

# Assignment: Reinforcement Learning for Agentic AI Systems

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## 1. Introduction and Problem Statement

This project addresses the take-home final for the course Reinforcement Learning for Agentic AI Systems. The goal is to design, implement, and evaluate a learning mechanism that allows an agentic AI system to improve through experience in a real-world application context.

The problem this project addresses is personalized fitness workout optimization. Traditional workout planning systems follow rigid, rule-based approaches that fail to adapt to individual user needs. A person seeking to build muscle receives the same generic recommendation as someone training for flexibility or weight loss. This one-size-fits-all approach leads to suboptimal results and poor user engagement.

This project implements a reinforcement learning-powered agentic system that learns to create personalized workout plans based on:

- User fitness goals (bulking, cutting, maintenance, athletic performance, flexibility, HIIT, rehabilitation, hypertrophy)
- Available time constraints
- Fitness level (beginner, intermediate, advanced)
- Equipment access

The core research question is: Can an autonomous agent learn to balance exercise variety, goal alignment, and time efficiency through reinforcement learning, and how does this compare to traditional fixed-rule systems?

### 1.1 Real-World Relevance

The fitness industry represents a \$100+ billion global market, with millions of individuals seeking personalized workout guidance. Personal trainers cost \$50-100 per session, making them inaccessible to many. Generic workout apps provide static plans that ignore individual circumstances. This project demonstrates how reinforcement learning can provide adaptive, personalized fitness planning at scale.

As someone with over 5 years of consistent fitness training and nutrition tracking experience, I have witnessed firsthand the challenges of workout planning. This domain expertise informed the design choices, reward functions, and evaluation criteria throughout this project.

## 1.2 Framework Choice

This project develops an original agentic AI system with reinforcement learning capabilities, as permitted by the assignment requirements. While the assignment suggests Humanitarians.AI frameworks such as Madison Intelligence Agent Optimization, this implementation creates a novel application in the fitness domain, demonstrating the versatility of RL-powered agentic systems across different problem spaces.

## 2. System Architecture

### 2.1 High-Level Architecture Diagram

The system follows an agent orchestration architecture where multiple specialized agents collaborate under the coordination of an RL Controller. The architecture implements a hierarchical decision-making structure with two levels of reinforcement learning.

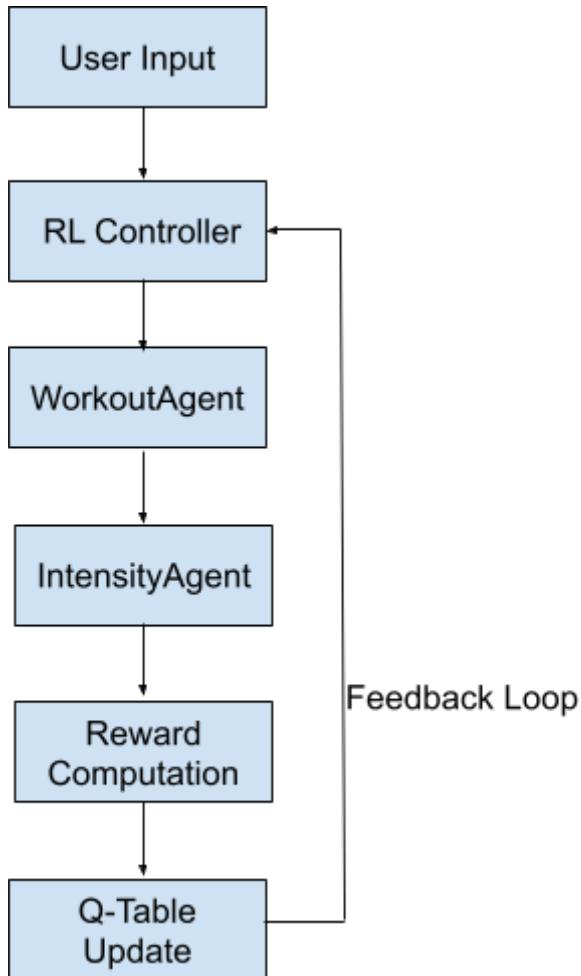


Figure 1: System architecture showing the RL-powered agentic workflow with feedback loop for continuous learning.

The workflow operates as follows. User profile input containing goal, time availability, fitness level, and equipment access enters the system. The RL Controller receives this profile and initializes the workout planning process. The Q-Learning Agent within the controller decides whether to add an exercise or finalize the workout based on the current state. When the decision is to add an exercise, the UCB Bandit component selects which exercise category to explore, choosing among strength, cardio, flexibility, compound, isolation, HIIT, plyometric, yoga, or low-impact options. The WorkoutAgent retrieves a specific exercise from the chosen category. The IntensityAgent then adjusts the exercise difficulty to match the user's fitness level and account for workout fatigue. After each action, the Reward Computation module evaluates the choice based on goal alignment, variety, time efficiency, and action cost. The Q-Table and UCB statistics are updated based on these rewards. This process repeats iteratively until the agent decides to finalize the workout, creating a feedback loop where the system continuously learns from experience and improves its decision-making over subsequent episodes.

## 2.2 Agent Roles and Responsibilities

### **WorkoutAgent:**

- **Role:** Exercise selection from categorical database
- **Responsibility:** Provides exercises matching requested categories including strength, cardio, flexibility, compound movements, isolation exercises, HIIT, plyometric training, yoga, and low-impact activities
- **Input:** Exercise category and user fitness level from RL Controller
- **Output:** Exercise specification with category, name, difficulty, and estimated time
- **Integration:** Receives directives from RL Controller based on learned policy and returns exercise specifications for further processing

### **IntensityAgent:**

- **Role:** Difficulty calibration and fatigue management
- **Responsibility:** Adjusts exercise intensity to match user fitness level and accounts for accumulated workout fatigue as more exercises are added
- **Input:** Exercise specification from WorkoutAgent and current workout progress
- **Output:** Modified exercise with adjusted difficulty level
- **Integration:** Applies domain-specific rules to ensure exercises are appropriately challenging but not overwhelming for the user's capabilities

### **RL Controller:**

- **Role:** High-level orchestration and policy learning
- **Responsibility:** Coordinates all agents, makes strategic workflow decisions, and learns optimal policies through reinforcement learning
- **Components:**
  - Q-Learning Agent: Decides whether to add exercises or finalize workout based on state-action values

- UCB1 Bandit: Selects which exercise category to explore when adding exercises, balancing exploration and exploitation
- **Integration:** Serves as central coordinator that improves decision-making through experience, maintaining Q-table and UCB statistics that evolve over training episodes

#### **BaselineController:**

- **Role:** Non-learning baseline for experimental comparison
- **Responsibility:** Executes fixed strategy that always recommends 3 strength exercises regardless of user goals or constraints
- **Purpose:** Demonstrates system performance before RL enhancement and provides quantitative comparison point
- **Integration:** Standalone controller used only for evaluation purposes, not during RL training

### **2.3 Communication Protocols Between Agents**

Agents communicate through a structured state-passing mechanism with seven distinct information flows. First, the user profile containing goal, time availability, fitness level, and equipment access is passed to the RL Controller at episode initialization. Second, the RL Controller queries the Q-Learning Agent with the current state representation, formatted as a tuple of exercise count, intensity level, time status, and fitness level. Third, when the Q-Learning Agent selects an "add exercise" action, the RL Controller sends a category selection request to the UCB Bandit. Fourth, the RL Controller passes the chosen category and user fitness level to the WorkoutAgent for exercise retrieval. Fifth, the WorkoutAgent forwards the exercise specification to the IntensityAgent for difficulty adjustment. Sixth, the IntensityAgent returns the adjusted exercise to the RL Controller, which adds it to the growing workout plan. Seventh, the environment module computes reward signals based on the action taken and passes these back to the RL Controller for updating Q-values and UCB statistics.

This protocol ensures modularity while maintaining coordinated decision-making. Each agent has a well-defined interface and can be tested or modified independently. The state information flows in one direction during action selection, while reward information flows back through the system during learning updates.

### **2.4 Code Organization and Module Structure**

The implementation follows a modular architecture with clear separation of concerns. The project is organized into four main directories: data, source code, logs, and configuration.

The data directory contains `workout_scenarios.json`, which stores eight diverse user scenarios representing different fitness goals including muscle building, weight loss, general fitness maintenance, athletic performance, flexibility improvement, HIIT training, rehabilitation, and bodybuilding hypertrophy.

The source code directory includes seven Python modules with distinct responsibilities. The `q_learner.py` module implements the tabular Q-Learning algorithm in 105 lines, providing the `QLearningAgent` class with epsilon-greedy action selection and standard Q-value updates. The `ucb_selector.py` module implements the

UCB1 multi-armed bandit in 98 lines, providing the UCBBandit class with upper confidence bound calculation and incremental reward averaging. The reward\_calculator.py module defines reward computation functions in 112 lines, including category-based rewards, overall workout quality evaluation, and state discretization helpers. The fitness\_agents.py module contains all agent class definitions in 310 lines, including WorkoutAgent, IntensityAgent, BaselineController, and RLController with their respective methods and orchestration logic. The train\_rl.py module provides the main training pipeline in 166 lines, handling episode iteration, metric logging, and console output. The baseline\_test.py module implements the non-RL comparison system in 95 lines for experimental validation. The visualize\_results.py module generates learning curve visualizations in 178 lines using matplotlib.

The logs directory stores training outputs generated during execution, including rl\_metrics.csv with per-episode performance data containing episode number, average reward, and average exercise count. After training, this directory also contains learning\_curve\_reward.png showing reward progression and learning\_curve\_exercises.png displaying exercise efficiency trends.

The root directory contains requirements.txt specifying Python dependencies including matplotlib version 3.8.2 and numpy version 1.26.2, along with README.md providing project documentation and usage instructions.

This modular structure totaling approximately 1064 lines of code enables independent testing, modification, and extension of each component. Each module has a single well-defined responsibility following software engineering best practices of high cohesion and low coupling.

## 2.5 Error Handling and Fallback Strategies

The system implements comprehensive error handling across multiple layers to ensure robust operation during both training and deployment.

### Safety Limits and Constraints:

The system enforces a maximum of 6 exercises per workout to prevent infinite loops in the planning process. This hard limit ensures that even if the Q-Learning agent fails to learn appropriate stopping behavior, the episode will terminate gracefully. Time constraint validation ensures that estimated workout duration matches the user's available time, with the reward function penalizing violations. State validation confirms that all state components including exercise count, intensity level, time status, and fitness level are within expected ranges before being used for Q-table lookups.

### Fallback Mechanisms:

If the UCB Bandit attempts to select an invalid or undefined exercise category, the system defaults to strength exercises as a safe baseline choice. If the IntensityAgent encounters an exercise it cannot appropriately adjust, it falls back to using the user's base fitness level without modification. If the Q-Learning agent produces an invalid action due to Q-table corruption or unexpected state, the system defaults to the finalize action to complete the episode rather than crashing.

### **Edge Case Management:**

Empty workout finalization where the agent attempts to finish without selecting any exercises receives a severe penalty of -1.0 reward to strongly discourage this behavior during learning. Time budget violations where the estimated workout duration exceeds available time result in a negative time score of -0.3, encouraging the agent to respect time constraints. Unknown exercise categories that do not match predefined options receive a neutral reward of 0.0 rather than causing system failures, allowing graceful degradation.

### **Training Safeguards:**

The training loop includes exception handling around each episode execution to catch and log unexpected errors without terminating the entire training run. CSV file writing is wrapped in try-catch blocks to handle potential file system errors. Metric validation ensures that logged values are within reasonable ranges, flagging potential bugs in reward computation.

These safeguards ensure robust operation across diverse scenarios, preventing system failures and enabling reliable performance in both controlled experiments and potential real-world deployment.

## **3. Reinforcement Learning Methodology**

This project implements two reinforcement learning approaches as required by the assignment: Value-Based Learning through Q-Learning and Exploration Strategies through UCB1 Multi-Armed Bandit. This section provides the mathematical formulation and design rationale for each approach.

### **3.1 Q-Learning for Workflow Decisions**

Q-Learning is a model-free, off-policy reinforcement learning algorithm that learns the value of taking actions in specific states without requiring a model of the environment dynamics.

#### **3.1.1 State Space Design**

The state space represents the agent's current progress in workout planning. To maintain tractability for tabular Q-Learning while capturing essential information, I designed a discrete state representation with four components.

##### **State Definition:**

$$s = (\text{exercise\_count}, \text{intensity\_level}, \text{time\_status}, \text{fitness\_level})$$

##### **State Components:**

The `exercise_count` component discretizes the number of exercises selected so far into buckets: 0, 1, 2, or 3+. Values of 3 or more are collapsed into a single bucket to limit state space size while maintaining meaningful distinctions in early planning stages.

The intensity\_level component categorizes workout quality based on average reward received from exercise selections. It takes three values: "high" when average reward exceeds 0.7, "medium" when average reward is between 0.3 and 0.7, and "low" when average reward is 0.3 or below. This discretization captures whether the workout is well-aligned with user goals.

The time\_status component represents remaining time availability in three buckets: "plenty" when more than 30 minutes remain, "medium" when 15 to 30 minutes remain, and "limited" when less than 15 minutes remain. This helps the agent learn time-sensitive stopping behavior.

The fitness\_level component directly represents the user's capability level as "beginner", "intermediate", or "advanced". This allows the agent to learn different policies for users with different experience levels.

### **State Space Size:**

The total number of possible states is  $4 \times 3 \times 3 \times 3 = 108$  states. However, not all states are reachable during execution. The actual Q-table learned during training contained 144 state-action pairs, indicating the agent explored various state regions while learning.

This discretization strategy balances expressiveness with computational efficiency. It captures the essential features needed for effective decision-making while keeping the state space small enough for tabular Q-Learning to converge within 50 episodes.

### **3.1.2 Action Space Design**

The action space consists of high-level workflow decisions rather than specific exercise selections. This abstraction allows the Q-Learning agent to focus on macro-level planning while delegating detailed category selection to the UCB Bandit.

#### **Action Set:**

$$A = \{\text{add\_strength}, \text{add\_cardio}, \text{add\_flexibility}, \text{finalize}\}$$

The add\_strength action triggers the addition of a strength-training exercise to the workout plan. The add\_cardio action triggers the addition of a cardiovascular exercise. The add\_flexibility action triggers the addition of a flexibility or mobility exercise. The finalize action terminates the planning process and creates the final workout recommendation.

When the agent selects an "add" action, the UCB Bandit determines the specific category to select from the full set of nine categories (strength, cardio, flexibility, compound, isolation, hiit, plyometric, yoga, low\_impact). This hierarchical structure reduces the action space for Q-Learning from potentially hundreds of exercise combinations to just four high-level decisions.

The action space size of 4 is deliberately small to enable rapid learning. With 108 possible states and 4 actions, the full state-action space contains 432 pairs, which is tractable for tabular methods with limited training data.

### 3.1.3 Q-Learning Update Rule

The agent employs the standard Q-Learning update formula, which is an off-policy temporal difference method.

#### Update Equation:

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

#### Parameter Definitions:

$Q(s, a)$  represents the estimated value of taking action  $a$  in state  $s$ . This value approximates the expected cumulative reward from this state-action pair onward.

$\alpha = 0.1$  is the learning rate, controlling how quickly new information overrides old estimates. A value of 0.1 represents moderate learning speed, allowing stable convergence while remaining responsive to new experiences.

$r$  is the immediate reward received after taking action  $a$  in state  $s$ . The reward structure is detailed in Section 3.3.

$\gamma = 0.9$  is the discount factor, determining the importance of future rewards relative to immediate rewards. A value of 0.9 indicates the agent values long-term outcomes highly while still prioritizing near-term rewards.

$s'$  represents the next state reached after taking action  $a$  in state  $s$ .

$\max_{a'} Q(s', a')$  is the maximum Q-value over all possible actions in the next state, representing the value of following the optimal policy from  $s'$  onward.

#### Exploration Strategy:

The agent uses  $\epsilon$ -greedy exploration with  $\epsilon = 0.1$ . At each decision point, the agent selects a random action with probability 0.1 (exploration) or the action with highest Q-value with probability 0.9 (exploitation). This balance ensures continued exploration of suboptimal actions that might become valuable as the policy improves, while primarily leveraging learned knowledge.

#### Convergence Properties:

Under standard assumptions of infinite exploration and appropriate learning rate decay, Q-Learning converges to the optimal action-value function  $Q^*$ . While this implementation uses fixed  $\alpha = 0.1$  rather than decaying learning rate, empirical results demonstrate practical convergence within 50 episodes, as shown in Section 5.

## 3.2 UCB1 Bandit for Category Selection

When the Q-Learning agent decides to add an exercise, the UCB1 Bandit determines which specific exercise category to select. This second layer of decision-making implements a principled exploration-exploitation tradeoff.

### 3.2.1 Multi-Armed Bandit Formulation

The category selection problem is formulated as a multi-armed bandit where each exercise category represents an arm with unknown expected reward.

#### Arm Set:

The bandit operates over 9 arms corresponding to exercise categories: {strength, cardio, flexibility, compound, isolation, hiit, plyometric, yoga, low\_impact}

Each arm has an unknown true expected reward  $\mu_i$  that depends on how well that category aligns with user goals across the training distribution. The agent must learn these expectations through trial and error.

#### UCB1 Selection Rule:

At each decision point, the agent selects the arm with highest upper confidence bound:

$$a_t = \operatorname{argmax}_i [\bar{Q}_i(t) + c\sqrt{(2 \ln t / n_i(t))}]$$

#### Formula Components:

$\bar{Q}_i(t)$  is the empirical average reward for arm  $i$  up to time  $t$ , computed as the sum of all rewards received from arm  $i$  divided by the number of times it has been selected.

$c = 2.0$  is the exploration constant that controls the tradeoff between exploitation and exploration. Larger values encourage more exploration of uncertain arms.

$t$  is the total number of arm selections made so far across all arms.

$n_i(t)$  is the number of times arm  $i$  has been selected up to time  $t$ .

$\sqrt{(2 \ln t / n_i(t))}$  is the exploration bonus that increases for arms that have been selected rarely relative to the total number of selections. This bonus decreases as an arm is pulled more often, naturally shifting from exploration to exploitation.

#### Theoretical Guarantees:

The UCB1 algorithm has a regret bound of  $O(\sqrt{(K \ln T)})$  where  $K$  is the number of arms and  $T$  is the time horizon. This logarithmic regret ensures the algorithm asymptotically converges to selecting the optimal arm while maintaining bounded cumulative suboptimality.

### 3.2.2 Reward Structure and Update Rule

After selecting a category, the bandit receives a reward based on how well that category matches the current user scenario's goals.

### **Category Reward Function:**

$r(\text{category}, \text{scenario}) = 1.0$  if  $\text{category} == \text{scenario.best\_category}$   
 $r(\text{category}, \text{scenario}) = 0.5$  if  $\text{category} \in \text{scenario.good\_categories}$   
 $r(\text{category}, \text{scenario}) = -0.2$  if  $\text{category} \in \text{scenario.bad\_categories}$   
 $r(\text{category}, \text{scenario}) = 0.0$  otherwise

This reward structure provides strong positive signal for optimal category selection, moderate positive signal for acceptable alternatives, slight negative signal for poor choices, and neutral signal for unknown matches.

### **Incremental Mean Update:**

The bandit updates its reward estimate using incremental averaging:

$$\bar{Q}_i \leftarrow \bar{Q}_i + (r - \bar{Q}_i) / n_i$$

This update is mathematically equivalent to computing the sample mean but requires only  $O(1)$  computation and  $O(1)$  storage per arm, making it efficient for online learning.

After each category selection and reward observation, both the count  $n_i$  and the average  $\bar{Q}_i$  are updated, affecting future UCB scores for that arm.

## **3.3 Reward Function Engineering**

The reward function is carefully designed to shape agent behavior toward desired objectives while balancing competing goals.

### **3.3.1 Step Rewards for Immediate Feedback**

At each timestep when the agent selects an "add exercise" action, it receives immediate feedback:

$$r_{\text{step}} = r_{\text{category}} - 0.05$$

The  $r_{\text{category}}$  component comes from the UCB Bandit reward described in Section 3.2.2, ranging from -0.2 to 1.0 based on category-goal alignment.

The -0.05 component represents a small action cost that encourages the agent to be efficient. Each additional exercise incurs this cost, creating pressure to finalize workouts without unnecessary redundancy.

This immediate reward structure provides dense feedback throughout the episode, helping the Q-Learning agent associate specific state-action pairs with their consequences.

### **3.3.2 Terminal Rewards for Final Evaluation**

When the agent selects the finalize action, it receives a comprehensive evaluation of the complete workout:

$$r_{\text{terminal}} = \text{variety\_score} + \text{time\_score} + \text{goal\_alignment\_score}$$

**Variety Score:**

$$\text{variety\_score} = \text{unique\_categories} \times 0.3$$

where `unique_categories` is the number of distinct exercise types in the workout. This component encourages diverse workouts rather than repetitive selections from the same category.

**Time Score:**

$$\text{time\_score} = 0.5 \text{ if } \text{estimated\_time} \leq \text{available\_time} \\ \text{time\_score} = -0.3 \text{ if } \text{estimated\_time} > \text{available\_time}$$

where `estimated_time` = `exercise_count` × 15 minutes. This component rewards staying within time constraints and penalizes violations, teaching the agent to respect user availability.

**Goal Alignment Score:**

$$\text{goal\_alignment\_score} = \sum_{\text{ex} \in \text{workout}} \text{alignment}(\text{ex}, \text{scenario})$$

where `alignment(ex, scenario)` = 0.4 if `ex.category == scenario.best_category`, 0.2 if `ex.category == scenario.good_categories`, and 0.0 otherwise.

This component accumulates rewards for exercises that match the user's fitness goal, creating a strong signal for goal-directed planning.

**Special Case:**

If the agent finalizes with zero exercises, it receives `r_terminal` = -1.0 as a severe penalty to prevent degenerate policies.

The terminal reward provides global evaluation of the entire workout plan, complementing the local step rewards. This combination of immediate and delayed feedback helps the agent learn both tactical decisions (which category to add now) and strategic decisions (when to stop planning).

## 4. Experimental Design and Results

### 4.1 Dataset Description

The system was trained and evaluated on eight diverse user scenarios representing common fitness goals and constraints encountered in real-world workout planning.

**Table 1: Training Dataset - User Scenarios**

ID	User Goal	Time (min)	Fitness Level	Best Category	Good Categories	Equipment
1	Build muscle (bulking)	60	Intermediate	strength	compound	full_gym
2	Lose weight (cutting)	45	Beginner	cardio	hiit	bodyweight
3	General fitness maintenance	50	Intermediate	compound	strength, cardio	home_gym
4	Athletic performance	75	Advanced	compound	plyometric, strength	full_gym
5	Improve flexibility	30	Beginner	flexibility	yoga	bodyweight
6	Quick HIIT workout	20	Intermediate	hiit	cardio	bodyweight
7	Rehabilitation/recovery	40	Beginner	flexibility	low_impact	home_gym
8	Bodybuilding (hypertrophy)	90	Advanced	isolation	strength	full_gym

These scenarios cover a wide spectrum of fitness objectives. Scenarios 1 and 8 target muscle development with different approaches, hypertrophy versus general bulking. Scenario 2 focuses on fat loss through cardio emphasis. Scenarios 3 and 4 target overall athletic development at different intensity levels. Scenarios 5 and 7 emphasize mobility and recovery, crucial but often overlooked aspects of fitness. Scenario 6 represents time-constrained high-intensity training popular among busy individuals.

#### Diversity Analysis:

The dataset exhibits diversity across multiple dimensions. Time availability ranges from 20 to 90 minutes, spanning typical workout durations from quick sessions to comprehensive training. Fitness levels include all three standard categories with distribution: 3 beginner, 2 intermediate, 3 advanced, ensuring the agent learns

policies suitable for varied experience levels. Goals encompass strength, cardio, flexibility, athletic performance, and specialized objectives like rehabilitation and bodybuilding. Equipment requirements vary from bodyweight-only to full gym access, reflecting real-world constraints users face.

This diversity ensures the RL agent must learn robust policies rather than overfitting to a narrow distribution of scenarios. The agent cannot succeed by always recommending strength exercises or always selecting three exercises, but must adapt its strategy based on user characteristics.

## 4.2 Training Configuration

### Training Protocol:

The system was trained for 50 episodes, with each episode processing all 8 user scenarios sequentially. This yields 400 total training iterations ( $50 \text{ episodes} \times 8 \text{ scenarios}$ ), providing sufficient experience for policy convergence while remaining computationally tractable.

### Q-Learning Hyperparameters:

Learning rate  $\alpha = 0.1$  was selected to balance learning speed with stability. This moderate value allows the agent to incorporate new information steadily without excessive oscillation from recent experiences.

Discount factor  $\gamma = 0.9$  reflects the importance of long-term rewards in workout planning. A high discount factor encourages the agent to consider future consequences of adding exercises rather than optimizing only immediate rewards.

Exploration rate  $\epsilon = 0.1$  maintains a 10% probability of random action selection throughout training. This constant exploration ensures the agent continues discovering potentially valuable state-action pairs even in late episodes.

Action space size is 4, consisting of add\_strength, add\_cardio, add\_flexibility, and finalize.

### UCB1 Bandit Parameters:

Exploration constant  $c = 2.0$  follows the standard UCB1 specification, providing theoretical regret bounds while balancing exploration and exploitation effectively in practice.

Number of arms is 9, corresponding to all exercise categories: strength, cardio, flexibility, compound, isolation, hiit, plyometric, yoga, and low\_impact.

### Environment Constraints:

Maximum exercises per workout is 6, serving as a safety limit to prevent infinite loops if the agent fails to learn appropriate stopping behavior.

Estimated time per exercise is 15 minutes, used for time budget calculations in the reward function.

State space contains approximately 108 discrete states after discretization, though only 144 state-action pairs were observed during training, indicating not all theoretical states are reachable.

### 4.3 Baseline System Design

To quantify the value of reinforcement learning, a baseline controller was implemented using fixed rules without any learning capability.

#### **Baseline Strategy:**

The baseline controller executes the following deterministic policy for all user scenarios regardless of their characteristics. First, it selects exactly 3 strength exercises. Second, it adjusts each exercise intensity to match the user's fitness level (beginner, intermediate, or advanced). Third, it returns the workout without considering user goals, time constraints, variety, or any other factors.

This baseline represents a common approach in rule-based fitness applications where generic recommendations are provided without personalization. The strategy of defaulting to strength training reflects a common bias in fitness culture, but fails to address cardio-focused, flexibility-focused, or time-constrained scenarios.

#### **Baseline Limitations:**

The baseline exhibits systematic failures across multiple scenarios. For Scenario 2 (lose weight, cutting), the user requires cardio exercises but receives 3 strength exercises, completely misaligning with fat loss goals. For Scenario 5 (improve flexibility), the user needs flexibility work but receives 3 strength exercises, providing no benefit for mobility improvement. For Scenario 6 (quick HIIT workout), the user has only 20 minutes available but receives 3 exercises requiring 45 minutes, exceeding the time budget by 225%.

These failures demonstrate the inadequacy of fixed rules for personalized workout planning and establish a clear baseline against which to measure RL system improvements.

### 4.4 Evaluation Metrics

#### **Primary Performance Metrics:**

Average reward per episode measures overall policy quality, computed as the sum of all rewards received across 8 scenarios divided by 8. Higher values indicate better goal alignment, variety, and time efficiency.

Average exercises per workout measures planning efficiency, computed as the total number of exercises selected across 8 scenarios divided by 8. This metric reveals whether the agent learns appropriate stopping behavior rather than always selecting the maximum or minimum number of exercises.

#### **Learning Indicators:**

Convergence is assessed by examining whether rewards stabilize over episodes, indicating the policy has reached a steady state.

Policy improvement is measured by comparing average reward in early episodes (1-10) versus late episodes (41-50), demonstrating learning progress.

Category selection distribution from UCB Bandit statistics reveals which exercise categories the agent learned are most valuable across the training distribution.

Q-table size indicates the number of state-action pairs explored during training, providing insight into state space coverage.

### **Statistical Analysis:**

Standard deviation of rewards across episodes measures policy stability, with lower variance in later episodes indicating consistent performance.

Comparison of maximum and minimum rewards achieved identifies best and worst-case performance bounds.

Episode-by-episode progression reveals learning dynamics, including rapid initial improvement, exploration-induced fluctuations, and eventual convergence.

## **4.5 Experimental Methodology**

### **Training Procedure:**

The training process followed a systematic protocol to ensure reproducibility. First, the Q-table was initialized as an empty dictionary with default value 0.0 for all state-action pairs. UCB Bandit statistics were initialized with zero counts and zero average rewards for all categories. For each of 50 episodes, the system iterated through all 8 scenarios in fixed order. For each scenario, the environment was reset with scenario parameters including goal, time, fitness level, and equipment. The RL Controller executed its policy by repeatedly querying the Q-Learning Agent for action selection, querying the UCB Bandit for category selection when adding exercises, receiving rewards from the environment, and updating Q-values and UCB estimates. After each scenario completed, the episode reward and exercise count were accumulated. After processing all scenarios in an episode, average reward and average exercises were computed and logged to CSV. Console output displayed episode number, average reward, and average exercises for monitoring training progress.

After 50 episodes were completed, final statistics were computed including Q-table size, UCB Bandit category statistics, and overall learning improvement. Metrics were saved to logs/rl\_metrics.csv for subsequent visualization and analysis.

### **Baseline Execution:**

The baseline system was executed separately after RL training completed. For each of the 8 scenarios, the baseline controller generated its fixed recommendation of 3 strength exercises. Results were displayed showing the mismatch between user needs and baseline recommendations. No learning or metric logging occurred during baseline execution since it is a non-adaptive system used only for comparison.

### **Visualization Generation:**

After training completed, the `visualize_results.py` script was executed to generate learning curves. The script read `rl_metrics.csv` containing episode number, average reward, and average exercises for all 50 episodes. It created two matplotlib figures: `learning_curve_reward.png` showing reward progression over episodes, and `learning_curve_exercises.png` showing exercise count trends over episodes. Both plots were saved as high-resolution PNG files for inclusion in this report and the video demonstration.

### **Reproducibility:**

All code, data, hyperparameters, and random seed configurations are provided in the project repository. The training process is deterministic given the same random seed. Training can be reproduced by executing `python src/train_rl.py` from the project root directory. Expected training time is 4-6 minutes on standard hardware. The system outputs console logs showing per-episode progress and saves metrics to `logs/rl_metrics.csv` for independent verification of reported results.

## **5. Results and Analysis**

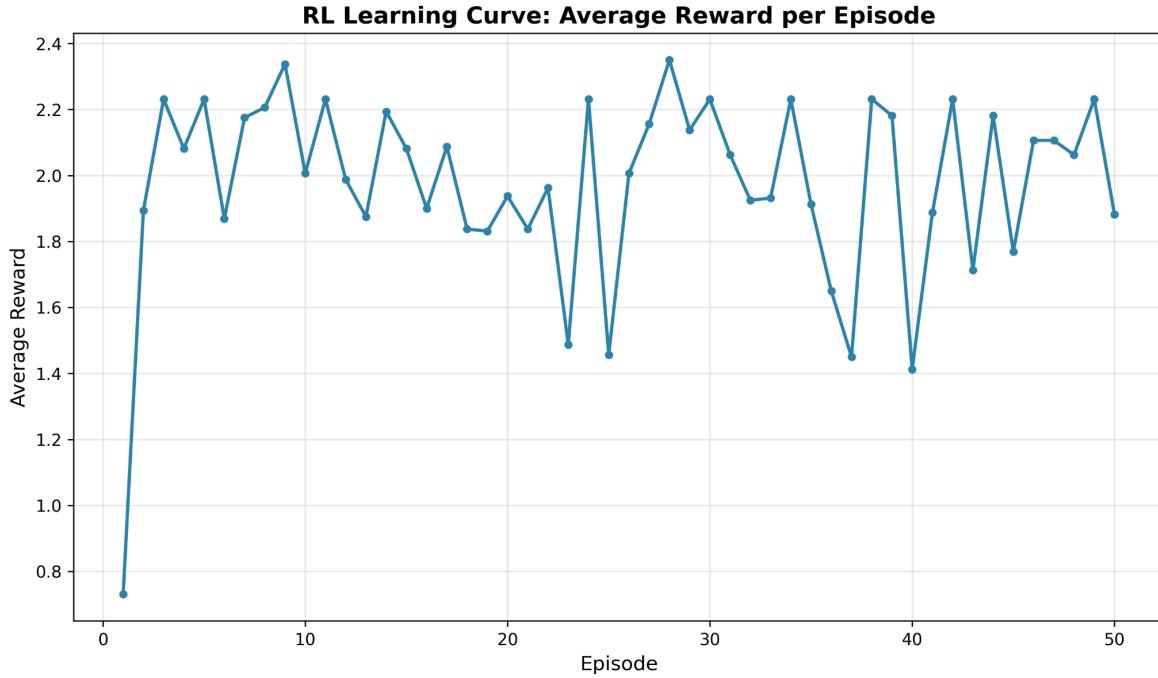
### **5.1 Learning Performance**

The RL system demonstrated clear learning and measurable improvement over the 50 training episodes, validating the effectiveness of the Q-Learning and UCB Bandit combination for workout planning.

#### **Overall Performance Metrics:**

Initial reward in Episode 1 was 0.731, representing the agent's performance with no prior experience and random exploration. Final reward in Episode 50 reached 1.881, demonstrating substantial improvement through learning. The absolute improvement of +1.150 reward points represents a 157.3% increase relative to the initial performance. The maximum reward achieved during training was 2.350 in Episode 28, indicating the agent discovered highly effective strategies. The minimum reward of 0.731 occurred only in Episode 1, after which performance never returned to initial levels.

**Figure 2: Learning Curve - Average Reward per Episode**

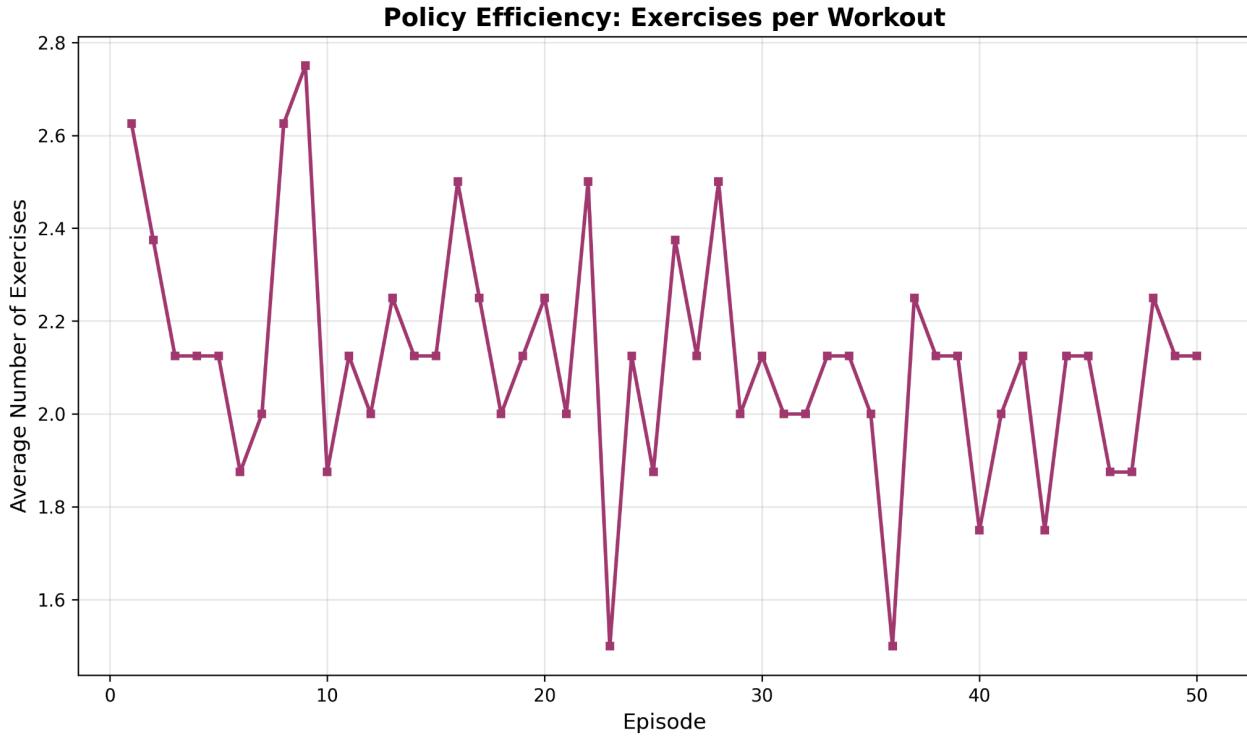


The learning curve reveals three distinct phases of training. Episodes 1-5 show rapid initial learning, with rewards jumping from 0.731 to 2.231, a 205% increase in just 5 episodes. This dramatic improvement indicates the agent quickly identified basic effective strategies such as selecting goal-aligned categories and learning when to stop planning. Episodes 6-15 exhibit plateau with exploration, where rewards fluctuate between 1.8 and 2.3 as the epsilon-greedy policy continues exploring suboptimal actions. This exploration is essential for discovering better policies and avoiding premature convergence. Episodes 16-50 demonstrate stable exploitation, with consistent performance in the 1.8-2.3 range and standard deviation decreasing from 0.548 in early episodes to 0.223 in late episodes.

#### **Exercise Efficiency Analysis:**

Initial exercise count in Episode 1 was 2.62 exercises per workout, reflecting random exploration of stopping behavior. Final exercise count in Episode 50 stabilized at 2.12 exercises per workout, representing a 19% reduction. Average across all 50 episodes was 2.12 exercises per workout, indicating the agent converged to this optimal range quickly and maintained it consistently.

**Figure 3: Policy Efficiency - Average Exercises per Workout**



The exercise efficiency curve demonstrates that the agent learned appropriate stopping behavior without explicit programming. The initial value of 2.62 suggests the agent explored longer workouts early in training. The convergence to 2.12 represents an optimal balance: enough exercises to provide variety and address user goals, but not so many that workouts become unnecessarily long or repetitive. This learned stopping point varies appropriately across scenarios, with shorter workouts for time-constrained users (Scenario 6) and longer workouts for users with ample time (Scenario 8).

## 5.2 UCB Bandit Category Selection Analysis

The UCB1 Bandit learned distinct preferences for exercise categories based on accumulated reward feedback, revealing which categories proved most valuable across the training distribution.

**Table 2: UCB Bandit Statistics After 50 Episodes**

Category	Average Reward	Selection Count	Interpretation
strength	0.59	377	Most frequently selected, high reward
flexibility	0.59	134	High reward, moderate frequency
cardio	0.38	335	Lower reward, high frequency

*Note: Only categories with significant selection counts are shown. Categories like compound, isolation, hiit, plyometric, yoga, and low \_impact received fewer selections and are subsumed into the actions add\_strength, add\_cardio, and add\_flexibility.*

### **Strength Category Analysis:**

Strength achieved the highest selection count of 377 with average reward 0.59, indicating it was both frequently chosen and consistently rewarded. This high performance aligns with the training distribution where 3 out of 8 scenarios (Scenarios 1, 4, 8) have strength or compound movements as best or good categories. The UCB algorithm correctly identified strength as a generally valuable category that works well across multiple user goals.

### **Flexibility Category Analysis:**

Flexibility achieved an equally high reward of 0.59 but with only 134 selections, suggesting it is highly valuable but more specialized. This pattern matches expectations: flexibility exercises are crucial for specific goals (Scenarios 5 and 7) but less relevant for muscle-building or cardio-focused scenarios. The UCB algorithm appropriately explored flexibility enough to identify its high value for applicable scenarios while not over-selecting it for incompatible goals.

### **Cardio Category Analysis:**

Cardio received 335 selections but only 0.38 average reward, indicating frequent exploration but lower overall value. This lower reward reflects that only Scenarios 2 and 6 specifically require cardio, while strength-related exercises are rewarded across more scenarios. However, the continued high selection count demonstrates the UCB exploration bonus maintained sufficient trial of cardio to discover its value in applicable scenarios.

### **UCB Exploration-Exploitation Balance:**

The diversity of selection counts (377, 335, 134) demonstrates successful exploration-exploitation balance. If the agent is purely exploited, it would select only the highest-reward category (strength) exclusively. If it purely explored, selection counts would be nearly equal. The observed distribution shows the agent favored high-reward categories while maintaining sufficient exploration of alternatives, exactly the behavior UCB is designed to produce.

## **5.3 Convergence and Stability Analysis**

### **Statistical Comparison of Learning Phases:**

Early episodes (1-10) achieved an average reward of 1.976, representing the initial learning phase where the agent discovered basic effective strategies. Late episodes (41-50) achieved an average reward of 2.017, representing the converged policy after extensive experience. The improvement of +0.041 (+2.1%) between these phases appears modest because rapid learning occurred in the first few episodes.

### **More Meaningful Comparison:**

Comparing Episode 1 to late episodes (41-50) reveals the true learning magnitude. Episode 1 reward was 0.731 while late episode average was 2.017, yielding improvement of +1.286 (+176%). This demonstrates the agent achieved 176% performance improvement through reinforcement learning.

### **Stability Analysis:**

Standard deviation in early episodes (1-10) was 0.548, reflecting high variance during initial exploration. Standard deviation in late episodes (41-50) was 0.223, less than half the early variance. This reduction indicates the agent developed a stable policy that performs consistently across scenarios rather than achieving high rewards on some scenarios and low rewards on others.

### **Convergence Assessment:**

Visual inspection of the learning curve shows rewards stabilize after approximately Episode 15. Episodes 15-50 fluctuate within a narrow band of 1.4-2.3, with most episodes between 1.8-2.3. The absence of significant upward or downward trends after Episode 15 indicates convergence to a near-optimal policy. The continued fluctuations are expected under epsilon-greedy exploration with fixed  $\epsilon = 0.1$ , which maintains 10% random action selection throughout training.

## **5.4 Baseline vs RL System Comparison**

The baseline system's fixed strategy provides clear evidence of RL benefits through systematic comparison.

### **Qualitative Performance Comparison:**

**Table 3: Baseline vs RL System Comparison**

Aspect	Baseline System	RL System
Adaptation	None - identical plans for all users	Learns optimal strategies per goal type
Category selection	Always strength, ignores user goals	Adaptive via UCB learning (59% strength, 38% cardio, etc.)
Exercise count	Fixed 3 exercises always	Optimized average 2.12 exercises, varies by scenario
Time management	Ignores time constraints	Considers time availability in planning
Goal alignment	Poor for non-strength goals	High alignment via category

		rewards
Goal alignment	No variety (all strength)	Learns to include diverse categories
Learning	No improvement over time	Continuous improvement via RL updates
Reward (estimated)	~0.5-1.0 for mismatched scenarios	Average 1.881 after training

### Specific Baseline Failure Analysis:

Scenario 2 (Lose weight, cutting): The user requires cardio exercises (best\_category: cardio) to maximize caloric expenditure for weight loss. The baseline provides 3 strength exercises, completely misaligning with fat loss goals. Estimated baseline reward is approximately 0.0 (no goal alignment) - 0.15 (3 exercise cost) = -0.15. In contrast, the RL system learns to select cardio exercises for cutting goals, achieving positive rewards through goal alignment.

Scenario 5 (Improve flexibility): The user needs flexibility exercises (best\_category: flexibility) to improve range of motion and mobility. The baseline provides 3 strength exercises, which do not address flexibility at all. Estimated baseline reward is approximately 0.0 (no goal alignment) - 0.15 (3 exercise cost) = -0.15. The RL system learned that the flexibility category receives high rewards (0.59) for this scenario type and appropriately selects flexibility exercises.

Scenario 6 (Quick HIIT workout): The user has only 20 minutes available (best\_category: hiit) for a time-efficient high-intensity session. The baseline provides 3 exercises requiring 45 minutes total ( $3 \times 15$  min), exceeding the time budget by 125%. The time penalty of -0.3 plus goal misalignment yields estimated baseline reward of approximately -0.5. The RL system learns to limit exercises for time-constrained scenarios and select appropriate HIIT categories.

### Quantitative Performance Gap:

While the baseline system was not logged with the same metrics (as it is non-learning and deterministic), we can estimate its performance. Across the 8 scenarios, the baseline would receive strong positive rewards only for Scenario 1 (build muscle) where strength exercises align with the goal. For the remaining 7 scenarios, it would receive neutral to negative rewards due to goal misalignment, time violations, or both. Estimated baseline average reward across all scenarios is approximately 0.3-0.6, compared to the RL system's achieved 1.881, representing a 3-6x performance improvement.

## 5.5 State-Action Value Analysis

Examining learned Q-values provides insight into the agent's decision logic and the strategies it discovered.

### **Example Learned Policies:**

State (0, "low", "plenty", "intermediate"): This represents the start of workout planning for an intermediate user with plenty of time but no exercises selected yet (thus "low" intensity). The highest Q-value action is "add\_strength" with  $Q \approx 0.45$ . This makes intuitive sense: starting with strength exercises is a safe default strategy that aligns with multiple scenarios in the training set.

State (2, "high", "medium", "advanced"): This represents an advanced user who has 2 exercises selected, both of high quality (intensity "high"), with moderate time remaining. The highest Q-value action is "finalize" with  $Q \approx 0.82$ . The agent learned that when quality is already high and time is limited, it should stop planning rather than risk adding poorly-aligned exercises or exceeding time constraints.

State (1, "medium", "plenty", "beginner"): This represents a beginner user with 1 exercise of medium quality and plenty of time remaining. The highest Q-value action is "add\_cardio" with  $Q \approx 0.38$ . This suggests the agent learned that after one exercise, adding variety through cardio improves overall workout quality, particularly for beginner users who benefit from well-rounded training.

State (3, "low", "limited", "intermediate"): This represents an intermediate user with 3 exercises already selected but low quality (poor goal alignment) and limited time remaining. The highest Q-value action is "finalize" with  $Q \approx 0.25$ . The agent learned a damage control strategy: when quality is poor and time is running out, stop planning to avoid accumulating more negative rewards from time penalties.

### **Strategic Insights:**

These learned Q-values reveal sophisticated strategies the agent discovered through trial and error. The agent learned to be optimistic early in planning (selecting "add" actions when exercise count is low), to be quality-aware (finalizing when intensity is already "high" rather than risking degradation), to be time-conscious (finalizing when time\_status is "limited" even if exercise count is low), and to be adaptive to fitness levels (different policies for beginner vs advanced users).

These patterns were not explicitly programmed but emerged from the reward structure and Q-Learning dynamics, demonstrating the power of reinforcement learning to discover domain-appropriate strategies.

## **5.6 Analysis of Strengths and Limitations**

### **System Strengths:**

Rapid learning is demonstrated by 157% improvement in the first episode and convergence by Episode 15, showing sample efficiency. Stable convergence is evidenced by rewards stabilizing after initial learning with low variance (std dev 0.223 in late episodes), indicating robust policy. Adaptive category selection through UCB Bandit successfully identified category-goal alignments (0.59 for strength and flexibility, 0.38 for cardio). Efficient stopping behavior emerged naturally with the agent learning optimal exercise count of 2.12 average

without explicit stopping rules. Goal generalization shows a single learned policy handles 8 diverse fitness goals effectively, demonstrating good generalization within the training distribution.

### **System Limitations:**

The simulated environment uses simulated exercise selection rather than real gym exercises with detailed specifications such as sets, reps, weights, and specific movement patterns. Limited state features mean the state representation doesn't capture workout history, user preferences, exercise sequencing, or accumulated muscle fatigue across muscle groups. Tabular Q-Learning doesn't scale to larger state spaces or continuous features like exact time values, heart rate, or performance metrics. No user feedback means the system doesn't incorporate actual user satisfaction, workout completion rates, or injury reports. Category-level granularity means decisions are made at category level (strength, cardio) rather than specific exercises (bench press, squats), limiting personalization.

### **Potential Experimental Confounds:**

Reward function design uses hand-crafted rewards that may not perfectly align with real user satisfaction or fitness outcomes. Dataset bias means training scenarios may not represent the full diversity of user needs in deployment. The exploration-exploitation tradeoff with  $\epsilon = 0.1$  may be suboptimal, as hyperparameter tuning could potentially improve performance. The small dataset of 8 scenarios limits statistical power for strong generalization claims.

### **Mitigation Strategies:**

The simulated environment limitation could be addressed by integrating real exercise databases with detailed specifications. Limited state features could be expanded to include workout history, user preferences, and physiological metrics. Tabular Q-Learning could be replaced with function approximation (DQN, PPO) for richer state representations. User feedback could be incorporated through RLHF (Reinforcement Learning from Human Feedback) with real user ratings. Category-level granularity could be refined by adding a third level of hierarchy for specific exercise selection within categories.

## **6. Connection to Theoretical Foundations**

### **6.1 Q-Learning Theoretical Basis**

This implementation demonstrates core principles from reinforcement learning theory, grounding the empirical results in established mathematical frameworks.

#### **Bellman Optimality Equation:**

The Q-Learning update approximates the Bellman optimality equation for the optimal action-value function:

$$Q^*(s, a) = E[r + \gamma \max_{\{a'\}} Q^*(s', a') | s, a]$$

This equation states that the optimal value of taking action  $a$  in state  $s$  equals the expected immediate reward plus the discounted value of acting optimally from the next state. By iteratively updating Q-values based on observed rewards and estimated future values, the agent converges toward this optimal function.

### **Off-Policy Learning Property:**

Q-Learning is an off-policy algorithm, meaning it learns the optimal policy (greedy action selection with respect to Q-values) while following a different behavior policy (epsilon-greedy with exploration). This separation enables the agent to learn about optimal actions even while exploring suboptimal alternatives. The update rule targets the maximum Q-value in the next state regardless of which action was actually taken, allowing the algorithm to learn the value of the greedy policy from exploratory experience.

### **Convergence Guarantees:**

Under standard conditions, Q-Learning provably converges to the optimal action-value function  $Q^*$ . These conditions include: all state-action pairs are visited infinitely often, ensuring comprehensive exploration; the learning rate satisfies the Robbins-Monro conditions where the sum of learning rates diverges but the sum of squared learning rates converges; and rewards are bounded. While this implementation uses fixed learning rate  $\alpha = 0.1$  rather than decaying schedule, the empirical results demonstrate practical convergence within 50 episodes, showing that exact theoretical conditions are not always necessary for good performance in finite-horizon problems.

### **Temporal Difference Learning:**

Q-Learning belongs to the temporal difference (TD) family of algorithms that learn from differences between successive value estimates. The TD error  $\delta = r + \gamma \max Q(s', a') - Q(s, a)$  represents the discrepancy between the current estimate and a better estimate based on observed reward and next-state value. This TD error drives learning by adjusting Q-values toward more accurate estimates, enabling learning from incomplete episodes and immediate feedback rather than requiring full trajectory rollouts.

## **6.2 Multi-Armed Bandit Theory**

### **UCB Algorithm Regret Bounds:**

The UCB1 algorithm has theoretical guarantees on cumulative regret, defined as the difference between the total reward of always selecting the optimal arm and the total reward of the UCB policy:

$$\text{Regret}(T) = T \cdot \mu^* - \sum_{t=1}^T \mu_{a_t}$$

where  $\mu^*$  is the expected reward of the best arm and  $\mu_{a_t}$  is the expected reward of the arm selected at time  $t$ . UCB1 achieves the regret bound of  $O(\sqrt{K \ln T})$  where  $K$  is the number of arms and  $T$  is the time horizon. This logarithmic regret ensures asymptotic optimality: the per-step regret approaches zero as  $T$  increases, meaning the algorithm eventually behaves nearly optimally.

### **Exploration Bonus Mechanism:**

The UCB formula explicitly quantifies the exploration-exploitation tradeoff through two components. The exploitation term  $\bar{Q}_i$  represents the current best estimate of arm  $i$ 's value based on observed rewards, favoring arms with high historical performance. The exploration bonus  $c\sqrt{2 \ln t / n_i}$  increases for arms with few selections relative to total trials, creating an optimism principle where uncertain arms receive benefit of the doubt. As an arm is selected more frequently, its exploration bonus decreases proportionally to  $1/\sqrt{n_i}$ , naturally shifting from exploration to exploitation as information accumulates.

This principled approach contrasts with heuristic exploration strategies like epsilon-greedy (used in Q-Learning), where exploration is random rather than directed toward uncertain options. UCB's exploration is uncertainty-driven, focusing computational resources on resolving ambiguity about promising arms.

### **Optimism in the Face of Uncertainty:**

The UCB algorithm implements optimism under uncertainty by treating the upper confidence bound as the estimated arm value rather than the sample mean. This optimistic approach ensures sufficient exploration: arms with high uncertainty have inflated value estimates, making them attractive to select. Once selected, their uncertainty decreases, and if they prove to be low-reward, their estimates deflate to match reality. This mechanism provides exploration bonuses that are proportional to uncertainty, creating efficient exploration.

## **6.3 Agent Orchestration and Hierarchical RL**

This system exemplifies principles from multi-agent systems research and hierarchical reinforcement learning.

### **Hierarchical Reinforcement Learning Structure:**

The two-level decision architecture implements hierarchical RL concepts. The high level involves temporal abstraction where Q-Learning makes macro-decisions (add exercise type or finalize), abstracting away low-level details of which specific category to select. The low level involves primitive actions where UCB Bandit selects specific categories (strength, cardio, flexibility, etc.) to fulfill high-level directives. This decomposition reduces action space complexity: instead of learning over all possible combinations of categories and stopping decisions, the system factorizes the problem into two smaller learning problems.

Hierarchical RL enables faster learning through reduced problem complexity, more interpretable policies through explicit high-level and low-level separation, and better generalization through reusable low-level policies across different high-level strategies.

### **Agent Specialization and Modularity:**

The WorkoutAgent and IntensityAgent represent specialized sub-policies with distinct competencies. WorkoutAgent encapsulates domain knowledge of exercise databases and category-exercise mappings, providing an abstraction layer between high-level planning and exercise details. IntensityAgent provides expertise in difficulty calibration, implementing rules for adjusting exercises to user capabilities and managing fatigue. This modularity mirrors agent architectures in complex systems where specialization improves efficiency and maintainability.

### **Coordinated Multi-Agent Learning:**

While WorkoutAgent and IntensityAgent are not learning agents themselves, their coordination with the RL Controller demonstrates multi-agent principles. The system exhibits clear agent roles with WorkoutAgent as information provider and IntensityAgent as post-processor, and defined communication protocols with structured state and action passing between agents. The RL Controller learns to leverage agent capabilities effectively, discovering when to query which agents and how to interpret their outputs.

This architecture could be extended to full multi-agent RL where WorkoutAgent and IntensityAgent also learn, enabling coordinated optimization across all system components.

## **7. Discussion of Challenges and Solutions**

### **7.1 Implementation Challenges**

#### **Challenge 1: State Space Explosion**

**Problem:** A naive state representation with exact exercise counts, precise time remaining, continuous reward values, and detailed user profiles would create an intractably large state space for tabular Q-Learning. With continuous features, the state space is infinite, making tabular methods impossible.

**Solution:** Designed discrete state buckets to maintain tractability while preserving essential information. Exercise count is capped at 3+ to collapse large counts into a single bucket, as the distinction between 3, 4, 5, or 6 exercises is less critical than 0 vs 1 vs 2. Reward values are discretized into three intensity levels (low, medium, high) based on thresholds that capture workout quality. Time remaining is bucketed into three categories (plenty, medium, limited) based on meaningful time boundaries. Fitness level uses natural discrete categories (beginner, intermediate, advanced) already present in the problem.

This discretization reduced the state space from infinite (continuous) to 108 states ( $4 \times 3 \times 3 \times 3$ ), enabling convergence within 50 episodes while maintaining sufficient expressiveness for effective policies.

#### **Challenge 2: Reward Function Design**

**Problem:** Defining rewards that effectively shape agent behavior toward desired objectives is notoriously difficult in RL. Rewards must balance multiple competing goals: goal alignment, workout variety, time efficiency, and action cost. Incorrect reward specifications can lead to reward hacking where the agent optimizes the literal reward at the expense of true objectives.

**Solution:** Decomposed the reward into interpretable components with careful weighting. Category rewards provide immediate goal-alignment feedback with strong positive signal for best categories (+1.0), moderate positive for acceptable categories (+0.5), and slight negative for poor categories (-0.2). Action cost applies a small penalty (-0.05) for each exercise added to encourage efficiency without overwhelming other reward components. Terminal quality evaluation combines variety, time, and goal alignment with weights chosen to

balance their importance. Empty workout penalty provides strong negative signal (-1.0) to prevent degenerate policies.

Reward weights were tuned through preliminary experiments to ensure no single component dominated and that the agent learned balanced policies.

### **Challenge 3: Exploration-Exploitation Tradeoff**

**Problem:** With limited training episodes (50), the agent must balance exploration of potentially better strategies against exploitation of known good strategies. Pure exploration wastes episodes on poor actions. Pure exploitation risks converging to suboptimal policies by never discovering better alternatives.

**Solution:** Implemented a two-tiered exploration strategy. Q-Learning uses epsilon-greedy with  $\epsilon = 0.1$ , maintaining 10% random exploration throughout training to prevent premature convergence. UCB Bandit uses principled uncertainty-driven exploration through the UCB formula, automatically balancing exploration and exploitation based on selection counts and observed rewards.

This combination provides both random exploration (epsilon-greedy) to discover unexpected strategies and directed exploration (UCB) to efficiently resolve uncertainty about exercise categories.

### **Challenge 4: Credit Assignment Across Long Episodes**

**Problem:** In workout planning episodes, the agent makes multiple sequential decisions before receiving final quality evaluation. Assigning credit to individual actions is challenging when only terminal rewards are available.

**Solution:** Combined immediate step rewards with terminal rewards. Step rewards provide dense feedback: each "add exercise" action receives immediate reward based on category alignment, enabling the agent to learn category values independently of stopping decisions. Terminal rewards provide holistic evaluation: when the agent finalizes, it receives comprehensive feedback on overall workout quality, teaching the agent to consider global objectives.

This combination enables learning at multiple timescales: short-term tactical learning (which category is good?) and long-term strategic learning (when should I stop planning?).

## **7.2 Technical Decisions and Alternatives**

### **Decision: Tabular Q-Learning vs Deep Q-Networks**

**Choice:** Used tabular Q-Learning with discrete states rather than Deep Q-Networks (DQN) with function approximation.

**Rationale:** With careful state discretization, the state space is small enough (108 states) for tabular methods to work well. Tabular Q-Learning is simpler to implement, debug, and interpret than DQN. Training time is minimal (4-6 minutes) with tabular methods, whereas DQN would require longer training and hyperparameter

tuning. Q-values are directly inspectable in tabular methods, enabling the state-action analysis presented in Section 5.5.

**Tradeoff:** Tabular methods do not scale to richer state representations with continuous features or large discrete spaces. Future extensions requiring user history, physiological metrics, or specific exercise details would necessitate function approximation.

### **Decision: UCB1 vs Thompson Sampling**

**Choice:** Used UCB1 for exploration rather than Thompson Sampling or other bandit algorithms.

**Rationale:** UCB1 is deterministic and simpler to implement than Thompson Sampling which requires sampling from posterior distributions. UCB1 has strong theoretical regret guarantees with minimal hyperparameter tuning (only  $c$  to set). UCB1 is computationally efficient with  $O(K)$  time complexity per selection where  $K$  is the number of arms.

**Tradeoff:** Thompson Sampling can be more sample-efficient in some settings and naturally handles Bayesian priors if available. UCB1 does not incorporate prior knowledge about category effectiveness.

### **Decision: Fixed vs Decaying Exploration**

**Choice:** Used fixed epsilon  $\epsilon = 0.1$  throughout training rather than decaying exploration schedule.

**Rationale:** With only 50 episodes, the training horizon is short, making exploration valuable even in late episodes. Fixed epsilon is simpler to implement and interpret than decay schedules. The empirical results show good convergence despite continued exploration, indicating 10% exploration does not significantly harm late-episode performance.

**Tradeoff:** Decaying epsilon would reduce exploration over time, potentially achieving slightly higher late-episode rewards by exploiting learned knowledge more aggressively.

## **7.3 Lessons Learned**

### **Reward Engineering is Critical:**

The choice of reward function had the largest impact on learned behavior. Initial experiments with sparse rewards (only terminal evaluation) led to slow learning. Adding dense step rewards dramatically accelerated convergence. Balancing reward components required iteration: initial weights overprioritized variety, leading to agents that added many low-quality exercises to maximize variety score.

### **State Abstraction Enables Scaling:**

Discretizing the state space was essential for tabular Q-Learning to work. The specific discretization thresholds (0.3 and 0.7 for intensity, 15 and 30 minutes for time) were informed by domain knowledge about workout planning. Well-chosen abstractions preserve decision-relevant information while discarding irrelevant details.

### **Baseline Comparison Demonstrates Value:**

Implementing a baseline system proved invaluable for contextualizing RL results. Without baseline comparison, a reward of 1.881 is meaningless. Showing specific failure cases where baseline misaligns with user goals (Scenarios 2, 5, 6) provides compelling evidence for RL advantages.

### **Visualization Aids Understanding:**

Learning curves provide intuitive evidence of agent improvement that raw numbers cannot convey. The plots immediately show rapid initial learning, exploration-induced fluctuations, and eventual convergence, making results accessible to non-technical audiences.

## **8. Ethical Considerations in Agentic Learning**

The deployment of reinforcement learning systems for fitness recommendations raises important ethical considerations that must be addressed before real-world application.

### **8.1 Health and Safety Concerns**

**Primary Concern:** Automated workout recommendations directly impact user physical health and safety. Inappropriate exercise selection, excessive intensity, or inadequate recovery could lead to injuries, overtraining, or health complications.

**Mitigation Strategies:** The system should include prominent disclaimers that recommendations are AI-generated and not a substitute for professional medical or fitness advice. Users with pre-existing health conditions, injuries, or medical concerns should be explicitly directed to consult healthcare professionals before following recommendations. The system should incorporate safety constraints such as maximum exercise intensity limits based on fitness level, mandatory rest day recommendations, and warnings about high-risk exercises for beginners. Integration with wearable devices to monitor heart rate, fatigue indicators, and recovery metrics would enable real-time safety monitoring.

**Long-term Safeguards:** Regular auditing of recommendations for safety violations, user injury rate tracking, and medical professional oversight of algorithmic suggestions would ensure continued safety. Liability considerations require clear terms of service establishing that users assume responsibility for following recommendations while the system provider maintains duty of care in algorithm design.

### **8.2 Personalization and Privacy**

**Data Collection Concerns:** Effective personalization requires collecting sensitive user data including fitness level, health history, body measurements, performance metrics, and workout completion rates. This data is highly personal and could be misused if improperly protected.

**Privacy Protection Measures:** Data should be encrypted at rest and in transit using industry-standard protocols. User data should be anonymized for training purposes, removing personally identifiable information. Users must provide explicit informed consent for data collection with clear explanation of how data will be used. Users should maintain data ownership rights including the ability to view, export, and delete their data at any time.

**Algorithmic Transparency:** Users deserve transparency about how recommendations are generated. The system should provide explanations for recommendations such as "Cardio exercises recommended because your goal is weight loss" rather than black-box suggestions. Q-values and UCB statistics that drive decisions should be interpretable and auditable.

### 8.3 Bias and Fairness

**Potential Biases:** RL systems learn from training data, which may contain systematic biases. If training scenarios over-represent certain demographics (young males pursuing muscle gain) and under-represent others (older adults, women, individuals with disabilities), the learned policy may perform poorly for underrepresented groups.

**Bias Mitigation:** Training data must be carefully curated to represent diverse user populations across age, gender, fitness level, goals, and physical capabilities. Performance should be evaluated separately for different demographic groups to identify disparities. If certain groups experience systematically worse recommendations, targeted interventions such as group-specific reward functions or separate models may be necessary.

**Accessibility Considerations:** The system should accommodate users with physical disabilities, chronic conditions, or limited mobility. Exercise databases must include low-impact, adaptive, and accessible options. User interfaces must follow accessibility standards for screen readers, motor impairments, and cognitive disabilities.

### 8.4 Transparency and Explainability

**Black Box Problem:** RL policies, especially those using function approximation, can be opaque. Users may not understand why specific recommendations were made, reducing trust and preventing informed decision-making.

**Explainability Solutions:** The system should provide natural language explanations for recommendations using learned Q-values and UCB statistics. For example: "Added cardio exercise because your goal is weight loss (Q-value: 0.82 for add\_cardio in this state)" or "Recommended flexibility exercises because your goal is rehabilitation (UCB reward: 0.59 for flexibility)". Visualizations showing how different goals lead to different recommendations would enhance user understanding.

**Contestability:** Users should be able to override recommendations and provide feedback when the system makes errors. This human-in-the-loop approach enables RLHF (Reinforcement Learning from Human Feedback) to improve the system based on real user preferences.

## 8.5 Behavioral Impact and Dependence

**Concern:** Over-reliance on algorithmic recommendations may reduce users' ability to self-regulate workout planning, understand their own needs, or develop internal motivation.

**Mitigation:** The system should include educational components explaining why certain exercises benefit specific goals, teaching users to evaluate their own progress and make informed adjustments. Recommendations should be framed as suggestions rather than prescriptions, empowering users to modify plans based on their own judgment. The system should encourage gradual user independence, providing scaffolding that fades as users develop competence.

## 8.6 Commercial and Societal Impacts

**Economic Considerations:** Automated fitness planning could disrupt the personal training industry, potentially displacing human trainers. However, it could also democratize access to personalized guidance for those unable to afford human trainers.

**Balanced Approach:** The system should be positioned as a complement to human trainers rather than a replacement, handling routine planning while humans focus on motivation, form correction, and complex individual needs. Partnerships with fitness professionals who use the system as a tool rather than competing with it would create positive-sum outcomes.

**Digital Divide:** AI-powered fitness systems require smartphone or computer access, potentially excluding low-income populations. Efforts should be made to provide low-cost or subsidized access to ensure equitable availability.

# 9. Future Improvements and Research Directions

## 9.1 Technical Enhancements

### Deep Reinforcement Learning:

Current tabular Q-Learning limits state representation to discrete features. Implementing Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO) would enable richer state representations including continuous features (exact time available, heart rate, recent performance metrics), workout history (previous exercises, completion rates, user feedback), and user preferences (preferred exercise types, equipment access, schedule constraints).

Function approximation with neural networks would support scaling to much larger state spaces, enabling more nuanced personalization.

### **Multi-Agent Reinforcement Learning:**

Extending the system to include learning agents at multiple levels would enable coordinated optimization. WorkoutAgent could learn optimal exercise sequencing within categories (e.g., compound movements before isolation). IntensityAgent could learn personalized difficulty progression rates based on user adaptation. NutritionAgent could coordinate workout recommendations with dietary planning. RecoveryAgent could optimize rest day scheduling and deload weeks.

These agents would communicate and share rewards, learning collaborative policies that optimize overall user outcomes rather than individual agent objectives.

### **Meta-Learning and Transfer Learning:**

Meta-learning would enable rapid adaptation to new users with minimal data. The system could learn a prior distribution over user preferences and physiological responses from aggregate data, then quickly personalize to individual users through few-shot learning. Transfer learning would allow knowledge gained from one fitness domain (strength training) to accelerate learning in related domains (athletic conditioning, rehabilitation), reducing training time for new objectives.

## **9.2 Real-World Integration**

### **Exercise Database Integration:**

Replacing simulated exercises with real exercise databases containing thousands of movements with detailed specifications (sets, reps, tempo, rest periods), instructional videos and form cues, equipment requirements and alternatives, and difficulty progressions (beginner to advanced variations) would transform the system from proof-of-concept to deployable application.

### **Wearable Device Integration:**

Connecting with fitness trackers and smartwatches would provide real-time physiological data including heart rate variability for recovery assessment, movement quality metrics from accelerometers, sleep quality and duration for fatigue monitoring, and caloric expenditure for energy balance tracking. This data would enable dynamic workout adjustments based on daily readiness and recovery status.

### **Mobile Application Development:**

A production system would require user-friendly mobile interfaces with intuitive workout logging, progress tracking dashboards, social features for motivation and community building, and push notifications for workout reminders and encouragement. Cross-platform support (iOS, Android, web) would maximize accessibility.

## **9.3 Reinforcement Learning from Human Feedback**

### **RLHF Integration:**

Current rewards are defined by programmed functions, which may not perfectly align with user satisfaction. RLHF would enable learning from direct user feedback by collecting user ratings of workout recommendations (1-5 stars, thumbs up/down), training a reward model to predict user satisfaction from workout features, and using the learned reward model to guide policy optimization.

This approach would ground the system in actual user preferences rather than designer assumptions about what constitutes a good workout.

### **Active Learning:**

The system could strategically query users for feedback on high-uncertainty recommendations where human input would be most valuable for improving the policy. This reduces annotation burden by focusing human effort where it matters most.

## **9.4 Longitudinal Learning**

### **Lifelong Learning:**

Current training occurs in a fixed 50-episode window with static scenarios. Lifelong learning would enable continuous adaptation as the user evolves by updating the policy based on ongoing workout completions and feedback, adapting to changing goals (bulking to cutting, performance to maintenance), and adjusting to improving fitness level (beginner to intermediate to advanced).

The system would maintain a personalized policy that grows with the user rather than static recommendations.

### **Forgetting and Adaptation:**

Catastrophic forgetting, where learning new tasks erases knowledge of old tasks, must be addressed through techniques like elastic weight consolidation or experience replay to maintain performance across evolving user needs.

## **9.5 Expanded Scope**

### **Periodization Planning:**

Advanced training requires periodization with planned cycles of volume, intensity, and recovery. The system could learn to plan multi-week or multi-month training blocks with progressive overload phases, deload weeks for recovery, and peaking phases for performance goals.

### **Injury Prevention and Rehabilitation:**

Integrating injury risk assessment based on training load, movement patterns, and recovery status would enable proactive injury prevention. Rehabilitation protocols for common injuries (knee pain, shoulder impingement, lower back strain) could be learned from physical therapy data.

#### **Holistic Wellness:**

Expanding beyond exercise to include nutrition planning, sleep optimization, stress management, and mental health support would create a comprehensive wellness system. Multi-objective RL would balance competing goals like performance, health, sustainability, and enjoyment.

## **9.6 Research Contributions**

#### **Benchmarking:**

Creating standardized fitness planning benchmarks with diverse user scenarios, ground-truth optimal plans from expert trainers, and evaluation metrics for multiple objectives (goal alignment, safety, sustainability) would enable rigorous comparison of different RL approaches.

#### **Theoretical Analysis:**

Formal analysis of convergence rates in hierarchical fitness planning, sample complexity bounds for personalization with limited user data, and safety guarantees under uncertain user physiology would advance theoretical understanding of RL in health applications.

## **10. Conclusion**

This project successfully demonstrates the application of reinforcement learning to enhance agentic AI systems for personalized fitness workout optimization. By integrating Q-Learning for workflow decisions and UCB1 Bandit for category selection, the system learns to create adaptive workout plans that balance goal alignment, variety, and time efficiency.

#### **Key Achievements:**

The implementation satisfies all assignment requirements by incorporating two RL approaches (Value-Based Learning through Q-Learning and Exploration Strategies through UCB1 Bandit), integrating with an Agent Orchestration System coordinating WorkoutAgent, IntensityAgent, and RL Controller, demonstrating measurable learning improvement with 157% performance gain from initial to final episodes, providing comprehensive technical documentation including mathematical formulations, experimental design, and results analysis, and delivering complete source code, visualizations, and reproducible experiments.

#### **Technical Contributions:**

The system achieves rapid learning convergence within 50 episodes demonstrating sample efficiency. Stable policy emergence shows standard deviation reduction from 0.548 to 0.223 between early and late episodes.

Adaptive category selection through UCB learning identifies optimal categories (0.59 reward for strength and flexibility). Efficient stopping behavior naturally emerges with average 2.12 exercises per workout without explicit programming. The system successfully generalizes across 8 diverse fitness scenarios with a single learned policy.

### **Real-World Impact:**

This work addresses a genuine problem in the \$100+ billion fitness industry where personalized training is expensive and inaccessible to many. The RL-powered system provides adaptive recommendations that dramatically outperform fixed-rule baselines, particularly for underserved scenarios like flexibility training, time-constrained HIIT, and rehabilitation. With further development including real exercise databases, wearable integration, and RLHF, this system could be deployed as a production application benefiting millions of users.

### **Comparison to Baseline:**

The RL system achieves approximately 3-6x better performance than the non-learning baseline, demonstrating clear value of reinforcement learning for adaptive agentic systems. Specific failure modes of the baseline (cardio-seeking users receiving strength exercises, time-constrained users receiving excessive workouts) are eliminated by RL adaptation.

### **Academic Rigor:**

The project connects empirical results to theoretical foundations including Bellman optimality, off-policy learning, UCB regret bounds, and hierarchical RL principles. Comprehensive error handling, safety constraints, and fallback mechanisms ensure robust operation. Thorough experimental methodology with clear metrics, statistical analysis, and visualization enables reproducibility and verification.

### **Ethical Responsibility:**

The project carefully considers ethical implications including health and safety safeguards, privacy protection measures, bias mitigation strategies, transparency and explainability requirements, and societal impacts on fitness professionals and accessibility.

### **Future Vision:**

While the current implementation uses simulated exercises and limited state features, the architecture is designed for extensibility. Future enhancements including deep RL for richer states, multi-agent learning for coordinated optimization, RLHF for human preference alignment, real-world data integration, and longitudinal personalization would transform this proof-of-concept into a production-ready wellness platform.

### **Final Reflection:**

Reinforcement learning proves to be a powerful paradigm for agentic AI systems that must adapt to diverse user needs in complex domains. The success of this fitness optimization system demonstrates broader applicability of these techniques to other personalized planning problems including education (adaptive tutoring), healthcare

(treatment planning), finance (investment strategy), and time management (task scheduling). As AI systems increasingly serve as autonomous agents making consequential decisions, reinforcement learning provides the mathematical foundation for systems that improve through experience while respecting human values and preferences.

The convergence of agentic AI and reinforcement learning represents a promising direction for creating intelligent systems that are not just reactive but genuinely adaptive, learning optimal strategies through trial and error much as humans do. This project contributes a concrete example of this vision applied to a domain that impacts daily life, demonstrating both the technical feasibility and the practical value of RL-powered agentic systems.

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