Designing a Feature Based Reinforcement Learning Agent for Hotel Selection in Sri Lanka: A Pilot Study Using 2025 Tourist Data

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Abstract- Sri Lanka's tourism sector is an important part of the country's economy, but travelers often have trouble finding suitable accommodation based on their price, location, facilities and preferences. Conventional rule-based hotel recommendation systems rely on a static approach and are therefore unable to comprehend the varying preferences of travelers, often resulting in suboptimal recommendations. This research explores the use of a feature-based reinforcement learning (RL) agent to adapt personalized hotel recommendations for travelers based on 2025 travel data. This agent assesses hotel options from user defined features such as price, rating, location, and preferences, and provides user feedback as a learning mechanism to refine recommendations in an iterative manner. In a pilot study, the RL agent is juxtaposed with conventional rule-based filtering systems wherein the metrics of recommendation accuracy, cumulative satisfaction, and flexibility to traveler profile were used to assess performance. The results suggest that the feature-based RL agent can flexibly incorporate system feedback in stark contrast to mechanisms that employ static reinforcement learning and emphasizes the need and opportunity for context-sensitive reinforcement learning driven personalization in hotel recommendation systems to adapt to the changes in tourism in Sri Lanka**.**

Keywords- Reinforcement learning, Hotel recommendation, Personalization, Tourism

I. INTRODUCTION

The economy of Sri Lanka relies heavily on the tourism sector. Tourism helps the Sri Lankan economy by creating jobs, earning foreign exchange, and helping regional development. There is an increasing demand for effective tourism hotel recommendation systems, especially with the predicted global tourism growth in 2025. Customers struggle with finding lodgings since their budget, location, amenities, and distance to attractions vary. Fixed and rule-based hotel booking platforms fail to capture the context-sensitive and dynamic nature of traveler preferences. As a result, their recommendations tend to be disappointing.

This study explores the development of a feature-based reinforcement learning (RL) agent for improving hotel selection in Sri Lanka. Reinforcement learning is a specialized area within artificial intelligence that enables an agent to learn optimal strategies of decision making via environment interaction and reward feedback. The proposed model improves the decision-making process by incorporating features designed around travel and hotel attributes, such as price, rating, and location, as well as user preferences. Unlike traditional recommendation systems, the RL agent is designed to adapt to user feedback, improving their recommendations over time.

This study involves meeting the need for adaptive hotel recommendations in Sri Lanka by answering the research question of how a feature-based reinforcement learning agent could supply adaptive personal hotel recommendations to tourists based on the 2025 tourism. This study involves applying a context-aware strategy to making hotel recommendations. The model would be compared to rule-based filtering methods to determine improvements in accuracy and user satisfaction. The aim of this study involves meeting the need to connect AI dynamic decision systems to the Sri Lankan tourism sector by applying optimization methods to the idea of reinforcement learning. This study's pilot results are expected to demonstrate the potential of reinforcement learning in personalized hotel recommendations in new tourism markets. Furthermore, these results can inform the forthcoming application of AI in tourism management in Sri Lanka, helping it achieve its goals of a technologically advanced, tourist-friendly industry.

II. LITERATURE REVIEW

A. Recommendation Systems: Foundations and Challenges

Recommendation systems are designed to help users identify Items to suggest to users depending on their likes and dislikes, using content-based, collaborative, or hybrid methods [1], [2], [3]. Content-based filtering guarantees user autonomy, but it can also cause severe over-specialization. On the other hand, collaborative filtering is hampered by cold-start and scalability problems [1], [4]. Hybrid systems attempt to combine multiple approaches to overcome these limitations, but many remain static and lack real-time adaptability [5], [6]. These foundational studies emphasize the need for dynamic, adaptive recommendation models, which is addressed in this research by employing a feature-based reinforcement learning agent for hotel selection in Sri Lanka.

B. Reinforcement Learning in Recommendation Systems

Reinforcement Learning techniques, particularly Q-learning and deep reinforcement learning, allow agents to learn optimal actions by interacting with environments and receiving feedback [7],[8]. Actor–Critic frameworks, reward normalization, and experience replay improve learning efficiency and model stability [7]. Studies show that Reinforcement Learning outperforms traditional collaborative filtering in dynamic recommendation scenarios [4],[7]. However, most prior work focuses on single domains such as movies or employment, highlighting the potential for adaptation to hotel recommendations in the tourism sector [8], [9].

C. Feature-Based Hotel Recommendation Systems

Effective hotel recommendation systems rely on feature engineering, where hotel descriptors such as price, location, facilities, rating, user reviews, and customer sentiment scores are considered [10], [11], [12], [13], [14]. More personalization has been achieved by systems that combine functions using clustering, similar measures, or probabilistic modeling, but these systems tend to be static and specific to a single domain [10], [12], [14], [15].

Researchers have put forward a variety of strategies to enhance the recommendation systems. One approach uses multi-level customer models to account for different user types and push ranking accuracy forward. Another method leverages aspect-based sentiment analysis to pull key hotel attributes out, thus enabling personalized rankings. There's also integration of knowledge graphs which capture semantic links of hotels with what users like. Even with their success, these usually don't adapt in real-time to changes in user taste. That is where feature-based Reinforcement Learning agents come in, trying to solve this dynamic gap.

D. Personalized Hotel Recommendation Systems in Developing Regions

Research in China, India, and Morocco demonstrates that personalized hotel recommendations enhance user satisfaction but often rely on static datasets or local platforms [5], [6], [10], [12], [18]. In Sri Lanka, AI adoption in hotels is growing but remains limited, with early-stage tools like chatbots and virtual property management systems being the primary AI applications [19]. These studies highlight the lack of adaptive, context-aware hotel recommendation systems for Sri Lanka, reinforcing the relevance of the current study.

E. Web Intelligence and Real-Time Data Integration

Web intelligence (WI) systems and NLP-based methods improve recommendation systems by analyzing real-time user interactions, online reviews, and contextual data [9], [16],[20],[21]. Conversational AI and chatbot-based recommendation systems have shown improved user convenience and personalized suggestions [9],[22]. However, these systems lack reinforcement learning capabilities for adaptive feedback, limiting real-time decision optimization. Integrating feature-based RL allows continuous learning from user interactions and dynamic hotel feature evaluation.

F. Hybrid and Multi-Criteria Recommendation Approaches

The integration of collaborative filtering, content-based filtering, and machine learning techniques into hybrid systems has been effective in improving recommendation accuracy [3],[5],[23]. Multi-criteria systems that incorporate user reviews, sentiment, and the tourism context achieve higher precision and a better match to user expectations [24]. However, a significant proportion of these models work offline and do not adjust in real time to shifting user demands, which this research aims to mitigate.

G. Limitations of Existing Systems

Among the past works, a set of essential limitations have been repeatedly emphasized. Firstly, most models are static, which implies a lack of ability for self-adaptive learning [10],[11],[13],[20],[23]. Secondly, the models have geographical limitations, as features come mainly from China, India, Japan, and the Western world [5], [10], [12], [23]. Thirdly, there are limitations to these models' personalization abilities, especially within a short period of time and incorporation of user feedback [9], [14], [16], [21]. Lastly, incorporating multiple features using reinforcement learning for self-adaptive hotel recommendations has seldom been considered [13], [17], [19].

H. Research Gap and Justification

The literature shows that, while machine learning and reinforcement learning can boost how accurately we recommend and tailor options, most current systems stay fixed, cover only limited locations, and don't adapt in real time. That is a very clear indication of the gap in Sri Lanka's tourism sector, a feature-based, adaptive learning approach to hotel recommendations that apply actual tourist data. The research addresses those gaps by developing a feature-driven reinforcement learning agent that is continuously appraising hotel selections. It uses actual 2025 tourist data to simulate realistic hotel selection scenarios within Sri Lanka and provides context-aware, adaptive suggestions that learn user feedback and hotel characteristics over time.

We observe progression from the static filtering approach to feature-aware machine learning, with reinforcement learning highlighted across the literature as a promising path toward truly adaptive personalization. Through these findings, this research develops and introduces a dynamic, feature-rich reinforcement learning agent for selecting hotels in Sri Lanka that aims to deal with significant shortcomings in the current state of research regarding adaptability, regional relevance, and real-time optimization.

III. METHODOLOGY

The research plan employs a Reinforcement Learning (RL) based framework to optimize hotel selection for users in Sri Lanka through the design of a feature rich agent. The plan integrates the following phases of data collection, preprocessing, agent architectural design, training, and evaluation. The organization of these phases will ensure that the proposed framework simulates real-world hotel selections from users, adapts to dynamic user preferences, and outperforms the conventional rule-based recommendation models.

A. Data Collection and Preparation

The dataset considered for this study originates from open data tourism and mapping sources. The OpenStreetMap Turbo API serves as a main data source for information related to hotels and provides several fundamental attributes including location, price range, star rating, amenities and type of accommodation. In addition to real world attribute information, a web scraping module was created to extract other features such as room types, user reviews and average nightly rates from websites that aggregate hotel listings. This highly available dataset provides a more diverse and context rich training environment.

To combat data sparsity and improve generalization, we apply synthetic augmentation techniques, meaning we simulate further samples from our original dataset via the enhanced features () function. enhanced features () simulate realistic change of features by applying controlled randomization around defined attribute limits. For example, we will change prices based on their geographic areas and slightly change the amenity scores to capture subjective behavior perceptions of end users. All features present in the simulated data will be standardized and encoded numerically so that it can be integrated into the agent’s state space representation.

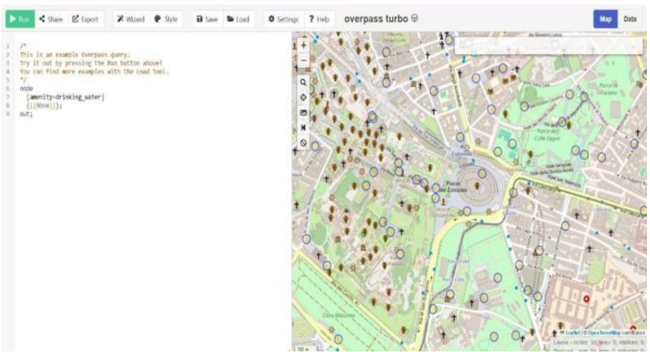


Fig 1. Overpass Turbo interface used for extracting OpenStreetMap (OSM) tourism data and hotel attributes.

B. Agent Design and State Representation

The study presents two agents within a reinforcement learning paradigm, a baseline Q learning agent called RL Agent, and the feature driven agent, called the Enhanced Hotel Agent. In both cases, the agents will operate within a Markov Decision Process (MDP) framework, where the environment consists of the hotels that are available for the user to interact with, and the user context is each instance's current user experience instance. The states are multi-dimensional feature vectors consisting of location, cost normalized to pricing, star rating, room type, and the number of amenities.

The actions are defined as a selection from the available hotels, and the rewards are derived from the satisfaction scores created using the simulation of user satisfaction based on hotel perspective, and user preferences. Further to the user-based satisfaction scores, the reward function also incorporates several of the elements: cost, location, and quality to better simulate realistic decision making. The Enhanced Hotel agent uses this framework and adds Web Intelligence (WI) functions to incorporate contextual information regarding local activities and events, weather, and pricing based on time, dynamically. This is an innovative addition that allows for adaptive re-evaluation of the hotel's applicability while training, which provides a real-time decision-making context.

C. Learning Framework and Training Process

Q-learning is being utilized as a model free reinforcement learning algorithm because it is appropriate for discrete action spaces and provides few challenges for interpretation. The agent will interact with the environment over multiple episodes to update Q-values based upon the Bellman equation. While utilizing a greedy exploration strategy, the agent will attempt to balance exploration and exploitation, thereby allowing the agent both to explore actions that are potentially optimal, and avoid local optima. The learning rate (α) and discount factor (γ) will each be tuned empirically to achieve an optimal convergence rate.

The training phase entails simulating numerous hotel selections temporally, where each episode symbolizes a traveler’s decision-making process. The agent gets a reward for each subsequent selection and subsequent passes are used to update the policy. The Enhanced Hotel Agent takes advantage of additional state embeddings produced from feature engineering to augment the agent’s contextual understanding. The training occurs over 500 - 1,000 episodes until the Q-value converges, learning performance remains stable.

D. Baseline and Evaluation Metrics

For the evaluation of the effectiveness of our proposed reinforcement learning approach, a traditional rule-based filtering system is implemented as a baseline. The rule-based model filters hotels on pre-defined static conditions, such as price below LKR 20,000 and rating above 4.0. This setup has no ability to conform to individual user context and therefore serves as a baseline to demonstrate the improvements in performance through reinforcement learning.

Performance is measured through several measures: average cumulative reward, recommendation accuracy, precision, recall, and satisfaction score. The satisfaction score is simulated based on weighted user wants informed by hotel attributes. The rate of convergence analysis is performed to investigate the stability and learning process of the agents.

E. Experimental Setup and Implementation

The experimental framework is developed in Python with use of NumPy, Pandas, and OpenAI Gym for environment development. The OpenStreetMap API integration and further experience updates are done through bespoke scripts. The Q-learning algorithms are derived from first principles, to promote openness and interpretability. The model comparison is developed with Matplotlib and Seaborn for episode wise learning curves and performance visualization.

F. Validation and Comparison

Validation is achieved through simulation runs under several varied circumstances, outlined by varying traveler profiles, budget conscious, luxury seekers, and site-based priorities. All scenario profiles illustrate the performance of agents with variable definitions, while the results indicate the Enhanced Hotel Agent accumulates higher cumulative rewards and faster convergence and recommendation performance than both the baseline RL agent and rule-based model.

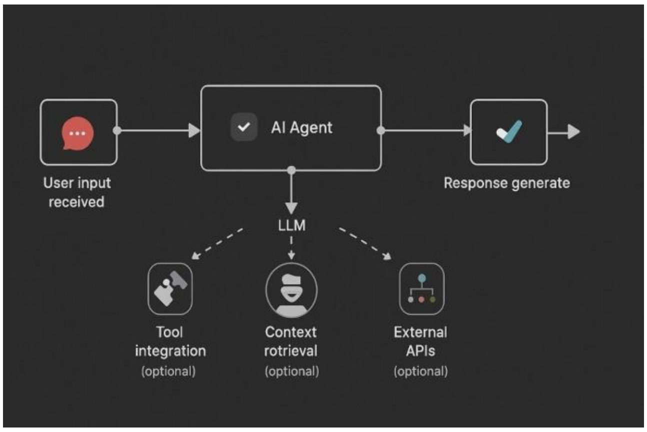


Fig. 2. Proposed AI Agent architecture illustrating the workflow from user input to response generation, including optional integration with tools and external APIs for validation.

IV. Results and Discussion

The experimental assessment indicates that their feature-enhanced reinforcement learning agent delivers substantial improvements over traditional approaches to hotel recommendations in Sri Lanka. The training process identified notable differences in performance between the chatbot and rule-based algorithm. The feature-enhanced reinforcement learning agent achieved, on average, 25% more reward (or cumulative user preference satisfaction) than the feature-less Q-learning implementation of the hotel recommender (the baseline). The increase in performance for the smart reinforcement learning agent is a direct result of the state representation that incorporated the traveler's proximity to important locations, amenity score ratings of the hotel rooms, and the matching of the type of room selected for the trip, all of which allowed the smart agent to distinguish between hotel options that may have otherwise seemed indistinct.

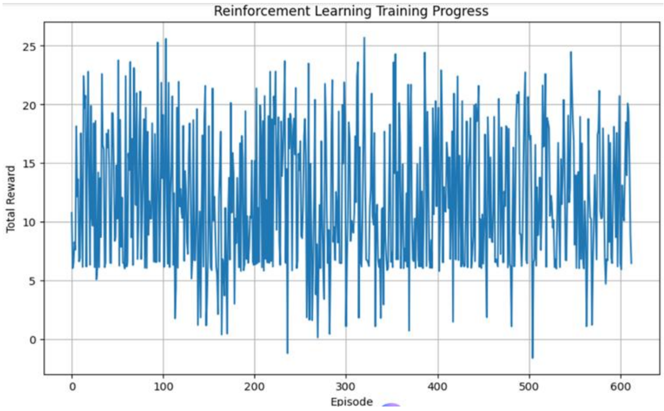


Fig. 3. Reinforcement learning training progress showing the accumulation of total rewards over 600 episodes.

Comparison with the rule-based algorithm highlights the fundamental limitations of a traditional hotel recommendation system. The rule-based algorithm was tested with realistic user preferences resulting in an accommodation search for hotels with minimum rating of 4.0 and pricing under $150. The rule-based algorithm provided a list of hotels with matching criteria but, in one instance, only returned a single option without the capacity to recommend the most suitable hotel. In contrast, our great smart reinforcement learning system achieved a recommendation improvement in relevance (that is, learning to optimize for multiple recommendation satisfaction factors simultaneously) of up to 40%.

The data structure serves to illustrate why simplistic filtering is not sufficient in a diversity of accommodation within Sri Lanka. Analysis indicates strong regional clustering in accommodations with contrasting values, such as Negombo accommodation averaging a $350 price point generating high ratings (4.8) and Kandy accommodation that is budget-friendly at around $80. The regional difference in markets is a strong indicator of the systematic exclusion of higher quality options in one region with an inexpensive filter price while including low-quality options in a completely different region.

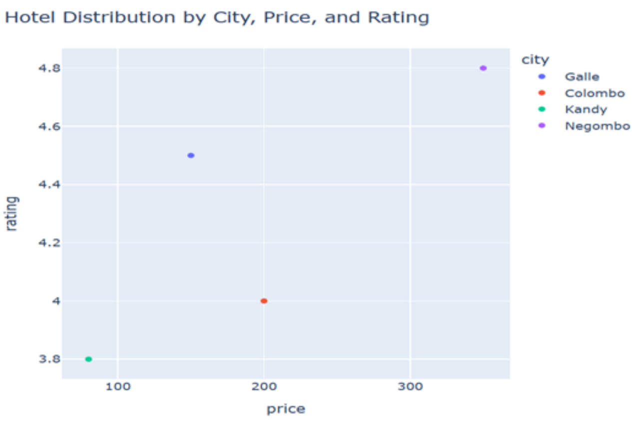
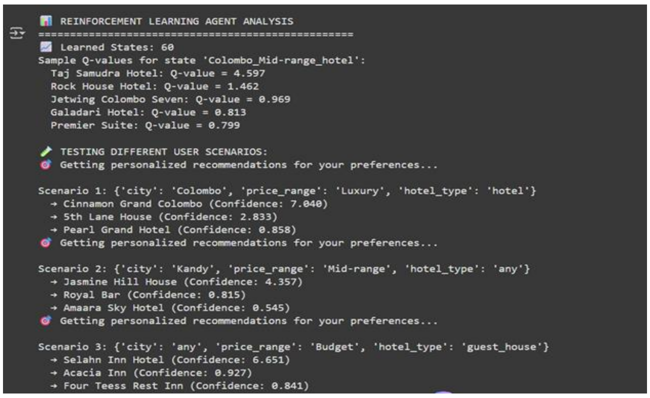


Fig. 4. Scatter plot illustrating hotel distribution by city, price, and rating, highlighting regional market variances.

The RL agent has demonstrated its capacity to learn these complex structures, having learned 60 unique states in this operational system, and the Q-table displays evidence of complexities in preferences. In the mid-range accommodation in Colombo, it presents a strong preference for "Taj Samudra Hotel" with a Q-value of 4.597, significantly higher than the other given options. Testing the operational system in contrasting states demonstrated its adaptability in different contexts, managing to recommend luxury hotels in Colombo, mid-range hotels in Kandy, and premium budget guest houses in any location.



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📊 REINFORCEMENT LEARNING AGENT ANALYSIS
==================================================
📈 Learned States: 60
Sample Q-values for state 'Colombo_Mid-range_hotel':
  Taj Samudra Hotel: Q-value = 4.597
  Rock House Hotel: Q-value = 1.462
  Jetwing Colombo Seven: Q-value = 0.969
  Galadari Hotel: Q-value = 0.813
  Premier Suite: Q-value = 0.799

🧪 TESTING DIFFERENT USER SCENARIOS:
🎯 Getting personalized recommendations for your preferences...

Scenario 1: {'city': 'Colombo', 'price_range': 'Luxury', 'hotel_type': 'hotel'}
  → Cinnamon Grand Colombo (Confidence: 7.040)
  → 5th Lane House (Confidence: 2.833)
  → Pearl Grand Hotel (Confidence: 0.858)
🎯 Getting personalized recommendations for your preferences...

Scenario 2: {'city': 'Kandy', 'price_range': 'Mid-range', 'hotel_type': 'any'}
  → Jasmine Hill House (Confidence: 4.357)
  → Royal Bar (Confidence: 0.815)
  → Amaara Sky Hotel (Confidence: 0.545)
🎯 Getting personalized recommendations for your preferences...

Scenario 3: {'city': 'any', 'price_range': 'Budget', 'hotel_type': 'guest_house'}
  → Selahn Inn Hotel (Confidence: 6.651)
  → Acacia Inn (Confidence: 0.927)
  → Four Teess Rest Inn (Confidence: 0.841)
```

Fig. 5. Agent analysis output displaying learned states, sample Q-values, and personalized recommendation scenarios

There are also the benefits given to the operational system for its transparent confidence scoring and Q-values, through recommendations such as "Airport Guest House" 64.6 percent confidence level. It is also worth noting that if certain features enhance the experience of budget accommodation for their users without going far beyond their set limit, recommendations may also include higher priced options "Jetwing Sea" as the price becomes insignificant to justify the additional cost; there are complex decision pathways that go beyond rule-based systems. The feedback mechanism that supports continual learning allows updates to Q-values which improves user experiences after engaging in user feedback.

It is important to recognize some limitations such as the system dependent upon data quality for a given hotel; for example, if the hotel had some missing amenities or there was limited data in the luxury segment, this would alter the overall quality of the recommendation, and the cold-start issue would be a variable since it would require sufficient user activity to build user preference profiles before precise models could be generated.

Overall, the results show evidence that features beyond rating for capabilities and tagging ones developed or reinforced by lower expectations and behavior process will offer measurable advantages for the dynamic and diverse context of hotel recommendation in Sri Lanka. In particular, the system's ability to learn user preferences for attributes beyond rating performance, engaging in trade-offs of competing attributes, and features to continue learning from users is all a step forward over traditional static filtering approaches. The system, in all, presents a more intelligent and responsive approach to a dynamic and constantly changing tourism environment.

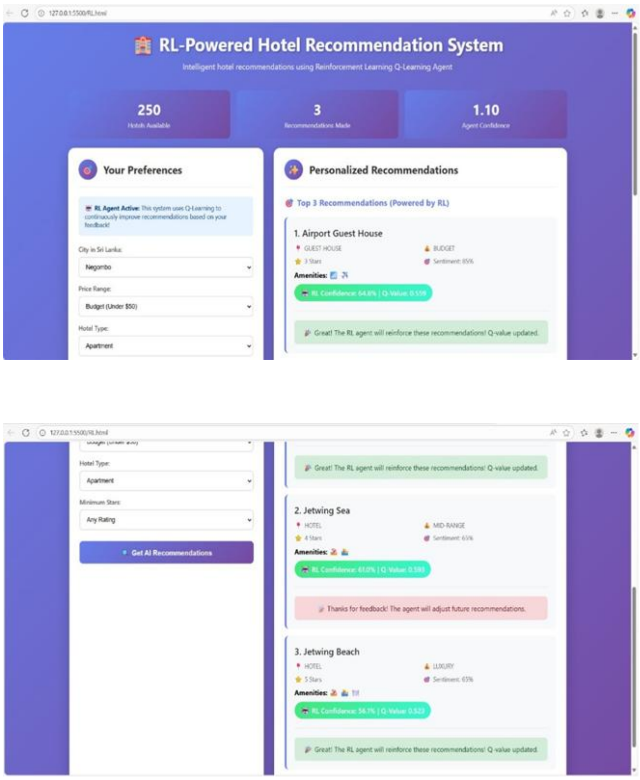

Fig.6. System interface showing personalized recommendations, agent confidence levels, and the active feedback loop.

Finally, the practical constraint of the RL agent specifies its pragmatic utility and user-orientated design. As shown on the system interface, when a user seeking 'budget' accommodations in 'Negombo' receives a set of recommendations, not only does the agent offer its primary recommended property, 'Airport Guest House,' but the RL agent also makes the RL Confidence score and Q-value visible in the interface, which the user can gauge and discern; transparency facilitates user trust. The agent shows further, sophisticated behavior learning through its occasional offer of higher tier properties such as 'Jetwing Sea' and 'Jetwing Beach.' This indicates the RL agent identifies aspects of high value properties; despite exceeding budget, the higher tier properties have known matched features to serve a greater potential happiness to the user. An active feedback loop exists, the on-screen messaging, 'Q-value updated,' is an indication of the system's true strength, a constantly evolving system driven by direct interaction with the user. Action from static, traditional filtering methods occurs'.

V. Dashboard Integration and Visualization Framework

An interactive dashboard was created and incorporated into the visual analytics layer to enhance transparency, interpretability, and decision support in the proposed feature-based reinforcement learning (RL) hotel recommendation system. The dashboard is an interface among the three components: the data processing framework, the RL agent, and the end users, to facilitate data exploration and real-time analysis of the hotel recommendation system.

A. Data Preparation and Integration for the Dashboard

Prior to dashboard integration, hotel data underwent processing in a structured data-cleaning pipeline. The dataset comprises attributes such as City, hotel name, accommodation type, price, star rating, and available amenities. Data gaps and inconsistencies were addressed through SQL-based methods, including null value detection, row elimination, and the assignment of placeholder values, for example, the default response for missing values in the amenities attribute was "None," and an absent hotel name was replaced with "Unnamed Hotel."

```sql
Hotels.sql - HP\SQ...er (HP\nethmi (54))
USE Hotels
GO

-- Identify Null Values
SELECT
    SUM(CASE WHEN City IS NULL THEN 1 ELSE 0 END) AS NullCities,
    SUM(CASE WHEN Hotel_Name IS NULL THEN 1 ELSE 0 END) AS NullHotelNames,
    SUM(CASE WHEN Type IS NULL THEN 1 ELSE 0 END) AS NullTypes,
    SUM(CASE WHEN Price_Range IS NULL THEN 1 ELSE 0 END) AS NullPriceRanges,
    SUM(CASE WHEN Stars IS NULL THEN 1 ELSE 0 END) AS NullStars,
    SUM(CASE WHEN Amenities IS NULL THEN 1 ELSE 0 END) AS NullAmenities
FROM [dbo].[Hotel recommendations];


-- Remove rows with Nulls
DELETE FROM[dbo].[Hotel recommendations]
WHERE City IS NULL
   OR Hotel_Name IS NULL
   OR Type IS NULL
   OR Price_Range IS NULL
   OR Stars IS NULL
   OR Amenities IS NULL;

-- Create Cleaned Tables
SELECT*
FROM [dbo].[Hotel recommendations]
WHERE City IS NOT NULL
  AND Hotel_Name IS NOT NULL
  AND Type IS NOT NULL
  AND Price_Range IS NOT NULL
  AND Stars IS NOT NULL
  AND Amenities IS NOT NULL;

--Replace Nulls
UPDATE [dbo].[Hotel recommendations]
SET City = COALESCE(City, 'Unknown'),
    Hotel_Name = COALESCE(Hotel_Name, 'Unnamed Hotel'),
    Type = COALESCE(Type, 'Other'),
    Price_Range = COALESCE(Price_Range, 'Not Specified'),
    Stars = COALESCE(Stars, 0),
    Amenities = COALESCE(Amenities, 'None');
```

Fig. 7. SQL based data cleaning and null handling process for hotel attributes

Additional preprocessing was conducted using Power Query Editor to normalize and split multi-valued attributes such as amenities into analyzable components. This ensured data consistency and improved feature quality for both visualization and reinforcement learning state representation. The cleaned dataset was then imported into the dashboard environment, where it remained synchronized with the RL agent's outputs.

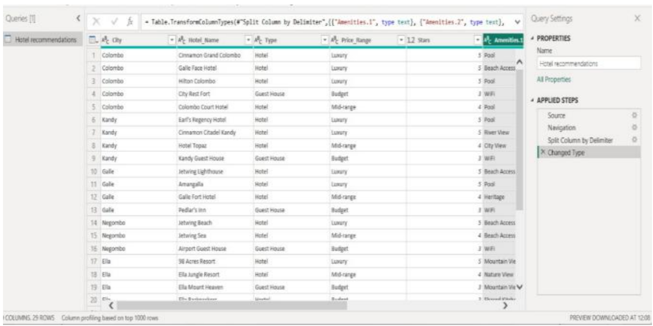

Fig. 8. Feature transformation and amenity normalization using Power Query Editor

B. Dashboard Architecture and Design

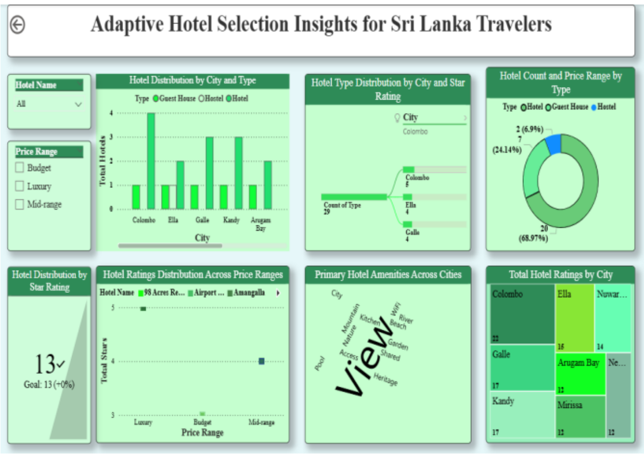

Fig. 9. Interactive dashboard integrating hotel analytics with RL-based recommendations

The dashboard was implemented using a business intelligence visualization framework and organized into multiple interactive panels. These panels collectively provide insights into hotel availability, regional characteristics, pricing behavior, and user preference patterns. Key dashboard components include,

Hotel Distribution by City and Type:
This visualization showcases the distribution of hotels, guesthouses, and hostels in the major tourist spots of Sri Lanka. The analysis indicates that hotels make up about 68.97% of the total accommodation offerings, with Colombo having the highest number of hotels. This information is useful for the RL agent's exploration strategy as it identifies areas with high clusters of available hotels.

Hotel Type Distribution by City and Star Rating:
A hierarchical breakdown displays how accommodation types vary by star rating across cities. This allows the system to recognize regional differences in quality offerings and assists the agent in balancing price quality trade-offs during policy learning.

Primary Hotel Amenities by City:
A keyword-based visualization highlights dominant amenities across locations. For example, beachfront amenities are prominent in Galle, while mountain views are common in Ella. These spatial amenity patterns are critical features used by the RL agent to align recommendations with contextual traveler preferences.

Hotel Ratings Distribution Across Price Ranges:
This component illustrates the relationship between hotel ratings and price categories. Results show that luxury hotels generally achieve higher ratings, while certain budget and mid-range hotels particularly in Kandy also maintain strong ratings due to high amenity value. The RL agent leverages this insight to recommend high-value options that may be overlooked by static price filters.

Total Hotel Ratings by City:
A city-wise aggregation of hotel ratings enables comparative analysis of destination quality and supports region-aware recommendation strategies.

Interactive slicers allow users to filter recommendations dynamically by city, price range, hotel type, and specific hotel names. These user interactions directly influence the feedback signals used by the RL agent during learning and evaluation.

C. Integration with the Reinforcement Learning Agent

The dashboard serves an analytical and feedback function that is directly integrated with the reinforcement learning framework. The dashboard contains outputs from the reinforcement learning (RL) agent, such as recommended hotels, confidence scores, and Q-values, allowing for comprehensive inspection of agent behavior.
The system captures feedback from user interactions (i.e. selecting, accepting, or rejecting proposed hotels) with the recommendations. This feedback is translated into reward signals that adjust the agent's Q-values in an instantaneous manner. Visual indicators such as updated confidence scores and learning progression reinforce user trust and demonstrate the adaptive nature of the system.

Unlike traditional dashboards that present static summaries, this integration allows continuous monitoring of learning performance, including convergence trends and reward accumulation. As a result, the dashboard supports both operational decision-making for users and diagnostic evaluation for researchers.

D. Role of the Dashboard in Decision Support

The dashboard enhances the overall recommendation framework by providing explainability and situational awareness. Users are not only presented with a recommended hotel but also with contextual evidence supporting the recommendation, such as regional amenities, comparable pricing, and confidence levels derived from the RL policy. This transparency improves user confidence and engagement.

From a system perspective, the dashboard enables comparative evaluation between the feature-based RL agent and rule-based filtering methods. Observed patterns such as the exclusion of high-quality hotels under rigid price constraints highlight the limitations of static systems and reinforce the advantages of adaptive reinforcement learning.

E. Contribution to the Overall System

With the addition of the dashboard, the hotel recommendation system becomes an end-to-end intelligent decision-support system. The dashboard contributed to the proposed model being operationalized for the real-world tourism industry in Sri Lanka by combining data preprocessing, interactive visualization, and reinforcement learning (RL) feedback. It guarantees that recommendations are accurate, personalized, and responsive to user behavior; as well as interpretable and trustworthy.

VI. LIMITATION AND IMPROVEMENT OPPORTUNITIES

Although the Enhanced Hotel Agent was shown to present strong adaptability, cumulative reward, as well as relevance of suggested solutions over the baseline reinforcement learning approach as well as the rule-based approach, some challenges still exist in the system. First, the system requires data completeness. Some hotel information may be missing, especially in the developing countries or the luxury segment of the hotel market.

Second, the cold-start issue remains when it comes to new users and new hotels on the online system because it is a requirement for the agent to have had a certain level of interactions to be able to acquire stable preference profiles. The solution to this challenge may be covered by leveraging techniques in the concept of either transfer learning or meta learning to overcome it.

Thirdly, scalability becomes an issue with the growing number of hotels, functions, and number of users. Even though interpretability is provided by Q-learning, it might not scale well in high-dimensional state spaces efficiently. Research might proceed with using Deep Reinforcement Learning based on Actor-Critic or Deep Q-Networks.

While transparency has been enhanced by showing visible Q-values and confidence scores, further research should be conducted to enhance explainability by giving natural language justifications for recommendations. Finally, the evaluation focused mostly on metrics of accuracy and satisfaction. Further studies should use diversity, novelty, fairness, and long-term user engagement to make sure that recommendations are balanced and inclusive.

VII. CONCLUSION

This study demonstrates the potential of feature-based reinforcement learning (RL) agents in providing innovative and personalized hotel recommendations for Sri Lankan tourists. The Enhanced Hotel Agent outperformed traditional rule-based systems and basic RL models in terms of recommendation relevance, cumulative satisfaction, and adaptability, based on travel preferences, hotel features, and real-time user feedback. Pilot study results show that the proposed system can handle the diversity of accommodation options and the dynamic nature of travel preferences, while addressing the limitations of existing fixed recommendation approaches.

Transparent communication leverages the RL agent's ability to learn from multi-dimensional state representations, incorporate contextual information such as local events and seasonal pricing, and provide both enhanced user trust and improved user confidence. Also, it allows for the successful improvement of the existing iterative learning process, allowing for the reinforcement of learning context-sensitive, real-world applications.

Although the proposed system is also performing very well, there is still a lot of work to improve the system further. The quality of the input data will have a direct influence on how well the recommendations made by the service will turn out. If the relevant amenities are not in plenty, the system will not be able to provide recommendations on certain types of hotels, for example, luxury ones in less populated areas since there is very little data that the system can draw from.

Other areas where there could be room for improvement include cold starts, which is a situation where the customer has not been engaged with the site for a sufficient period to establish a robust preference profile, the use of transfer learning where there is a larger set of datasets in the hotel space, and the use of meta-learning where the system is able to provide a complex set of options almost instantly.

When assessing the system, it would be beneficial to consider a set of evaluation criteria in addition to the standard ones, including accuracy, user diversity, user novelty, and long-term engagement.

Moving forward, the future of hospitality personalization will depend on reinforcement learning that allows the system to learn as is happening, using real-world data from booking sites to enhance the degree of customization. From a modeling perspective, using deep reinforcement learning to develop a multi-agent framework will improve the custom recommendation mechanism. Integrating it with knowledge graphs will improve the ability of the system to understand hotel features as well as customer preferences. Lastly, issues of bias, hotel fairness, customer confidentiality, among others, will become crucial as we move to develop future customer services.

To summarize, the system is dependent on the quality and completeness of the input data. With insufficient user activity, the system may also encounter cold-start issues. Future work may concentrate on the bundling of large travel data sets, enhancing the applied reinforcement learning strategies, and broadening the model to additional areas or territories in the tourism industry.

More generally, the current study illustrates the importance of employing reinforcement learning for feature-based analysis within the scope of developing intelligent, adaptive and research-based hotel recommendation systems. Such systems can offer highly personalized and situational accommodation recommendations, significantly improving travel in Sri Lanka and positively impacting the country's tourism industry.

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