.**

***Keywords-anchoring bias; decision-making; human participant user study.***

## I. Introduction

Cognitive biases in human decision-making while solving a problem are known to affect the problem's outcome [1]. These biases usually degrade the outcome's value to the decision maker and to others that are affected by the problem's outcome. Researchers have proposed several techniques to detect and analyze cognitive biases in decision making. In this paper, we analyze a commonly encountered cognitive bias called the anchoring bias [2] while focusing on problems that involve time-extended or sequential decision-making. Time-extended decision-making instances abound in daily living tasks as well as longer term decision problems.

Recently, researchers [3,4] have reported the presence of anchoring bias in decision making for time-extended tasks. However, in these research studies, while making the decision for the current task the decision maker had access to the features of the current task, in addition to their experience from past decisions on similar tasks stored in their memories. In contrast, if access to the current task's features while making the decision for the task were to be taken away, and the decision maker had to rely solely on experiences from memory from similar tasks to make decisions, is anchoring bias still present? This question does not seem to have been investigated reasonably well in existing anchoring bias research.

To address this research gap, we design a study where an autonomous agent dynamically adapts the current tasks' features, which are then incrementally revealed to the decision maker via the decisions made by the decision maker. The decisions made by the decision maker are then analyzed for anchoring bias. Figure 1 illustrates our design idea. The conventional sequential decision making process, where the history of decision outcomes – as well as the current task features – affect the decision on the current task, is shown in Figure 1(a). In contrast, the decision-making process we investigate in this paper is shown in Figure 1(b), where the current task's values are invisible or masked and the current task's decision is based only on past decision outcomes. We employed a game to enable human subjects make successive time-extended decisions and developed algorithms to analyze the presence of anchoring bias in the decisions as well as predict the propensity of displaying anchoring bias based on past decisions. Our results, performed with a group of 74 human subjects, show strong evidence of anchoring bias across 90% of the subjects, while our anchoring bias prediction model shows accuracy in the range of 77–80%. These results support the correctness of our study and the anchoring bias prediction model. Our results also show that anchoring often persisted beyond the first trial, although the prediction model's accuracy beyond the first trial diminished substantially.

The remainder of the paper is organized as follows: In Section II, we review related work. In Section III, we introduce our game designed to elicit anchoring bias in sequential decision-making. In Section IV, we describe the human user study we conducted and our analysis of the resulting data. In Section V, we discuss our study and the lessons we believe we can learn from it. Section VI offers some concluding remarks and directions for future work.

## II. Related Work

Anchoring bias [2] causes humans to rely heavily on an initial piece of information, called an *anchor*. Because of this, humans tend to overlook information that would lead to better choices in subsequent decisions, and, instead, gravitate towards choices that align with the anchor. Initial research on analyzing anchoring biases focused on single-point decision problems. The main experimental roundup used for anchoring bias in such single-point decisions is the following: first, a decision maker is exposed to a certain piece of information, called the

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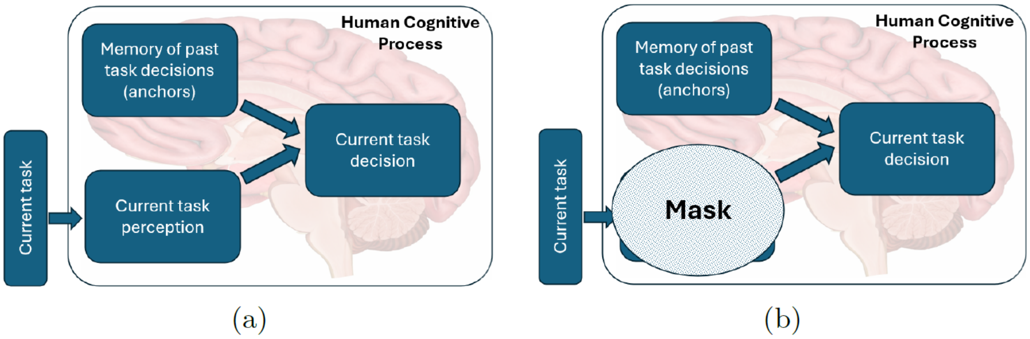


Figure 1. (a) Conventional decision-making process based on perception of current task's features and memory of past decision outcomes, (b) Masked decision-making process where current task features are not available; decisions are based on memory of past decisions.

anchor, about the likely outcome of a decision. Thereafter, the decision maker is asked to make the same or a very similar decision. Anchoring bias is claimed to affect the latter decision if the latter decision's outcome is similar to the initial decision outcome. A canonical example is to anchor the decision maker to a price point, e.g., 100 for a certain piece of clothing. Subsequently, the decision maker is shown a similar piece of clothing that is priced well-below (or well-above) 100, without revealing the price, and asked its worth. If the decision maker says that the clothing is worth around 100, it indicates that they are anchored to the initial price of 100.

Subsequently, researchers extended the study of anchoring bias to successive decisions such as perceived loudness of sounds played in sequence, group decision-making [5,6], evaluations of facial attractiveness and ringtone likeability [7], financial decision-making [8], reviews of books and college applications [3,4,9]. In the experiment design in these research efforts, the decision maker had to determine a decision outcome (in other words, evaluate) tasks that appeared in a sequence. Each task had a fixed set of features or attributes and the decision outcome was a function of the attribute's values. The task remained the same over time, but the values of the task's attributes were different for each task. The decision maker was affected by anchoring bias if they bypassed or shortcut through the function that maps the attribute values to the decision outcome, but, instead used a previously encountered task's decision outcome to determine the current task's decision outcome. For example, in admissions decisions, if the reviewer did not scrutinize the current applicant's credentials closely, but instead relied on a decision made for a previously seen, albeit similar (in terms of credentials) applicant, the decision was marked as influenced by anchoring bias.

These research settings are complementary to the research in this paper. The two main differences between our work and these are, first, we do not reveal the current problem's features (e.g., current book or college application under review) to the decision maker and the decision maker has to rely only on past task features and decisions from memory to make the current task's decision. Another slight distinction is that these technique use offline data that was not generated specifically for the bias studies and there was limited information about the background

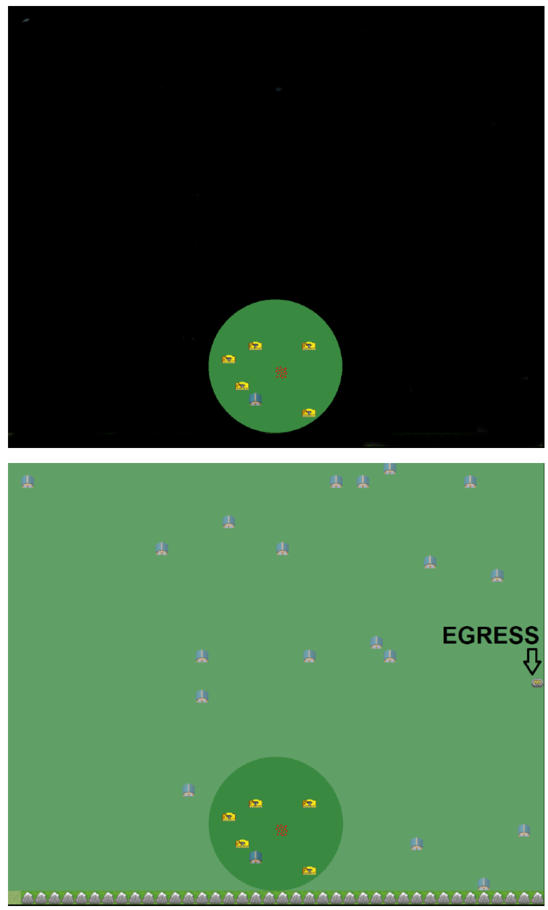


Figure 2. Top: Tankgame with viewport on; the red cluster of dots at the middle of the viewport is the player's game-piece. Bottom: Tankgame with grayed map outside viewport (for legibility).

of the decision maker. on the other hand, the subjects in our study are people that were familiar with computer-game playing and decision-making in scenarios similar to our game.

## III. Method for Anchoring Bias Detection

Recently, the concept of gamification or using computer-based games as an enabler for humans to perform learning or decision-making tasks has been extensively used in the fields of education and cognitive analysis [10]. Following this, we

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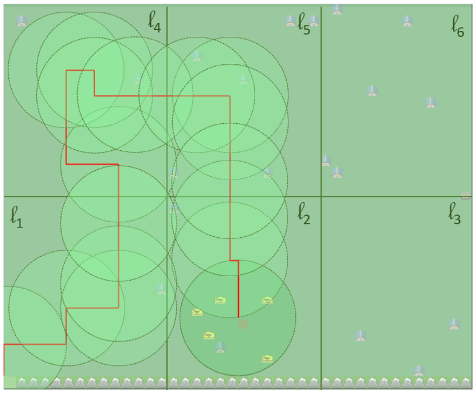


Figure 3. A sample trajectory (red curve) taken by a player. Lighter green dashed circles show the player's viewport as it moves along the trajectory. Only the current viewport was visible at any point along the trajectory.

describe a technique for detecting anchoring bias in a sequential decision making task implemented as computer-based game. In our game, a player has to move around a game-piece in a grid-based 2-D environment. At any point in the game, the player can only see a portion of the game board revealed via a circular viewport of radius rview centered around the game-piece's current location (red clusters of dots), as shown in Figure 2 (top). The environment contains objects called tanks that are placed in a cluster around a certain location in the environment. Figure 2 (bottom) shows the tanks on the game board with the region outside the viewport grayed out for legibility. A tank can be removed or cleared by the player by pressing a specific key on the game controller (e.g., keyboard space bar) when the game-piece is in the vicinity of the tank. There is also an egress at a specific location in the environment (elliptical pad on the right edge in Figure 2 (bottom)). The egress can be view only when it is in the players' viewport, but its location is known to the player from the start of the game. The player has two objectives: 1) detect and clear all the tanks in the environment, 2) after clearing all the tanks in the environment, navigate to the egress and exit the environment. Due to the limited size of the viewport, a player cannot know beforehand where the tanks are located inside the environment. Consequently, they have to search the environment by moving around the game-piece. Once the tanks are visible inside the viewport, they can move the game-piece to each tank's vicinity, clear the tanks, and finally move to the egress. The game-piece can be moved in four cardinal directions, Up, Down, Left or Right, and the game board is discretized into a grid-like environment for the purpose of tracking the game-piece's location. Figure 3 shows a trajectory of game-play (red curve) taken by a player while playing the game. Only the current viewport was visible to the player at any moment of the game; however, the figure shows the full game board for illustrative purposes.

We leverage the searching behavior of the player to study whether repeated placement of the tanks around the same location in the environment in initial iterations of the game induces the player to expect to look for the tanks at the same location in later iterations.

### A. Inducing Anchoring Bias via Spatial Placement of Tasks

We partition the environment into $L = l_1, l_2, l_3, ...$ cells. The anchoring bias experiment consists of $n_r$ game rounds. Each game round is divided into two phases:

- **Anchoring Phase**: During the anchoring phase, the game-piece is placed in cell $l_1$, while all tanks are placed inside a randomly selected cell, $l_i \in L - \{l_1\}$. The location of the tanks is not observable by the player. The player then plays the game $n_{anc}$ times; the value of $n_{anc}$ is not revealed to the player. We call each game-play a run. At the start of each run, the game is reset by placing the game-piece in $l_1$ and the tanks in the same cell, $l_i$, as in the first run.
- **Evaluation Phase**: For the evaluation phase, the game-piece is placed in $l_1$, while tanks are randomly placed in a cell $l_j \in L - \{l_1, l_i\}$. The player plays $n_{eval}$ runs of the game and at the start of each run, the game-piece is placed in $l_1$ and tanks are placed in $l_j$. As before, the number of evaluation runs, $n_{eval}$ is not revealed to the player.

At the end of each game round, the random number generator seed is randomized to prevent correlations between the random placement locations of tanks across game rounds. The player session is saved upon the completion of $n_r$ game rounds. Overall, each player plays the game for a total of $n_r(n_{anc} + n_{eval})$ runs. Player data during each game run is collected in the form of a trajectory, $\tau = (s_0, a_0, s_1, a_1, ...)$. Here, $s_i$ denotes the location or grid cell currently occupied by the game-piece, $a_i$ denotes the action or direction in which the game piece was moved, and $i$ denotes the time-step. We informally denote the time-step as the time required to move the game-piece from one grid cell to one of its adjacent grid cells. $\tau_{anc}$ and $\tau_{eval}$ denote trajectories generated during the anchoring and evaluation phases respectively.

### B. Detecting Anchoring Bias

For detecting anchoring bias, we check whether, during an evaluation run, the player visited the location where the tanks were during the anchoring runs before exploring other regions of the map. Recall that the map of the game board outside the view port is not visible to the player while playing the game. So, the only reason for a player to go towards the anchoring location would be due to anchoring bias induced by the location retained in their memory during anchoring runs. To quickly determine if the player started exploring the map instead of going towards the anchoring location, we partition the map into cells, as shown in Figure 3. We then check if the evaluation trajectory of the player shows excursions into cells that that do not contain the shortest trajectory between the start and anchoring locations. A positive outcome of the latter check confirms anchoring, a negative outcome indicates no anchoring.

### C. Model-based Prediction of Anchoring Bias

We further analyzed the trajectories from the anchoring runs in each game round to determine if the player had developed

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a propensity towards being biased by the anchor. For this, we used the model for the influence from the anchor proposed [6]. Their model parameterized the anchor's influence as a linear combination of three factors: the stimulus from the current task perception, the stimulus from the task in the previous time-step, and the outcome of the decision in the last time-step. In our setting, because we mask the current task perception, we consider that the influence of the anchor in the current time-step as a linear combination of the stimulus from the anchors stored in the memory. We consider the distance of the player moves the game-piece (that is, the length of the trajectory) up to viewing the first tank in the viewport during an anchoring run as the stimulus or attraction from that anchor. Based on this idea, we define the anchor's influence during an evaluation run as:

$$J_{eval} = \alpha + \sum_{i=1}^{n_{anc}} \beta_i J_{anc,i}$$

where $\alpha$ and $\beta$ are constants and $J_{anc,i}$ is the influence of the $i^{\text{th}}$ anchor from memory and $n_{anc}$ is the number of anchoring runs. We used linear regression with least squares [11] to solve this equation. Let $m_{anc}$ denote the slope of the regression line. We then define the anchoring bias propensity as True if $m_{anc} < 0$ and False otherwise.

## IV. Anchoring Bias User Study

The computer game for testing anchoring bias was approved by the Naval Research Laboratory Institutional Review Board and given to U.S. Navy and Marine personnel at the Naval Aerospace Medical Institute (NAMI), Pensacola, FL, USA. The game was played by 74 human players on a voluntary basis; informed consent and demographic data were collected from each player. The average age range of the players was between 21 - 23 years. Each player was given a tutorial at the start of their session that gave the objective and rules of the game, and how to move the game-piece to navigate the game-board. For all games in our experiments, the size of the game map is 40 × 32 cells and the viewport radius $r_{view} = 5$ cells. Each player played $n_r = 2$ game rounds, each with $n_{anc} = 5$ anchoring runs and $n_{eval} = 2$ evaluation runs. We collected the following data for each player:

- game-play trajectory in the form of coordinates of the cells on the game board the player moved the game-piece through,
- number of time-steps (measured in number of cells traversed by the gamepiece) to locate the first tank,
- time spent by the player in playing the game including the tutorial.

We evaluated the following Research Questions (RQs) related to anchoring bias from the players' data. The overall rationale for these RQs is to determine whether anchoring bias, if present, affects a player's future decisions and for how long, in the context of a time-extended decision-making task.

RQ1 Do subjects show anchoring bias after 5 anchoring runs?
RQ2 Does anchoring bias, if present, last more than one run?
RQ3 Does a player who shows anchoring bias during anchoring runs also show anchoring bias in evaluation run(s)?

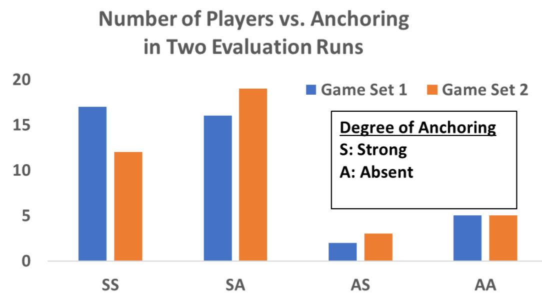


Figure 4. Bar chart showing the number of players (y-axis) that have Strong or no (Absent) anchoring (x-axis) in the two game rounds in our experiments.

### A. Game-play Data Analysis

From the 74 players that played our game for 2 game rounds each, we were able to collect 148 data instances, each instance comprising $n_{anc} = 5$ anchoring runs followed by $n_{eval} = 2$ evaluation runs. These data instances were analyzed for detecting anchoring bias. While analyzing, we found that some of the data instances had to be discarded owing to an oversight in the placement of the anchor: if the location of the tanks during the evaluation run was in-between or en-route from the start location and the location of tanks during the anchoring runs, then it was not possible to determine if the player was anchored or not. We discarded 69 of the 148 data points, leaving 79 valid data points.

*RQ1* We detect anchoring bias when the trajectory data from either the first or both evaluation runs meets the criteria above (Section III-B). The results are shown in Figure 4. In the figure, the x-axis labels indicate the degree of anchoring in evaluation run 1 followed by the degree of anchoring in evaluation run 2. Overall, these show a strong evidence of anchoring bias. Out of the 79 data instances, 64 data instances (roughly 81%) showed that the player had been anchored (SS and SA in Figure 4) either in both or only in the first evaluation runs. Across the two game rounds, there was very little variation (6%) in the number of subjects displaying anchoring bias. This indicates a strong propensity for anchoring bias among the subjects.

*a) RQ2:* We determined the number of data instances that showed strong anchoring in the first evaluation run versus those that showed strong anchoring in both evaluation runs (SA versus SS in Figure 4). We found that in 35 instances players showed that the effect of anchoring waned between the first and second evaluation runs, while the anchoring remained strong between the two evaluation runs for 29 instances. These values indicate that there is a small but non-negligible support that the effect of anchoring bias diminishes if the player gets information that contradicts the anchor.

We found that in the first game round, 16 players showed anchoring only in the first evaluation run and 17 showed anchoring in both evaluation runs. In the second game round, these numbers became 19 and 12 respectively. The decrease in strong anchoring in both evaluation runs between the first and second game rounds (from 17 to 12), and simultaneous increase in subjects that showed anchoring only in the first evaluation run (from 16 to 19) points further in the direction

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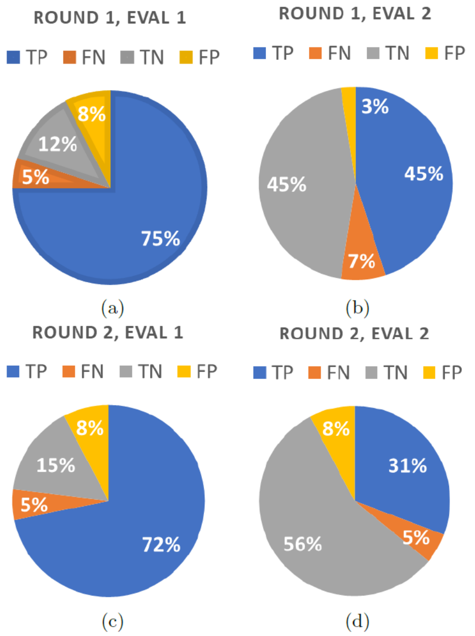


Figure 5. Effect of anchoring bias propensity during anchoring runs on decision in evaluation runs, for rounds 1 (40 trajectories) and 2 (39 trajectories).

that, as the player sees more information contradicting the anchor, the effect of anchoring diminishes. Players may have been more fatigued at the start the second round of evaluation runs, after playing 12 (5 anchoring runs in each of two game rounds plus 2 evaluations runs in first game round) of the game. Conventionally, fatigue would lead to the human brain making shortcuts via heuristics and strengthening the anchoring bias. However, in our experiments, we saw diminishing anchoring bias across game rounds. This seems to indicate that the disappointment of not finding the tanks at the anchoring location weakens the anchoring bias and motivates the player to explore in a more objective, less biased manner.

*b) RQ3:* The output from the bias prediction model (Section III-C) was compared with the detection criteria (Section III-B). We identified four combinations depending on the agreement between these two outputs. Figure 4 shows the results of this analysis for the two evaluation runs in each of the two rounds. We see that for the first evaluation run (Figures 4(a) and (c)), the model had an accuracy of 80% and 77% respectively in each round, in predicting whether the human would show anchoring bias. As expected, the prediction accuracy of the model diminishes considerably to 52% and 37% respectively in the two rounds (Figures 4(b) and (d)). The exposure to a different location of tanks than the anchoring runs in the first evaluation run reduced the player's reliance on the anchor to search for tank during the second evaluation run. Beyond two evaluation runs, the (binary) prediction was not relevant any more as the accuracy decreased below 50%.

Players played the two rounds of the game back-to-back without any break. We then ask the question: does the model predict if the player will get re-anchored in round 2 even if thew saw information (tank locations) contrary to the first round's anchor during the first round's evaluation runs? The answer from the game data analysis shows that the prediction model is still valid in round 2; its accuracy diminishes by only 3% for evaluation run 1 from the first to the second round. For evaluation run 2, the accuracy decreases by a larger amount of 15%. Overall, these results show that the linear regression model for anchoring bias is a reasonably reliable predictor for the decision of first evaluation after the anchor in both rounds, but not for decisions after the first evaluation. This result corresponds to the findings in other sequential decision-making applications like college admissions and book reviews in [4] where a positive decision's anchoring effect diminished as the decision maker was exposed to more information from successive decision problems that were contrary to the features of the problem in the positive decision instance. Overall, our findings of the anchoring bias prediction model indicate that a more robust prediction model would be worth investigating for longer term prediction of anchoring bias effects.

## V. Lessons Learned

During our study, we observed a few relevant points related to the human subject experiments, that we summarize here.

*a) Diminishing effect of anchor:* For a small fraction of the players (1 out of 74 instances in round 1 and 3 out of 74 instances in round 2), we found that they initially showed influence of the anchor during the first few anchoring runs, but in subsequent anchoring runs and in the evaluation run, the anchoring effect went away and they started exploring the map instead of heading to location where the found the tanks previously. An example is shown in Figure 6 where the first two anchoring runs (left image) shows anchoring but the subsequent anchoring runs do not. This de-anchoring effect was more pronounced in round 2. Possibly the two round 1 evaluation runs reduced the reliance of the player on the anchor during round 2 even after they found it and this prompted them to start exploring again.

*b) Ergonomic Factors Affecting Human Subjects:* The movement of game-piece in our computer-based game was controlled by keyboard arrow keys; thus, it was limited to the four cardinal directions. This resulted in players using long horizontal or vertical tracks to explore the environment. The number of keystrokes made by players in the game was not recorded and there is a possibility that some players were trying to reduce the number of keystrokes by continuing in the same direction for longer periods. This could again have stemmed for psychological factors like motivation, interest, and engagement with the game and overall experiment.

*c) Bias Intersection:* Anchoring bias, as we have used the term, intersects with other types of biases. For instance, sequential bias deals with the effect of repetitive decision outcomes on the choice made in sequential, albeit not necessarily time-extended tasks. Experiential bias considers the reliance of humans on experience from past decision outcomes on the current decision-making task. It would be interesting to analyze our results with appropriate theoretical models for these other

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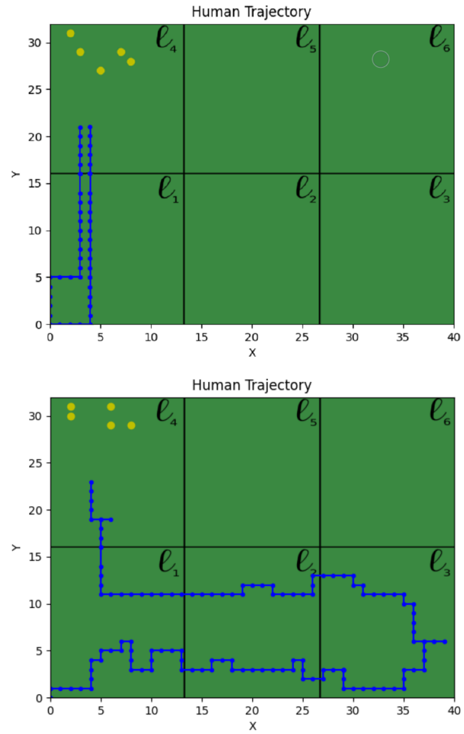


Figure 6. Trajectory of a player during round 2 anchoring runs 1 and 2 (left) and during anchoring run 3-5 (right).

biases as well to understand overlap, similarity, and divergence between these biases.

*d) Underlying Cause for Bias:* What causes humans to depend on anchors for making decisions? The conventionally accepted theory is the human brain is inclined to make shortcuts via heuristics [2] due to boredom, motivation, repetitiveness and other factors. In contrast, 12 and Strack's [12] selective accessibility model proposed an alternative theory that the brain made information related to the anchor more readily accessible to its decision process. The difference is subtle but consequential, as the former attributes the cause of anchoring bias to the internal working of the brain's decision-making process while the latter attributes it to the information presented to the brain's decision-making process. A deeper understanding, fortified with appropriate mathematical models for these two theories, would help with a clearer understanding of anchoring bias.

## VI. Conclusion and Future Work

In this paper, we presented a human subject study for detecting anchoring bias in time-extended decision-making tasks enabled through a computer game-based technique. The principal research question we studied was that if the current task's features are not available to the decision maker, does the influence from past information anchors affect the choice made by the decision maker? The results from our human subject study showed that past anchors significantly influence immediately future decision choices. This influence diminishes as the decision maker is exposed to information contrary to the anchor. But if the same decision maker is subsequently exposed to another anchor, anchoring bias is again observed, albeit with lesser effect than the first anchor. There are several directions we plan to extend this research. These include the effect of distractions and deceptions (e.g., mobile non-playing characters, tank-like objects that aren't real tanks), the effect of task complexity (e.g, clear tanks at multiple clustered locations in a larger map), the effect of multi-level decisions (e.g., while clearing tanks, explore the houses to retrieve a hidden key that let's the player unlock the egress from the game), and the effect of presence of teammates and/or adversaries in the game, on anchoring bias. Extending the game environment as platform for detecting other types of biases is also an area of interest. More efficient, clustering-based techniques instead of the linear regression model used in this research to analyze anchoring propensity, is another direction we are exploring. Finally, we are currently working on techniques for mitigating anchoring bias via automated decision aids that use the output from our anchoring bias detection model (Section III-C) and guide the decision maker towards less-biased decisions in real-time.

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