Contents


```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Main Simulation Script for BoundingOverwatch Project with R Integration
% Randomly 10 trials is used to validate predictions
% DFT Parameters:
% phi1 - sensitivity to attribute differences (typically 0.5-2)
% phi2 - memory/feedback strength (0-1)
% tau - decision time steps (integer > 0)
% error_sd - noise standard deviation (σ_ε)
% beta - attribute weights from R estimation
% w -  attention weights (default [0.5;0.5])
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clc;
clear all;
```

Step 1: Import CSV Data

(reference apolloMain_5 amd apolloMain_6 as example for data manipulation) biasData = readtable('user_choices.csv'); % Replace with the path to your data file disp('User bias data imported successfully.'); taskChoice_Data = readtable('user_choices.csv'); % Replace with the path to your data file disp('User task choice data imported successfully.');

```
robotChoice_Data = readtable('G:\My Drive\myResearch\Research Experimentation\Apollo\apollo\data\Bounding_Overwatch_Data\HumanData_Bounding_Overwatch - 20Split.csv'
% Convert all column headers to lowercase
robotChoice_Data.Properties.VariableNames = lower(robotChoice_Data.Properties.VariableNames);
disp('User robot choice data imported successfully.');

% Randomly select 10 rows (or all rows if fewer than 10)
numRows = height(robotChoice_Data);
randomIndices = randperm(numRows, min(10, numRows));
robotChoice_Data = robotChoice_Data(randomIndices, :);

% Extract robot state attributes dynamically
robot_states = struct();
attributeSuffixes = {'traversability', 'visibility'}; % No leading underscores
for i = 1:3
    for attr = attributeSuffixes
        csvColName = sprintf('robot%d_%s', i, attr{1});  % Matches CSV column names
        structFieldName = attr{1};  % Valid field name
        if ismember(csvColName, robotChoice_Data.Properties.VariableNames)
            robot_states.(['robot' num2str(i)]).(structFieldName) = robotChoice_Data.(csvColName);
        else
            warning('Missing attribute column: %s', csvColName);
            robot_states.(['robot' num2str(i)]).(structFieldName) = NaN(height(robotChoice_Data), 1);
        end
    end
end

% Extract choice data and other metadata
choices = robotChoice_Data.choice;
participant_ids = robotChoice_Data.id;
stake_types = robotChoice_Data.stakes;
time_spent = robotChoice_Data.timeelapsed;
```

```
User robot choice data imported successfully.
```

Step 2: R Bridge Implementation

```
disp('Initializing R bridge...');

% Configure paths
rscript_path = 'C:\Program Files\R\R-4.4.2\bin\x64\Rscript.exe';
r_script = 'G:\My Drive\myResearch\Research Experimentation\Apollo\apollo\example\DFT_Bounding_Overwatch.R';
csvFile = 'G:\My Drive\myResearch\Research Experimentation\Apollo\apollo\data\Bounding_Overwatch_Data\HumanData_Bounding_Overwatch - 80Split.csv';
outputDir = 'G:\My Drive\myResearch\Research Experimentation\Apollo\apollo\Output_BoundingOverwatch';

% Verify installations
if ~isfile(rscript_path)
    error('Rscript.exe not found at: %s', rscript_path);
elseif ~isfile(r_script)
    error('R script not found at: %s', r_script);
elseif ~isfile(csvFile)
    error('Input CSV not found at: %s', csvFile);
elseif ~isfolder(outputDir)
    warning('Output folder does not exist, creating: %s', outputDir);
```

```
    mkdir(outputDir);
end

% Execute R with JSON output
try
    % Use proper argument formatting
    cmd = sprintf(['"%s" "%s" ', ...
                '-i "%s" -o "%s"'], ...
                rscript_path, r_script, csvFile, outputDir);

[status,result] = system(cmd);

    if status == 0
        % Handle output path (whether directory or file)
        if isfolder(outputDir)
            jsonFile = fullfile(outputDir, 'DFT_output.json');
        else
            jsonFile = outputDir;
        end

        % Parse JSON output
        if exist(jsonFile, 'file')
            jsonText = fileread(jsonFile);
            params = jsondecode(jsonText);

            % Extract parameters with validation
            %Boundedphi1, phi2 parameters
            %phi1 = min(max(0, validateParam(params, 'phi1', 0.5)),5); % Ensure non-negative
            %phi2 = min(max(0, validateParam(params, 'phi2', 0.8)), 0.99); % Constrain 0-1
            %tau = min(1 + exp(validateParam(params, 'timesteps', 0.5)),100); %Constrain to 100

            %Raw phi1, phi2 parameters
            phi1 = validateParam(params, 'phi1', 0.5);
            phi2 = validateParam(params, 'phi2', 0.8);
            tau = 1 + exp(validateParam(params, 'timesteps', 0.5));
            error_sd = min(max(0.1, validateParam(params, 'error_sd', 0.1)), 1); % still clip here

            % Extract attribute weights
            beta_weights = [
                params.b_attr1;
                params.b_attr2;
                params.b_attr3;
                params.b_attr4
            ];

            % Get initial preferences from ASCs
            initial_P = [
                validateParam(params, 'asc_1', 0);
                validateParam(params, 'asc_2', 0);
                validateParam(params, 'asc_3', 0);
            ];

            disp('Estimated Parameters:');
            disp(['phi1: ', num2str(phi1)]);
            disp(['phi2: ', num2str(phi2)]);
            disp(['tau: ', num2str(tau)]);
            disp(['error_sd: ', num2str(error_sd)]);
            disp('Initial Preferences (from ASCs):');
            disp(initial_P');
        else
            error('R output file not found');
        end
    else
        error('R execution failed: %s', result);
    end
catch ME
    disp('Error during R execution:');
    disp(getReport(ME, 'extended'));
    [phi1, phi2, tau, error_sd] = getFallbackParams();
    beta_weights = [0.3; 0.2; 0.4; 0.5]; % Default weights
    initial_P = zeros(3,1); % Neutral initial preferences
end
```

```
Initializing R bridge...
```

Step 3a: MDFT Formulation to Calculate Preference Dynamics in Parallel

```
%%{
% (MDFT calculations based on estimated parameters)
% Create M matrix from current trial's attributes
% C11-C14 are consequence attributes for Robot 1
% C21-C24 are consequence attributes for Robot 2
% C31-C34 are consequence attributes for Robot 3
for current_trial = 1:height(robotChoice_Data)
```

```
num_attributes = 4;

M = [
    robotChoice_Data.c11(current_trial), robotChoice_Data.c12(current_trial), robotChoice_Data.c13(current_trial), robotChoice_Data.c14(current_trial);
    robotChoice_Data.c21(current_trial), robotChoice_Data.c22(current_trial), robotChoice_Data.c23(current_trial), robotChoice_Data.c24(current_trial);
    robotChoice_Data.c31(current_trial), robotChoice_Data.c32(current_trial), robotChoice_Data.c33(current_trial), robotChoice_Data.c34(current_trial)
];

% --- Global Min-Max Normalization ---
% Extract all attribute columns from the dataset
all_attributes = robotChoice_Data{:, {'c11','c12','c13','c14','c21','c22','c23','c24','c31','c32','c33','c34'}};

% Calculate global min and max (ignore NaN/Inf)
global_min = double(min(all_attributes(:), [], 'omitnan'));
global_max = double(max(all_attributes(:), [], 'omitnan'));

% Normalize M to [0, 1] range
if global_max ~= global_min  % Avoid division by zero
    M = (M - global_min) / (global_max - global_min);
else
    M = zeros(size(M));  % Fallback if all values are identical
end

% Optional: Clamp to [0.01, 1] to avoid extreme values
M = max(0.01, min(1, M));

% Normalize M values by dividing by 2 and clamping to [0.01, 1]
%{
M = M / 2;
M = max(0.01, min(1, M));
%}

% --- Global Max Normalization ---
%{

global_max = max(robotChoice_Data{:, {'c11','c12','c13','c14','c21','c22','c23','c24','c31','c32','c33','c34'}}, [], 'all', 'omitnan');
if ~isfinite(global_max) || global_max <= 0
    global_max = 1; % fallback in case of zero or NaN
end

M = M / global_max;              % Normalize by global max
M = max(0.01, min(1, M));        % Clamp to [0.01, 1]
%}

% --- Row-wise Min-Max Normalization ---
%{
for i = 1:size(M, 1)
    row = M(i, :);
    min_val = min(row);
    max_val = max(row);

    if max_val == min_val
        M(i, :) = pmax(0.01, pmin(1, row));  % constant row: clamp only
    else
        norm_row = (row - min_val) / (max_val - min_val);
        M(i, :) = max(0.01, min(1, norm_row));  % clamp to [0.01, 1]
    end
end
%}

attributes = {'C1 - Easy Nav, Low Exposure', 'C2 - Hard Nav, Low Exposure', 'C3 - Easy Nav, High Exposure', 'C4 - Hard Nav, High Exposure'};
beta = beta_weights ./ sum(abs(beta_weights));
beta = beta';

[E_P, V_P, choice_probs, P_tau] = calculateDFTdynamics(...
    phi1, phi2, tau, error_sd, beta, M, initial_P);

% Display results for the frame
disp('=== Trial Analysis ===');
disp(['Trial: ', num2str(current_trial)]);
disp(['Participant: ', num2str(participant_ids(current_trial))]);
disp(['Actual Choice: Robot ', num2str(choices(current_trial))]);

disp('M matrix (alternatives × attributes):');
disp(array2table(M, ...
    'RowNames', {'Robot1','Robot2','Robot3'}, ...
    'VariableNames', attributes));

disp('DFT Results:');
disp(['E_P: ', num2str(E_P', '%.2f  ')]);
disp(['Choice probabilities: ', num2str(choice_probs', '%.3f  ')]);
[~, predicted_choice] = max(choice_probs);
disp(['Predicted choice: Robot ', num2str(predicted_choice)]);
disp(['Actual choice: Robot ', num2str(choices(current_trial))]);
disp(' ');

if predicted_choice == choices(current_trial)
```

```
        disp('✓ Prediction matches actual choice');
    else
        disp('✗ Prediction differs from actual choice');
    end

    % Plot evolution
    figure;
    %plot(0:tau, P_tau);
    % Replace the plotting section with:
    tau_rounded = round(tau);  % Ensure integer steps
    if size(P_tau,2) == tau_rounded+1  % Validate dimensions
        plot(0:tau_rounded, P_tau);
    else
        warning('Dimension mismatch: P_tau has %d cols, expected %d',...
                size(P_tau,2), tau_rounded+1);
        plot(P_tau');  % Fallback plot
    end
    xlabel('Preference Step (\tau)');
    ylabel('Preference Strength');
    legend({'Robot1','Robot2','Robot3'});
    title(sprintf('Preference Evolution (Trial %d)', current_trial));
    grid on;
end
%%}
```

```
=== Trial Analysis ===
Trial: 1
Participant: 141831
Actual Choice: Robot 1
M matrix (alternatives × attributes):
              C1 - Easy Nav, Low Exposure    C2 - Hard Nav, Low Exposure    C3 - Easy Nav, High Exposure    C4 - Hard Nav, High Exposure
              ___________________________    ___________________________    ____________________________    ____________________________

    Robot1              0.59204                        0.28132                         0.32305                         0.012327
    Robot2              0.54968                        0.23452                         0.32325                             0.01
    Robot3              0.59284                        0.27768                         0.32757                         0.012407

DFT Results:
E_P: 14.76  -18.44    3.67
Choice probabilities: 1.000  0.000  0.000
Predicted choice: Robot 1
Actual choice: Robot 1

✓ Prediction matches actual choice
=== Trial Analysis ===
Trial: 2
Participant: 125802
Actual Choice: Robot 3
M matrix (alternatives × attributes):
              C1 - Easy Nav, Low Exposure    C2 - Hard Nav, Low Exposure    C3 - Easy Nav, High Exposure    C4 - Hard Nav, High Exposure
              ___________________________    ___________________________    ____________________________    ____________________________

    Robot1              0.78987                        0.45522                         0.36675                          0.03211
    Robot2              0.72879                           0.42                         0.33479                         0.026002
    Robot3              0.74019                        0.40841                         0.35891                         0.027142

DFT Results:
E_P: 3.96   20.46  -24.42
Choice probabilities: 0.000  1.000  0.000
Predicted choice: Robot 2
Actual choice: Robot 3

✗ Prediction differs from actual choice
=== Trial Analysis ===
Trial: 3
Participant: 125802
Actual Choice: Robot 3
M matrix (alternatives × attributes):
              C1 - Easy Nav, Low Exposure    C2 - Hard Nav, Low Exposure    C3 - Easy Nav, High Exposure    C4 - Hard Nav, High Exposure
              ___________________________    ___________________________    ____________________________    ____________________________

    Robot1              0.69059                         0.3343                         0.37847                         0.022182
    Robot2              0.81902                        0.45226                         0.40178                         0.035025
    Robot3               0.6391                        0.32118                         0.33495                         0.017033

DFT Results:
E_P: -36.31   17.27   19.06
Choice probabilities: 0.000  0.000  1.000
Predicted choice: Robot 3
Actual choice: Robot 3

✓ Prediction matches actual choice
=== Trial Analysis ===
Trial: 4
Participant: 141831
Actual Choice: Robot 1
```

M matrix (alternatives × attributes):

	C1 - Easy Nav, Low Exposure	C2 - Hard Nav, Low Exposure	C3 - Easy Nav, High Exposure	C4 - Hard Nav, High Exposure
Robot1	0.89138	0.45836	0.47528	0.042262
Robot2	0.89654	0.46437	0.47494	0.042777
Robot3	0.90969	0.48403	0.46975	0.044092

DFT Results:
E_P: -12.25 -6.60 18.85
Choice probabilities: 0.000 0.000 1.000
Predicted choice: Robot 3
Actual choice: Robot 1

✗ Prediction differs from actual choice
=== Trial Analysis ===
Trial: 5
Participant: 125802
Actual Choice: Robot 3
M matrix (alternatives × attributes):

	C1 - Easy Nav, Low Exposure	C2 - Hard Nav, Low Exposure	C3 - Easy Nav, High Exposure	C4 - Hard Nav, High Exposure
Robot1	0.85796	0.46159	0.43529	0.038919
Robot2	0.80416	0.43735	0.40035	0.03354
Robot3	0.89753	0.50604	0.43436	0.042876

DFT Results:
E_P: -24.12 9.13 14.99
Choice probabilities: 0.000 0.000 1.000
Predicted choice: Robot 3
Actual choice: Robot 3

✓ Prediction matches actual choice
=== Trial Analysis ===
Trial: 6
Participant: 125802
Actual Choice: Robot 2
M matrix (alternatives × attributes):

	C1 - Easy Nav, Low Exposure	C2 - Hard Nav, Low Exposure	C3 - Easy Nav, High Exposure	C4 - Hard Nav, High Exposure
Robot1	0.98664	0.49389	0.54454	0.051787
Robot2	0.93322	0.49881	0.48085	0.046445
Robot3	1	0.513	0.54013	0.053123

DFT Results:
E_P: -19.82 20.26 -0.43
Choice probabilities: 0.000 1.000 0.000
Predicted choice: Robot 2
Actual choice: Robot 2

✓ Prediction matches actual choice
=== Trial Analysis ===
Trial: 7
Participant: 141831
Actual Choice: Robot 1
M matrix (alternatives × attributes):

	C1 - Easy Nav, Low Exposure	C2 - Hard Nav, Low Exposure	C3 - Easy Nav, High Exposure	C4 - Hard Nav, High Exposure
Robot1	0.60885	0.33068	0.29218	0.014008
Robot2	0.56476	0.32263	0.25173	0.01
Robot3	0.46877	0.18594	0.28283	0.01

DFT Results:
E_P: 0.90 35.09 -35.99
Choice probabilities: 0.000 1.000 0.000
Predicted choice: Robot 2
Actual choice: Robot 1

✗ Prediction differs from actual choice
=== Trial Analysis ===
Trial: 8
Participant: 141831
Actual Choice: Robot 3
M matrix (alternatives × attributes):

	C1 - Easy Nav, Low Exposure	C2 - Hard Nav, Low Exposure	C3 - Easy Nav, High Exposure	C4 - Hard Nav, High Exposure
Robot1	0.70871	0.41994	0.31276	0.023994
Robot2	0.62479	0.40013	0.24027	0.015602
Robot3	0.69043	0.38945	0.32314	0.022166

DFT Results:
E_P: 7.30 15.55 -22.84
Choice probabilities: 0.000 1.000 0.000

Predicted choice: Robot 2
Actual choice: Robot 3

✗ Prediction differs from actual choice
=== Trial Analysis ===
Trial: 9
Participant: 125802
Actual Choice: Robot 1
M matrix (alternatives × attributes):

	C1 - Easy Nav, Low Exposure	C2 - Hard Nav, Low Exposure	C3 - Easy Nav, High Exposure	C4 - Hard Nav, High Exposure
Robot1	0.65391	0.29917	0.37326	0.018514
Robot2	0.83653	0.47249	0.40082	0.036776
Robot3	0.82446	0.4453	0.41473	0.035569

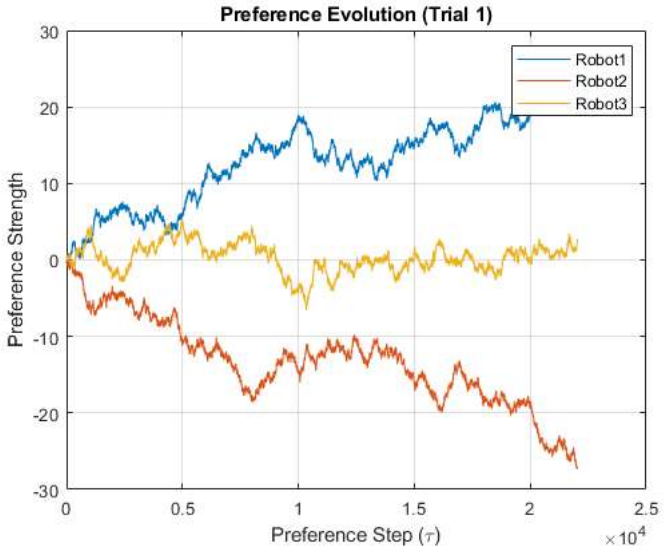
DFT Results:
E_P: -14.66 29.95 -15.29
Choice probabilities: 0.000 1.000 0.000
Predicted choice: Robot 2
Actual choice: Robot 1

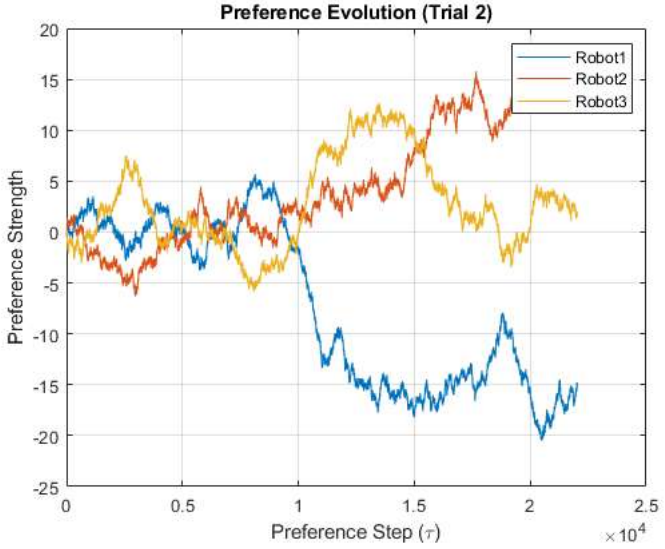
✗ Prediction differs from actual choice
=== Trial Analysis ===
Trial: 10
Participant: 125802
Actual Choice: Robot 2
M matrix (alternatives × attributes):

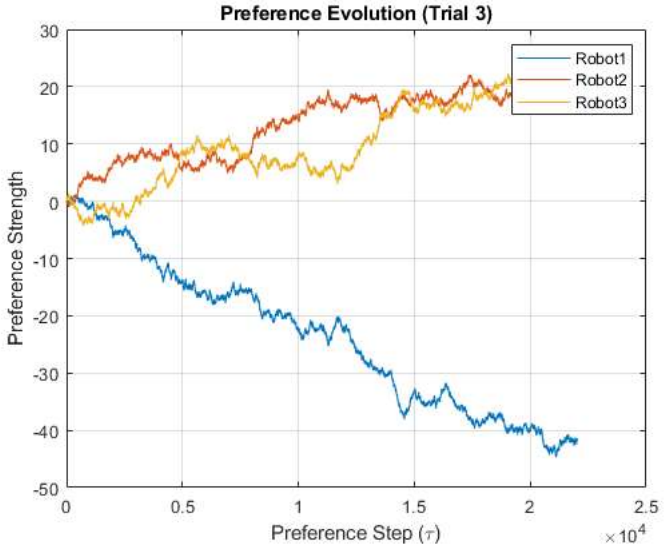
	C1 - Easy Nav, Low Exposure	C2 - Hard Nav, Low Exposure	C3 - Easy Nav, High Exposure	C4 - Hard Nav, High Exposure
Robot1	0.66226	0.37703	0.30458	0.019349
Robot2	0.51638	0.25254	0.2686	0.01
Robot3	0.5161	0.22512	0.29571	0.01

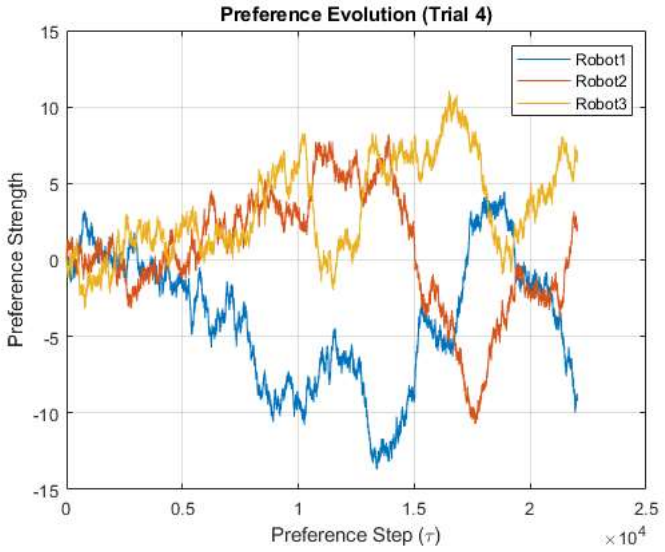
DFT Results:
E_P: 20.72 19.71 -40.43
Choice probabilities: 1.000 0.000 0.000
Predicted choice: Robot 1
Actual choice: Robot 2

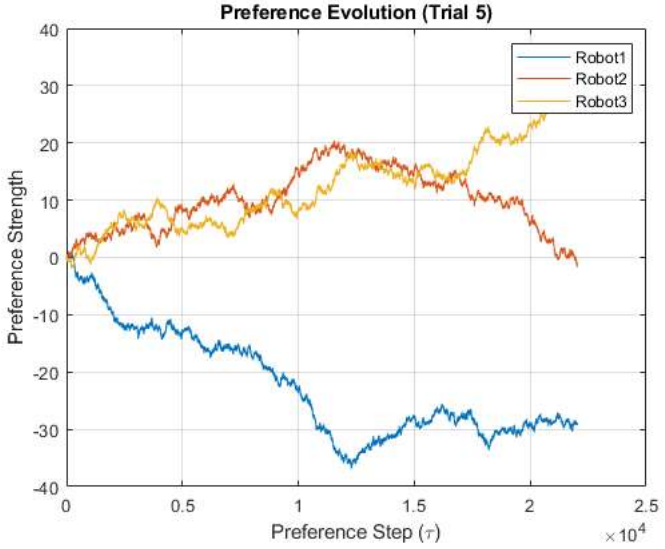
✗ Prediction differs from actual choice

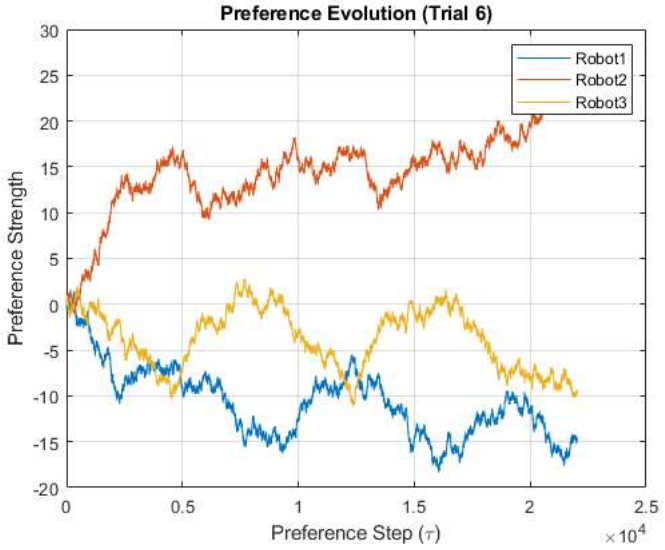

Preference Evolution (Trial 1)
Robot1
Robot2
Robot3
Preference Strength
Preference Step (τ)
$\times 10^4$

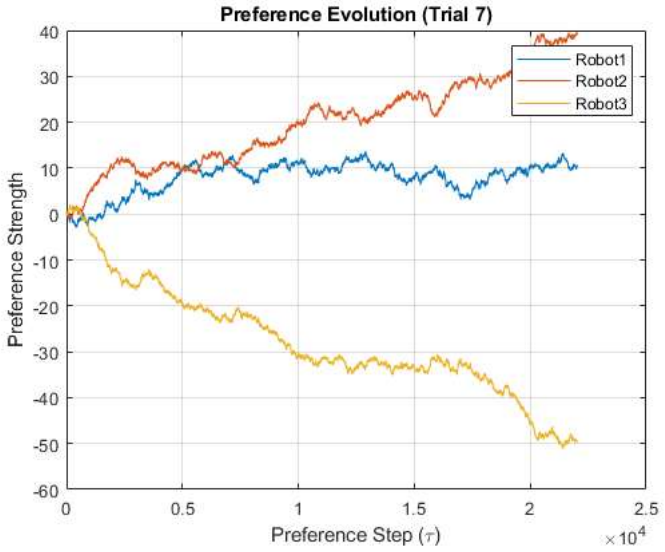

Preference Evolution (Trial 2)
Robot1
Robot2
Robot3
Preference Strength
Preference Step (τ)
$\times 10^4$

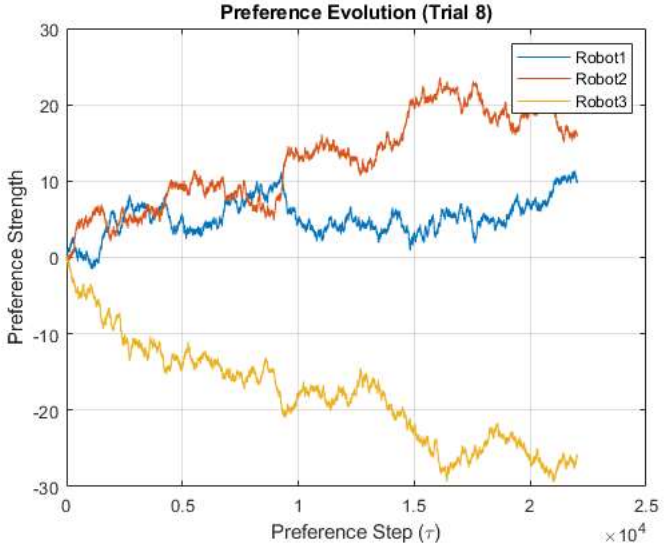

Preference Evolution (Trial 3)
Robot1
Robot2
Robot3
Preference Strength
Preference Step (τ)
$\times 10^4$

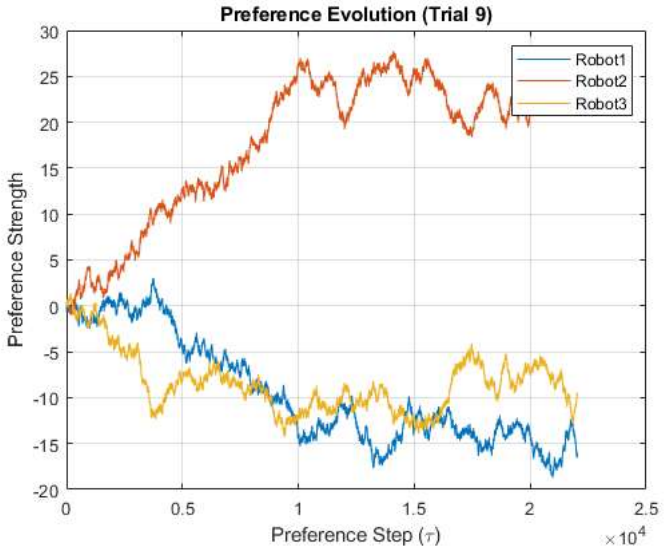

Preference Evolution (Trial 4)
Robot1
Robot2
Robot3
Preference Strength
Preference Step (τ)
$\times 10^4$

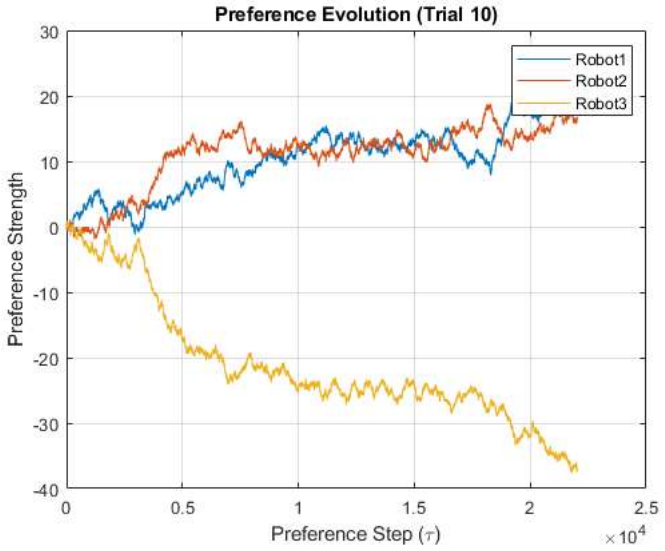

Preference Evolution (Trial 5)
Robot1
Robot2
Robot3
Preference Strength
Preference Step (τ)
$\times 10^4$


Preference Evolution (Trial 6)
Robot1
Robot2
Robot3
Preference Strength
Preference Step (τ)
$\times 10^4$


Preference Evolution (Trial 7)
Robot1
Robot2
Robot3
Preference Strength
Preference Step (τ)
$\times 10^4$


Preference Evolution (Trial 8)
Robot1
Robot2
Robot3
Preference Strength
Preference Step (τ)
$\times 10^4$





Step 3b: MDFT Formulation with State Continuity

```
%{
% Initialize preference state tracking
if ~exist('P_final_prev', 'var')
    P_final_prev = initial_P; % Use estimated initial preferences for first trial
end

for current_trial = 1:height(robotChoice_Data)
    % Create M matrix for current trial
    M = [
        robotChoice_Data.c11(current_trial), robotChoice_Data.c12(current_trial), robotChoice_Data.c13(current_trial), robotChoice_Data.c14(current_trial);
        robotChoice_Data.c21(current_trial), robotChoice_Data.c22(current_trial), robotChoice_Data.c23(current_trial), robotChoice_Data.c24(current_trial);
        robotChoice_Data.c31(current_trial), robotChoice_Data.c32(current_trial), robotChoice_Data.c33(current_trial), robotChoice_Data.c34(current_trial)
    ];

    % Normalize beta weights
    beta = beta_weights ./ sum(abs(beta_weights));

    % Calculate DFT dynamics using previous trial's final state
    [E_P, V_P, choice_probs, P_tau] = calculateDFTdynamics(...
        phi1, phi2, tau, error_sd, beta, M, P_final_prev);

    % Store final preference state for next trial
    P_final_prev = P_tau(:, end);

    % Display results
    disp('=== Trial Analysis ===');
    disp(['Trial: ', num2str(current_trial)]);
    disp(['Participant: ', num2str(participant_ids(current_trial))]);
    disp(['Actual Choice: Robot ', num2str(choices(current_trial))]);

    disp('Initial Preferences (from previous trial):');
    disp(array2table(P_tau(:,1)', 'VariableNames', {'Robot1','Robot2','Robot3'})); % Fixed this line
```

```
    disp('Final Preferences:');
    disp(array2table(P_tau(:,end)', 'VariableNames', {'Robot1','Robot2','Robot3'})); % Fixed this line

    % Enhanced plotting with initial/final state markers
    figure;
    plot(0:tau, P_tau, 'LineWidth', 2);
    hold on;
    % Mark initial state
    scatter(zeros(3,1), P_tau(:,1), 100, 'filled');
    % Mark final state
    scatter(tau*ones(3,1), P_tau(:,end), 100, 'x', 'LineWidth', 2);
    hold off;

    xlabel('Preference Step (\tau)');
    ylabel('Preference Strength');
    legend({'Robot1','Robot2','Robot3','Initial State','Final State'});
    title(sprintf('Preference Evolution (Trial %d)', current_trial));
    grid on;
end

%% Step 4: Output Results
disp('Saving results to CSV...');
output_table = table(E_P, V_P, P_tau(end,:)', ...
                     'VariableNames', {'ExpectedPreference', 'VariancePreference', 'FinalPreferences'});
writetable(output_table, 'results.csv');
disp('Results saved successfully!');
%}
```

Helper Functions

```
function param = validateParam(params, name, default)
    if isfield(params, name) && isnumeric(params.(name))
        param = params.(name);
    else
        warning('Using default for %s', name);
        param = default;
    end
end

function [phi1, phi2, tau, error_sd] = getFallbackParams()
    phi1 = 0.5 + 0.1*randn();
    phi2 = 0.8 + 0.1*randn();
    tau = 10 + randi(5);
    error_sd = 0.1 + 0.05*rand();
    warning('Using randomized default parameters');
end
```

```
Estimated Parameters:
phi1: 2.1035
phi2: 0.1
tau: 22027.4658
error_sd: 0.1
Initial Preferences (from ASCs):
    0.0150    0.0148         0
```

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