TOPIC

Time pressure changes how people explore and respond to uncertainty

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BSE 662 : DECISION MAKING AND THE BRAIN
END TERM

Extension

“ Effect of Computational Load on how people explore and respond to uncertainty ”

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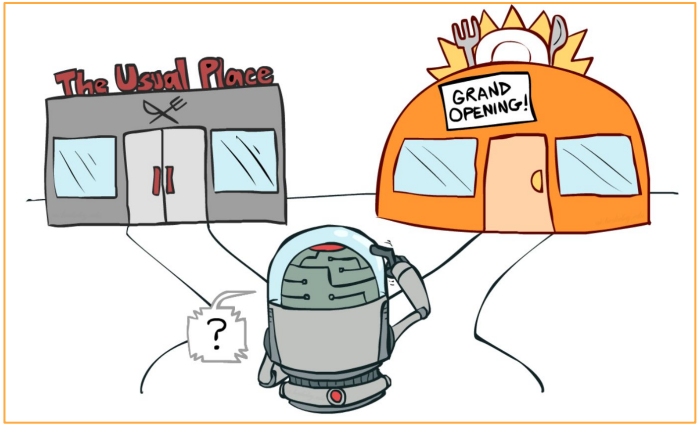
Past Research Work :

Previous studies on decision-making focused on individual factors such as time pressure and reward expectations. This paper stands out by combining these elements and using advanced learning models to understand decision-making comprehensively. Unlike singular-focused studies, this holistic approach, evident in studies like "**Temporal Constraints and Decision Speed**" and "**Reward Expectations in Exploration**," provides a more nuanced view of how time pressure and uncertainty influence exploration behavior.

Overview :

Investigates how time pressure shapes decision-making in exploration tasks. Manipulating **reward, uncertainty, and time constraints**, the research reveals that under limited time, participants opt for simpler, lower-cost strategies, reducing uncertainty-directed exploration and repeating choices more frequently. The findings shed light on **adaptive decision-making under cognitive constraints**.



Exploration- Exploitation Dilemma
Directed - Random
Accelerated - Repetition

Discussing the Extension Idea

Aim :
The core focus of our study is to investigate how varying computational loads, alongside time pressure, influence decision-making strategies, exploration of uncertainty, and response patterns.

Experimental Design :

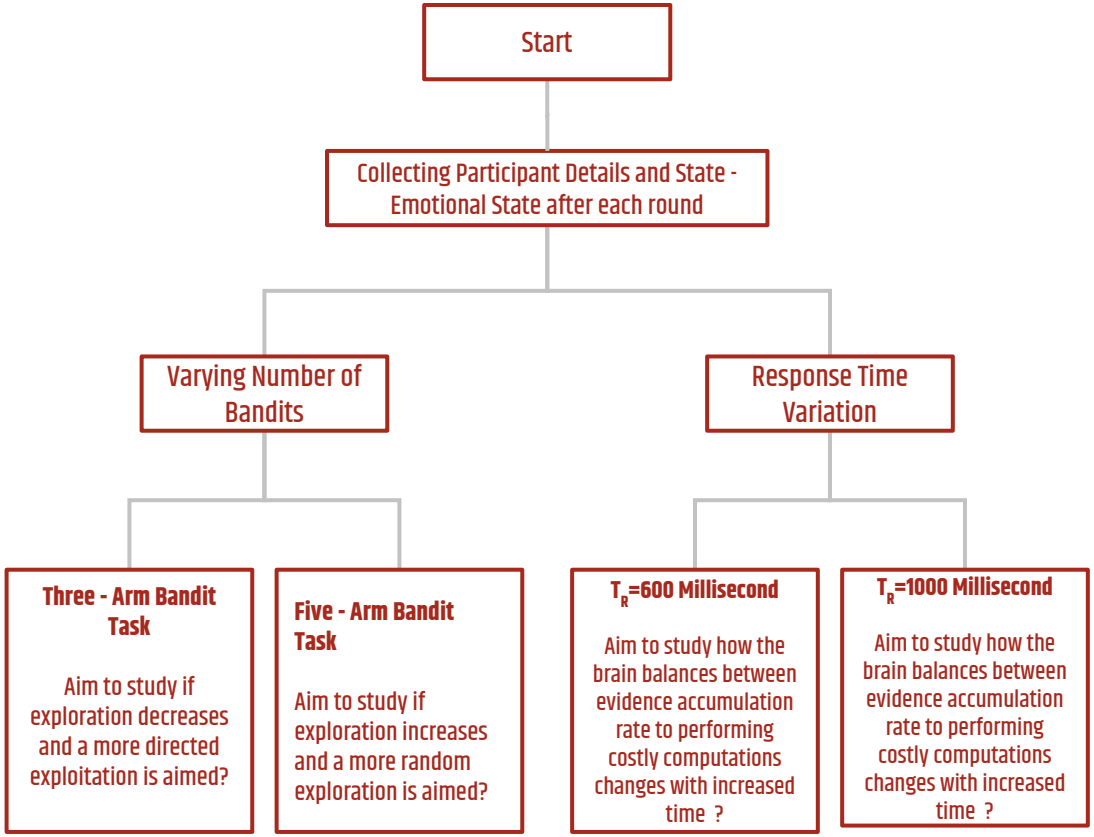
- **Varying the Number of Multi-Armed Bandits :** We will conduct two major variations:
  1. Case 1: 3-arm bandit task
  2. Case 2: 5-arm bandit task

Comparison with the results of the 4-arm bandit task from the referenced paper will be made.

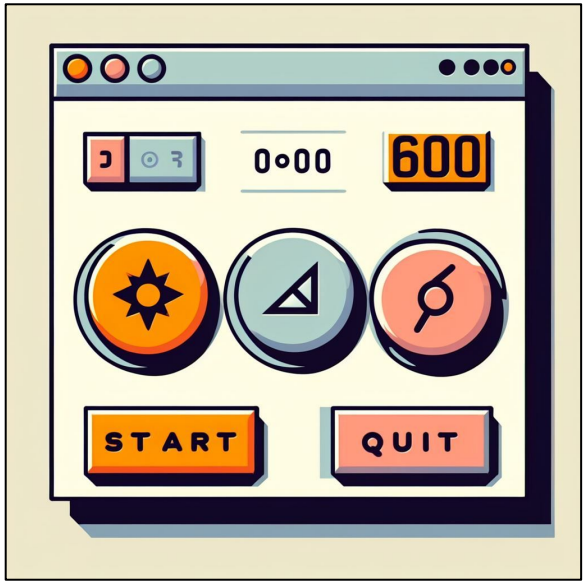
- **Varying Response Time :** Time pressure will be manipulated by varying response times from :
  1. Case 1 : 600 milliseconds &
  2. Case 2 : 1000 milliseconds

This variation aims to study the relationship between increased computational opportunity and decision-making strategies.
Implementation and Data Collection

Experimental Design



Experiment Workflow



Python Interfaced Multi - Arm Bandit Mechanism

Key Components

BanditArm Class:

- Represents each bandit arm with attributes such as **probability of success and reward range.**

Game Setup:

- Defines screen dimensions, colors, fonts, and game title using **Pygame's** initialization functions.
- Allows players to input their name, **emotional state**, and game settings like time limit and number of rounds.
- Utilizes graphical elements and keyboard input to capture player choices and preferences.

Game Execution:

- Implements the game loop where rounds are played based on user inputs and time constraints and handles events such as mouse clicks and keyboard inputs for arm selection and game progression.

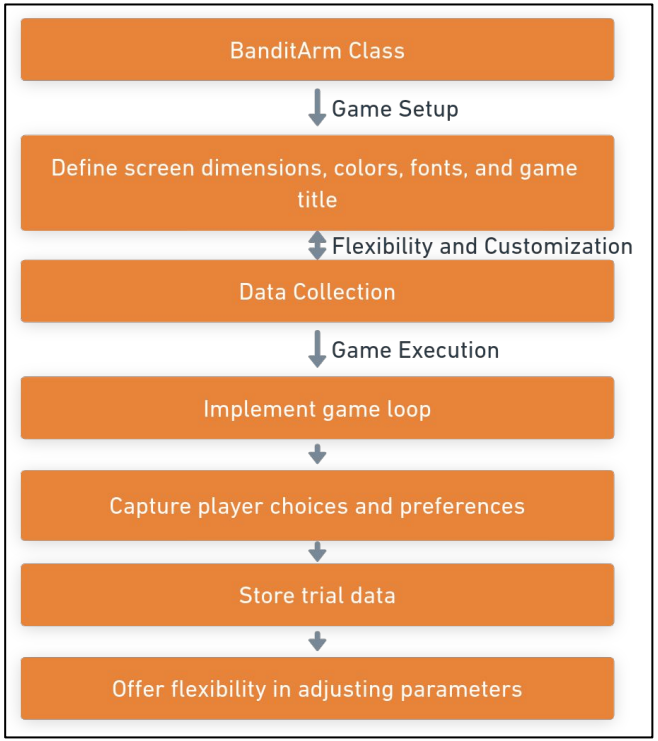
Data Collection:

- Stores trial data including round **number, response time, selected arm, and obtained reward** in a structured format (e.g., CSV file) that enables post-game analysis to study decision-making patterns and player strategies.

Flexibility and Customization:

- The framework offers flexibility in adjusting parameters such **as arm probabilities, reward ranges, time limits, and round counts.**

Programming Framework Multi Arm Bandit



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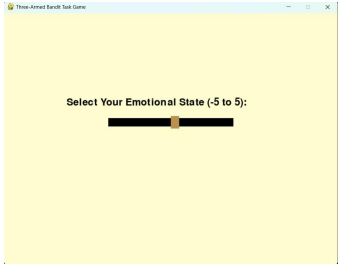
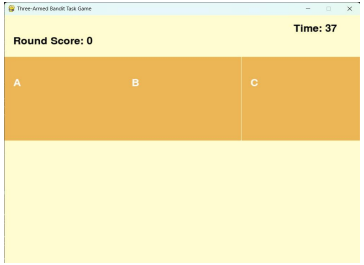
Data collection

How we collected data: We had participants play the three-armed and five-armed bandit python based game..They had to choose between the keys Q,W,E and Q,W, E.R,T and press those keys. We recorded every choice they made and how long it took them to decide.To avoid any unwanted conditions we made people play the game in a similar environment on the same device to allow uniformity. We also made sure the we ran trial rounds for each individual to get accustomed to the game as well as made sure they typed using their dominant hand.





What all data points are we collecting: As they played, we recorded every choice they made and how long it took them to decide. We also asked them to rate their emotional state before and after each round of the game. This was recorded on a scale of -5 to 5. Each key among Q,W,E and Q,W,E,R,T had a different reward system and each response generated some reward. We collected the response time as well and the total score shows the cumulative reward of a person. The total rounds indicate the rounds played out of 40 for every trial round. Also all this data was stored in a structural excel file that we later compiled in a sheet.

Participant Nar	Emotion			
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Round	SelectedArm	Reward	Response Tim	TotalScore
1	A	33.04437	600	33.04437
2	B	40.27763	200	73.322
3	C	60.0103	500	133.3323
4	B	43.43434	600	176.7666
5	B	59.69879	600	236.4654
6	C	35.51809	600	271.9835
7	C	68.29697	500	340.2805
8	A	22.76281	600	363.0433
9	B	42.32399	400	405.3673
10	C	59.55418	600	464.9215
11	C	68.13607	600	533.0575
12	C	75.25971	600	608.3172
13	A	39.90505	600	648.2223
14	B	56.68017	400	704.9025
15	B	29.78943	300	734.6919
16	C	63.04711	600	797.739
17	C	50.57377	500	848.3128
18	B	49.04951	600	897.3623
19	A	32.94832	300	930.3106
20	A	38.87756	300	969.1882
21	B	36.3325	500	1005.521
22	B	23.38861	600	1028.909
23	B	59.35824	600	1088.268
24	A	33.27917	600	1121.547
25	A	24.64028	600	1146.187

5arms-10secs | 3arms-10secs | 5Arms-6secs | 3 arms-6secs

Purposeful Data Collection for Analysis

Analyzing Response Time in 3-Arm and 5-Arm Bandit Tasks"

- We collected data from both 3-arm and 5-arm bandit tasks to examine the impact of exploration on response time.
- Our aim was to determine whether exploration strategies influenced response time and whether random exploration was intentional. Through analysis, we sought to understand participants' exploration patterns and repeated click behaviors. This investigation offers insights into how individuals navigate decision-making tasks and sheds light on the role of exploration in shaping response dynamics.

Strategic Arm Selection: Unraveling Reward Maximization Patterns

- Recording participants' chosen arms allowed us to discern their strategies for achieving the fastest response.
- Our objective was to uncover how individuals planned to maximize their rewards. Some participants repeatedly selected the same arm, banking on its perceived speed, while others opted for a more diversified approach, selecting two/more arms. Through this analysis, we explored the diverse methods participants employed to optimize their rewards, shedding light on their decision-making strategies in pursuit of efficiency.

The Keys

Purposeful Data Collection for Analysis

Analyzing Response Time

- We recorded response times to gauge participants' speed in reacting to the selected arm.
- Our goal was to analyze the most common methods used to achieve the fastest response and determine which methods were most effective in maximizing rewards. This investigation sheds light on strategies employed to optimize efficiency in reward attainment.

Reward Maximization in a Within-Subject Design

- The game's goal is to prompt participants to maximize rewards, measured by scores linked to the selected arm in each trial.
- Through this setup, we untangled the impact of varying reward expectations and uncertainty on choices. Additionally, we examined how time pressure shapes this influence, offering insights into decision-making processes within a single participant framework.

Emotional Influence on Response Time

- We recorded participants' emotional responses to examine how mood affected their response time in the game.
- Our aim was to discern whether individuals in a positive mood responded differently compared to those in a negative mood.
- By analyzing this relationship, we sought to understand how emotional states influence decision-making dynamics. This study delves into the intricate interplay between mood and response speed, shedding light on the psychological factors at play in decision tasks.