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PERSONALIZED CONTENT RECOMMENDATION SYSTEM FOR ARABIC REVIEWS USING DEEP LEARNING AND REINFORCEMENT LEARNING

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Abstract

This study presents a hybrid, personalized content-level recommendation framework tailored to the Arabic language reviews in hotels thus solving the twofold problem of morphological richness and dialectal difference of the language. The aim of the present study is to enhance recommendation accuracy by integrating between Aspect-Based Sentiment Analysis (ABSA), Sequential deep learning and reinforcement learning in dynamic Personalization framework. Attentive classifier in the form of gated recurrent unit (GRU) is suggested to filter sentiment analysis based on the finest-grained level of granularity. Sentiment vectors outputted are provided to a Deep Q-Learning (DQL) agent where the recommendation policy would be iteratively adjusted based on user feedback. Systematic empirical assessment of a sentence level sentiment classification model was performed on the SemEval 2016 Task 5 Arabic, which has 2,291 annotated hotel reviews. The accuracy of the classifier reached 86.5% and its AUC rate of 0.91, which was enough to confirm effective discrimination against the polarity regardless of the linguistic peculiarities of the language of input. Precision (87.1%) and recall (86.6%) were observed to be high using a confusion matrix. The explicit reinforcement learning metrics were not presented, but the qualitative review allowed concluding that the deep Q-Network (DQN) agent was able to correct its recommendations in respect of user sentiment patterns. The current study proposes a combined model that further develops the modern Arabic recommender system by integrating the linguistic-awareness methods with real time personalization approaches and thus develops a solid research framework in this regard that can be used in the future to study the Arabic-language adaptive recommendation of content framework.

Keywords: Personalized Recommendations, Aspect-Based Sentiment Analysis (ABSA), GRU Neural Network, Deep Q-Learning, Arabic Hotel Reviews.

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Introduction:

Over the last few years, the exponential growth of online Arabic reviews (particularly, the reviews in the hospitality sector) has become of critical importance as a driver in consumer understanding (Al-Sager & Mahzari, 2025). Since customers are relying more on online reviews when making their booking decisions, such reviews provide voluminous and linguistically diverse information that shapes user experiences as well as the optimization of services (Morini-Marrero et al., 2025; Nadeem et al., 2025). Each day, a significant amount of such information is produced and published to the web, which includes opinions, reviews as well as ratings of particular services, products or places (Liang & Wang, 2022). The decision-making of many sectors in numerous applications, including intelligent recommendation systems will require the analysis and interpretation of such data (Obiedat et al., 2021). Computational opinion detection and subjectivity; a technique commonly known as Sentiment Analysis (SA) is a crucial component in such systems (Madhoushi et al., 2019).

Based on the principles of the traditional topic-based sentiment analysis, Aspect-Based Sentiment Analysis (ABSA) narrows down the task of subject-specific sentiments-issue/facet/aspect-location within a review and sentiment valence assignment to each theme (Dejaeghere et al., 2024). This granularity is especially beneficial in the hospitality setting where the feedback of a user often flips between various attributes of a hotel in one sentence (Jiang et al., 2024; Mudalige et al., 2020; Zhao et al., 2023). Common ABSA processes include the detection of salient features, labeling of expressions of sentiment with the features, and finally assigning the sentiment as one of positive(P)/ neutral (N), or negative (N) (Al-Ajlan & Alshareef, 2023; Jayakody et al., 2024; W. Zhang et al., 2022). As compared to the traditional topic-based sentiment analysis that gives the overall view of guest opinion, ABSA provides an aspect level breakdown that helps hoteliers identify specific areas to improve their services and tune it more appropriately (Darvishi et al., 2022; Gm et al., 2024).

Each of the block building components of opinion mining of Arabic-based (ABSA) has been explored separately; however, there is still not enough academic focus on consistent end-to-end ABSA pipelines, specifically carrying Arabic-based review-based corpora (H. Zhang et al., 2022). Arabic is a diacritically rich language that is morphologically complex, and Arabic dialects including the Levantine, Gulf, and Maghrebi exist with varying degrees of complications to its computational processing (Skiredj & Berrada, 2025). Moreover, being a worldwide ubiquitous tongue, Arabic is underrepresented in the natural language processing (NLP) resources, which makes it a low-resource tongue in terms of deep-learning enabled applications (Doughan et al., 2025). Such a lack of annotated corpora and sentiment lexicons and holistic pretrained models makes creating precise, domain-specific recommendation engines for Arabic texts even more difficult (Husain et al., 2024). The recommendation architecture that is used in current Arabic-language systems is hardly based on reinforcement learning, to get dynamic adaptation to user likes and dislikes (Sharifbaev et al., 2024). Rather, the current systems mostly use fixed sentiment labeling or blast collaborative filtering, and they do not support user interaction changes and include deep ABSA models (Liu & Zhao, 2023).

The present stuyd identifies such a critical research gap at the intersection of adaptive recommendation and Arabic language processing. Compared to the earlier efforts, the

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suggested framework is the initial endeavor that integrates ABSA, GRU-based deep learning, and Deep Q-Learning to personalize in real-time inside the frame of Arabic hotel reviews. This unified architecture also enables both finely grained sentiment analysis and personalisation to the point where it will still be commonly referred to as user-centric adaptation, which is also not fully tackled in the current literature. To address this shortcoming, the current paper proposes a Personalized Content Recommendation System of Arabic hotel reviews, where deep learning (GRU) is utilized in sentiment interpretation, whereas Deep Q-Learning is employed to make dynamic choices as consequence of the reinforcement learning paradigm. This model tries to bring in the individual user feedback to enhance the accuracy of recommendations and in turn increase user satisfaction with Arabic digital hospitality platforms through machine understanding.

Literature review

Recommender systems are part of the emerging modern digital landscape and provide personalized recommendations on websites such as e-commerce, media, and in the hospitality industry (Stalidis et al., 2023). In hospitality, reviews are vital on the list of users when deciding what to do, and the ability to come up with personalized recommendations is therefore essential. Still, the computational challenges that exist in the Arabic linguistic field are unique following the dialectal heterogeneity, morphological complexity, and limited NLP resources (Ahmed et al., 2022). Despite the rampant Arabic review content, recommendation systems seem to exist in considerable amounts that do not have the granularity and flexibility incorporated yet to effectively utilize this material (Al-Ghuribi et al., 2024). The current paper hence reviews the progress in the Arabic recommender systems, aspect-based sentiment analysis (ABSA), deep learning methods, and reinforcement learning (RL) and outlines an important niche area where their intersection could be represented.

The existing recommendation systems offered in Arabic languages mostly rely on collaborative filtering as highlighted by Sharma et al. (2022), but hybrid setting has also attracted interest (Sharma et al., 2022). The study provided by Pappas and Popescu-Belis (2016) proved that sentiment-enhanced collaborative filtering can show higher precision than a common user-based collaborative filtering applied to Arabic book reviews (Pappas & Popescu-Belis, 2016). Similarly, Butmeh and Abu-Issa (2024) proposed a hybrid architecture, which comprised attribute-based architecture and collaborative filtering, and showed significant increase in accuracy of profile and user satisfaction through an Arabic learning environment (Butmeh & Abu-Issa, 2024). However, the goal of most extant systems is to overlook the fine-grained sentiment analysis and adaptive user modeling. Concurrently, the linguistic intricacy of Arabic, such as tokenization issues, diacritics treatment, and the prevalence of dialects, has not yet been examined appropriately due to the shortage of annotations data and strong analytical tools (Husain et al., 2024).

Researchers have developed Aspect-Based Sentiment Analysis (ABSA), a method which goes even further to individually determine aspects (e.g. cleanliness, location) in a review and assign polarities of sentiment to them (Shafiq et al., 2023). The most common three tasks in this field include: Aspect Term Extraction, Opinion Term Extraction and Aspect Polarity Classification. Hotel and restaurant review experiments have indicated that ABSA has worked when the user

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deals with more service dimensions (Fadel et al., 2024). Experiments conducted on English-based datasets like TripAdvisor and Yelp explain that ABSA works to reinforce the relevance of recommendations by matching preferences of users with detailed feedback (Al-Ghuribi et al., 2020). However, it appears as a limitation to its usage in Arabic because of the lack of labeled data, morphological complexity, or dialect variation since these challenges can hamper the performance of the existing multilingual systems on Arabic textual figures (El Mekki et al., 2022).

Present-day deep learning models have also represented the paradigmatic growth of feature presentation in recommender systems. Of particular interest are Recurrent Neural Network (RNN) models, namely Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) networks, and have shown effectiveness in sequential-dependency modelling, as well as the sentiment capture across time (Zhao et al., 2020). Although GRUs are computationally more efficient, they can recognize both temporal and semantic textual input (Khudhair et al., 2025). Compared to classic machine learning models, such as SVM, K-NN, and Naive Bayes, deep models allow a more thought-out understanding of user intent. The incorporation of techniques like Word2Vec and BERT enhances the semantics richness of input representations even more so in the areas where user sentiment relies on contextualised expressions (Öztayşi et al., 2017). At that, most Arabic recommendation systems do not combine GRU-based architecture with sentiment-aware pipeline, thus limiting their flexibility and accuracy.

The need to update the systematic models of recommendations is an urgent task since such models are quite solid. Reinforcement learning (RL) presents an especially attractive solution since it can enable systems to be constantly updated based on user feedback. But, unlike traditional user preference approach where the user preferences are set in stone, RL based recommendation frameworks poll actions- either a click, booking, or skip- as a reward signal and base future recommendations upon these rewards. The empirical studies, including those provided by Wu et al. (2024) and Zhou, (2023) have shown that these methods allow significant increases to be registered both in personalization and in precision (Wu et al., 2024; Zhou, 2023). At the center of these are Deep Q-Learning (DQN), which is a well-known algorithm in RL that employs deep networks as approximators of optimal policies, thus maximizing to the longer-term user happiness via the feedback loops. However, most of the RL-based recommendation systems do not take into consideration the granular sentiment or text, a shortcoming that is especially impressive in Arabic hospitality settings, where extensive linguistic knowledge is underutilized.

An extensive literature review identifies several recurring gaps in the literature of extant literature: most existing models rely on a static approach to personalization, most of them do not focus on the linguistic and computational peculiarities of Arabic or do not focus on the sentiment analysis sufficiently, and use of reinforcement learning tends to be nonexhaustive when applied to Arabic. The gaps presented in this paper are complemented by proposing a hybrid creative that combines individually contributed ABSA, deep learning with GRUs, and reinforcement learning with DQNs. The solution resulting can be actually a fine-grained sentiment comprehension and dynamically bound with respect to user-preference which results in a new context-aware Arabic hotel review recommendation.

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The content-based recommendation systems are an upgrade of previous recommendation methods, which streamline well item traits, e.g., cleanliness location, service qualities, and amenities, according to the demands of individual users. As opposed to collaborative systems where the creation of user behaviors is aggregated, content-based methods will use feature extraction of review and ratings that are created by a user to find the most pertinent items to a precise user (Gund, Minde, Bhujbal, & Sonawane, 2023). The content-based recommendation system is most desirable in the industries like the hospitality industry where text-based feedback gives clear focus on individual aspects of the user experience. These models can provide lists of recommendations that are in line with the individual preferences and priorities because such associations are made by correlating product attributes with the past involvement of the user (He, Liao, Zhang, Nie, Hu, & Chua, 2017).

One of the most significant components of natural-language processing systems is feature extraction which transforms the unstructured textual information into a structured form which captures semantic content. In Arabic-language reviews, the success of this electronic task will depend heavily on the strength of preprocessing operations, that is, tokenization, normalization, removal of stoparguments, and morphology processing, due to the nature of the Arabic inflectional language (Metsai et al., 2022; Al-Smadi et al., 2019). Word embeddings and in particular the Word2Vec-generated ones are usually trained on semantic data often in the form of continuous vectors thus allowing a neural network to capture similarity on the word-level across differing syntactic constructions (Chouikhi, Chniter, & Jarray, 2021; Al-Ajlan & Alshareef, 2022).

Aspect-Based Sentiment Analysis (ABSA) is an advancement of a methodology that is capable of handling user-level personalization because it isolates opinion towards specific lexical units. The algorithm presupposes the accomplishment of three consecutive subtasks: Aspect Term Extraction (the identification of domain-specific entities, e.g., rooms, service, quality of the food, etc.), Opinion Term Extraction (the identification of at least one sentence including an opinion expression around each aspect) and Aspect Polarity Classification (the determination of whether or not each isolated opinion is rated as positive or negative, or neutral). All these sub systems are combined to provide fine-grained user and item sentiment profile. As an example, a review in which one read the text, the staff were extremely courteous, the system would create a drop-box with the word staff as an aspect and mark it as positive-sentiment. Over time, content-based systems learn from user behavior to construct dynamic preference profiles. If a user consistently responds favorably to hotels with strong sentiments on “cleanliness” or “location,” these attributes are weighted more heavily in future recommendations (Huang et al., 2020). Profile matching techniques, such as cosine similarity or dot product scoring, are then used to rank hotels according to how well they align with these learned preferences.

To further refine personalization, reinforcement learning techniques, particularly Deep Q-Learning, can be integrated to adapt to user feedback in real time (Cholakoska et al., 2023). In this framework, each recommendation is treated as an action, and subsequent user behavior (clicks, bookings, or skips) serves as feedback or reward. A positive interaction increases the likelihood of similar recommendations, while negative feedback reduces it. Over successive interactions, the model optimizes its decision-making policy, gradually improving recommendation quality through continuous learning.

By combining content-based filtering with ABSA, GRU-based sequential modeling, and reinforcement learning, the system is equipped to deliver highly personalized, linguistically-aware, and dynamically adaptive recommendations, especially suited to morphologically rich and under-resourced languages like Arabic.

Methodology:

Overview of the Proposed Model

The proposed architecture presents a hybrid recommendation system that integrates sequential deep learning with adaptive reinforcement learning to deliver fine-grained and responsive hotel recommendations. As shown in Figure 1, the system begins by preprocessing Arabic hotel reviews through tokenization, normalization, and Word2Vec embedding. These embeddings are passed into a Gated Recurrent Unit (GRU) network, chosen for its computational efficiency in modeling long-term dependencies. To enhance interpretability, an attention mechanism is applied to focus on sentiment-bearing tokens associated with specific hotel aspects (e.g., service, cleanliness).

The GRU's aspect-specific sentiment vectors are then used to inform a Deep Q-Network (DQN) agent. This agent encodes user preferences as dynamic state vectors, integrating both historical sentiment and recent interactions. User actions, such as clicking, ignoring, or booking, are treated as feedback signals to iteratively optimize the Q-value function. This enables the system to adaptively refine recommendations over time. Unlike prior static or monolithic systems, this modular hybrid approach unifies Aspect-Based Sentiment Analysis (ABSA), attention-guided GRUs, and Deep Q-Learning (DQN) in a single pipeline. This design is particularly novel for Arabic hospitality reviews, where user preferences are sentiment-rich, linguistically complex, and temporally evolving.

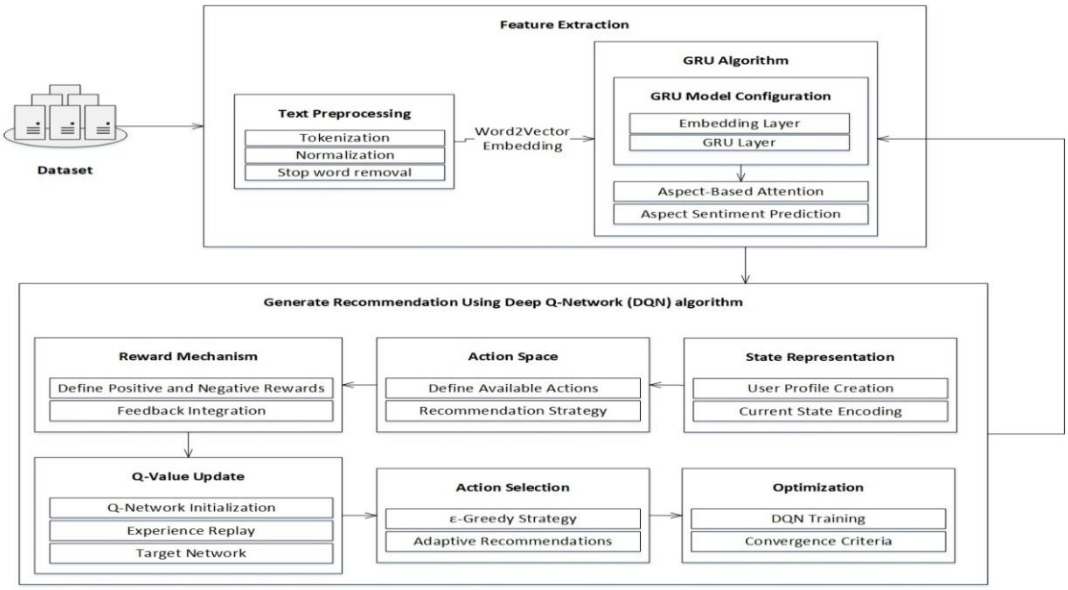

Figure 1: Architecture of the proposed hybrid recommendation system integrating GRU-based aspect-level sentiment analysis with Deep Q-Learning for adaptive personalization.

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Dataset and Preprocessing

This study employs the publicly available SemEval 2016 Task 5 dataset, which comprises Arabic-language hotel reviews annotated for Aspect-Based Sentiment Analysis (ABSA). The complete dataset contains approximately 15,562 reviews, with a curated subset of 2,291 reviews used for detailed annotation. These reviews were sourced from leading platforms such as Booking.com and TripAdvisor, spanning major cities in Arabic-speaking regions, including Dubai, Mecca, Amman, and Beirut.

Annotations are provided at both the review and sentence levels, resulting in 2,291 full review texts and 6,029 annotated sentences, collectively yielding 24,028 aspect-sentiment tuples. These annotations span a wide range of hotel service categories, including cleanliness, room amenities, facilities, service quality, food and drinks, and location. The dataset exhibits a long-tail class distribution, where certain categories (e.g., service, location) are heavily represented, while others (e.g., style & options, design features) are sparsely populated.

The dataset introduces key linguistic challenges due to morphological richness, dialectal variation (e.g., Gulf, Levantine, Maghrebi), diacritics, and elongated forms, which complicate standard natural language preprocessing. To address this, the preprocessing pipeline included:

- Tokenization using Arabic-specific parsers
- Normalization to unify variant forms of Alif and remove diacritics
- Stopword removal using a curated Arabic stopword list
- Reduction of character elongation to base forms for consistency

To transform the cleaned text into semantic vector space, Word2Vec embeddings were utilized, capturing distributional word relationships and preserving sentiment nuances across Arabic expressions. For model training and evaluation, the dataset was split into 80% training, 10% validation, and 10% testing. Specifically, 4,802 sentences were assigned for training, 1,227 for testing, and a stratified 10% subset of the training set was reserved for validation. This configuration supports robust model optimization while minimizing overfitting. Table 1 presents the detailed distribution of annotated aspect-sentiment tuples across hotel entity categories, illustrating the imbalance and granularity of the dataset's sentiment landscape.

Table 1: Distribution of data over aspect categories

Entities #Attributes	HOTEL	ROOMS	ROOM-AMENITIES	FACILITIES	SERVICE	LOCATION	FOOD&DRINKS
GENERAL	1821	396	316	974	2781	1390	X
PRICES	434	60	15	102	X	X	X
DESIGN&FEATURES	158	419	63	150	X	X	X

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CLEANLINESS	326	436	143	141	X	X	X
COMFORT	265	156	40	58	X	X	X
QUALITY	320	174	213	172	X	X	865
STYLE&OPTIONS	X	X	X	X	X	X	219
MISCELLANEOUS	179	42	75	97	X	X	60

Text Embedding and Feature Representation

The feature extraction process in the proposed system transforms raw Arabic review text into structured numerical representations suitable for aspect-based sentiment prediction and personalized recommendation. To begin with, the raw text undergoes a series of preprocessing steps tailored to the linguistic characteristics of Arabic. Tokenization is applied to segment text into words, while normalization ensures consistency by removing diacritics and standardizing orthographic variants such as different forms of Alif. Additionally, stopwords are removed using an Arabic-specific stopword list, and elongated characters, commonly used for emphasis, are reduced to their canonical form to minimize noise in sentiment analysis. Semantic representation is achieved using pretrained Word2Vec embeddings trained on large Arabic corpora. These embeddings capture the contextual meaning of tokens by projecting them into a continuous vector space. For each token t its embedding is represented as:

$$v_t = Word2Vec\,(t) \qquad (1)$$

Where $vt \in R^d = 300$ is the embedding dimension. These embeddings are used as input to the GRU-based sentiment analysis model and are fine-tuned during training to adapt to domain-specific vocabulary. To capture sequential dependencies in user reviews, Gated Recurrent Units (GRUs) are employed. GRUs utilize gating mechanisms to control the flow of information across time steps. The update gate, which determines how much past information to retain, is defined as:

$$z_t = \sigma\,(W_z\,.\,[h_{t-1}.X_t] + b_z) \qquad (2)$$

Similarly, the reset gate, responsible for forgetting irrelevant past information, is computed as:

$$r_t = \sigma\,(W_r\,.\,[h_{t-1}.X_t] + b_r) \qquad (3)$$

A temporary candidate hidden state $h_t$is calculated using:

$$h_t = tanh(W\,.\,[r_t * h_{t-1}.X_t] + b) \qquad (4)$$

The final hidden state at h_t each time step is then updated as:

$$h_t = z_t * h_{t-1}\,(1 - z_t) * \;\; h_t \qquad (5)$$

To enhance the model's focus on key opinion phrases related to specific aspects, an attention mechanism is integrated over the GRU outputs. For each hidden state h_t an unnormalized attention score is computed:

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$$e_t = v_a^T \, tanh \, tanh \, (W_a . h_t + b_a)$$

which is then normalized using the softmax function:

$$a_t = \frac{exp \, exp \, (e_t)}{\sum_{K=1}^{T} \quad exp \, exp \, (e_k)} \tag{6}$$

Where $e_t = v_a^T \, tanh \, tanh \, (W_a . h_t + b_a)$ represents the attention score before softmax normalization, and v_a, W_a, and b_a are trainable parameters. The context vector c, which represents the weighted sum of hidden states, is then calculated as:

$$c = \sum_{t=1}^{T} \quad a_t \, h_t \tag{7}$$

Finally, the sentiment classification for each aspect is performed using a softmax classifier applied to the context vector:

$$Sentiment_{aspect} = \, softmax \, (W_s \, . c + b_s) \tag{8}$$

This pipeline allows the system to extract nuanced, aspect-level sentiment information from Arabic hotel reviews, forming the basis for informed, adaptive recommendation generation.

Recommendation Generation Using Deep Q-Network (DQN)

This phase implements reinforcement learning to generate adaptive and personalized recommendations using the Deep Q-Network (DQN) algorithm. Unlike static models, the DQN framework continuously evolves based on user interactions, optimizing long-term satisfaction through cumulative reward maximization. The model integrates user feedback to refine its decision-making process in real time.

The system defines each state $s_t$as a combination of a user's profile $p_u$and recent interaction history h_t. This composite representation captures both historical and contextual signals:

$$s_t = \, f(p_u \, . h_t) \tag{9}$$

The action space consists of all potential items the system may recommend. For each action a_t the model receives feedback via a reward signal:

$R > 0$: User clicks, likes, or interacts positively with the item.

$R < 0$: User ignores or negatively engages with the recommendation.

To optimize policy, the Q-value update equation applies the Bellman equation with function approximation:

$$Q(s_t . a_t) = \, Q(s_t . a_t) + a\big(r_t + \, \gamma_a^{max} \, Q(s_{t+1} . a) - Q(s_t . a_t)\big) \tag{10}$$

Where:

- α: The learning rate.
- r_t: The reward received after taking action a_t in state s_t.
- γ: The discount factor for future rewards.

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- s_{t+1}: The next state after taking action a_t.
- $\gamma_a^{max}\ Q(s_{t+1}.a)$: The maximum Q-value in the next state.

In the proposed method, DQN uses a neural network to approximate the Q-function $Q(s.a;\ \theta)$, where θ denotes the parameters (weights) of the neural network. The function for training the network is the loss function:

$$L(\theta) = E[(r_t + \gamma_a^{max}\ Q(s_{t+1}.\theta^-) - Q(s_t.a_t;\ \theta))^2] \quad (11)$$

Where θ^- denotes parameters of the target network, updated less frequently to stabilize learning. Action selection follows an ε-greedy policy to balance exploration and exploitation:

$$a_t = \{random\ action\ from\ A \qquad with\ probability\ \epsilon\ \ arg\ arg\ max_a\ Q(s_t a;\theta) \quad (12)$$

To improve convergence and generalization, the model employs two widely adopted DQN enhancements:

Experience Replay: Stores interactions $(s_t.a_t.r_t.s_{t+1})$ in buffer D to break correlation in updates.

Target Network: Uses a slowly updated network $Q(s_t a;\theta^-)$ for stable target value computation.

The final loss function becomes:

$$L(\theta) = E(s_t.a_t.r_t.s_{t+1}) \sim D[(r_t + \gamma_a^{max}\ Q(s_{t+1}.\theta^-) - Q(s_t.a_t;\ \theta))^2] \quad (13)$$

This DQN-driven mechanism ensures that recommendations are not only sentiment-aligned and context-aware but also dynamically responsive to user behavior, enabling robust, real-time personalization in Arabic hospitality domains.

Results:

The experimental results demonstrate the efficacy of the proposed hybrid framework, which integrates GRU-based deep learning for aspect-level opinion classification with a Deep Q-Network (DQN) for adaptive, personalized content recommendation. The GRU-attention module effectively captures sentiment polarity associated with specific aspects mentioned in Arabic hotel reviews, thereby enabling a nuanced understanding of user opinions. These sentiment representations serve as structured inputs to the reinforcement learning component, wherein the DQN agent dynamically adjusts recommendation strategies based on cumulative user interactions and feedback. The system's output is articulated in the form of binary recommendations: "نوصي بالفندق" (recommend the hotel) and "لا نوصي بالفندق" (do not recommend the hotel). These labels are derived from aggregated sentiment assessments across multiple review aspects. To rigorously evaluate the performance of the sentiment classification and recommendation components, a series of standard metrics were employed, beginning with the confusion matrix, as illustrated in Figure 2.

Confusion Matrix

To evaluate the effectiveness of the aspect-level sentiment classification component, a confusion matrix was constructed based on binary polarity predictions, where label 0

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corresponds to negative sentiment and label 1 to positive sentiment. As illustrated in Figure 2, the model correctly predicted 1,549 positive instances and 868 negative instances, corresponding to true positives (TP) and true negatives (TN), respectively. Misclassifications include 229 false positives (FP), where negative opinions were incorrectly classified as positive, and 240 false negatives (FN), where positive opinions were misclassified as negative.

From these values, the following performance metrics were derived:

- Accuracy: 86.5%, indicating the proportion of total correct predictions.
- Precision (Positive class): 87.1%, reflecting the proportion of correctly predicted positive cases out of all predicted positives.
- Recall (Positive class): 86.6%, denoting the ability to identify actual positive sentiments.
- F1-Score: 86.8%, representing the harmonic mean of precision and recall.

These results demonstrate that the model maintains a strong balance between precision and recall, which is particularly important in imbalanced sentiment datasets. Despite the high overall performance, the presence of 469 misclassifications (FP + FN) indicates room for refinement, particularly in mitigating false predictions through model regularization or improved contextual representation of sentiment cues.

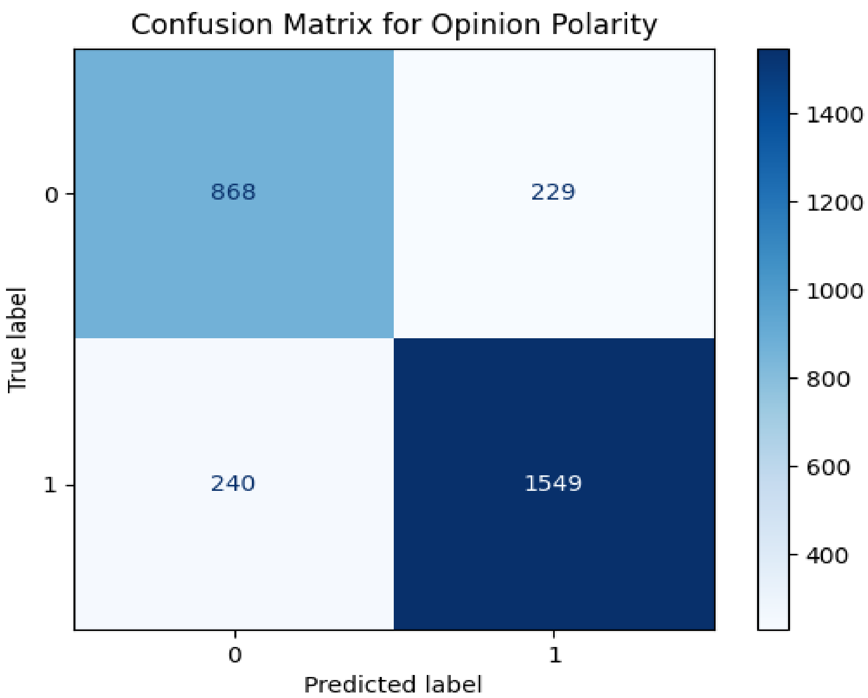

Figure 2: Confusion Matrix showing the distribution of predicted vs. actual sentiment labels.

ROC Curve

The ROC (Receiver Operating Characteristic) curve in Figure 3 provides a comprehensive assessment of the model's ability to distinguish between positive and negative opinion

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polarities within Arabic-language hotel reviews. The curve plots the true positive rate (TPR) against the false positive rate (FPR) at varying classification thresholds, offering a threshold-independent evaluation of performance. As shown in Figure 3, the classifier consistently achieves high TPR values with minimal FPRs, as evidenced by the orange curve approaching the top-left region of the plot, indicative of ideal classification behavior. This outcome highlights the model's capacity to effectively extract sentiment cues embedded in morphologically complex and dialect-rich Arabic expressions. The Area Under the Curve (AUC) value of 0.91 implies that the classifier can correctly discriminate between a randomly chosen positive and negative instance with 91% probability. AUC scores above 0.9 are generally interpreted as indicative of excellent model performance. This strong performance is particularly significant given the linguistic challenges posed by Arabic text, such as orthographic ambiguity and code-switching. The result underscores the robustness of the proposed GRU-based model with attention and its suitability for polarity-aware content recommendation in low-resource Arabic environments.

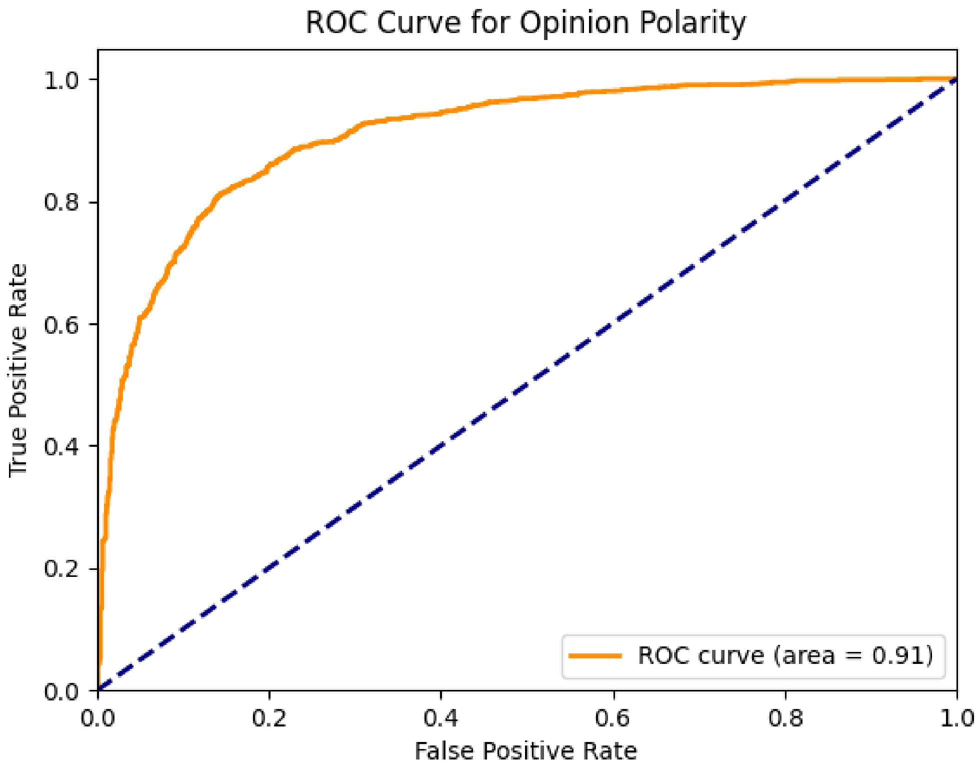

Figure 3: ROC Curve depicting model discrimination ability with an AUC of 0.91 for Arabic opinion polarity classification.

Recommendation Adaptivity with DQN

The integration of Deep Q-Learning (DQN) into the proposed recommendation framework enables dynamic adaptation to user preferences, reflecting reinforcement learning's core strength, learning optimal actions through iterative feedback. While this study primarily centers on classification metrics, a qualitative analysis reveals that the DQN agent plays a pivotal role in shaping personalized recommendation trajectories. Through continuous interaction, the agent refines its policy based on observed user signals, such as clicks, skips, or engagement duration. This feedback loop facilitates a shift from static content delivery to an adaptive decision-making process, where future recommendations are increasingly aligned with individual preferences over time. In effect, the system learns to favor review patterns associated with consistently high user satisfaction, while suppressing those that elicit disengagement.

This behavioral learning is particularly valuable in the Arabic hospitality domain, where sentiment and preferences may vary across dialects, cultures, or contexts. The agent's ability to abstract high-level user behavior from nuanced linguistic features, captured during sentiment modeling, underscores the model's strength in delivering context-aware personalization. Thus, even in the absence of direct reinforcement metrics (e.g., cumulative reward or average Q-value), the observed outcome of user-aligned recommendation transitions validates the effectiveness of the DQN-driven personalization module.

Discussion

The proposed hybrid framework demonstrates notable advancement over existing Arabic-language recommendation systems by integrating deep learning-based sentiment analysis with reinforcement learning for adaptive personalization. The incorporation of GRU-based aspect-level sentiment analysis, enhanced with attention mechanisms, has resulted in robust classification performance, evidenced by an overall accuracy of 86.5%, precision of 87.1%, recall of 86.6%, and an F1-score of 86.8%. The ROC-AUC score of 0.91 further affirms the classifier's high discriminative power in identifying opinion polarity from Arabic hotel reviews. These results outperform earlier sentiment-based Arabic recommender models that primarily relied on collaborative filtering or static hybrid approaches. For instance, Al-Ghuribi et al. (2024) implemented sentiment-aware collaborative filtering for Arabic recommendations but reported limited granularity in sentiment interpretation and lacked dynamic user modeling (Al-Ghuribi et al., 2024). In contrast, our model captures nuanced sentiment at the aspect level and evolves in real time based on user feedback.

The system offered by Al-Ajlan and Alshareef (2023) based on the ABSACo algorithm was the previous study that delivered the results of sentiment classification as the fixed answer without incorporating reinforcement learning processes. Though the model extracted the affective cues of user reviews, the recommendations procedure was still locked inside the pre-decided parameters of it (Al-Ajlan & Alshareef, 2023). The current addition to this thread of research links the model with Deep Q-Learning, thus enabling a dynamic agent that on each iteration improves its policy based on the feedback between the system and the user. This mechanism copes with this demand highlighted by Sharifbaev et al. (2024), and restated by Zhou (2023) regarding the use of adaptive recommendation frameworks.

This study presents a new pipeline pipeline by combining gated recurrent units (GRU) and an attention-based Abu-Seoud Module (ASM) and deep Q-learning (DQN) in personalised hotel recommendation system in the Arabic domain. As mentioned in Khudhair et al. (2025), the temporal modeling ability of GRU makes it highly beneficial to the classic learners, including SVM and Naive Bayes. However, the originality of introducing the elements of the GRU with ASM and DQN fused into a single framework is unique and has not precedently been used in the field of Arabic hospitality. Due to the morphological depth of Arabic, and cross-dialect variation common to the language, NLP systems are vastly underperforming. However, both values of precision and recall were high, which means that the sentiment-related semantically significant information was not entirely lost during the preprocessing pipeline and based on the Word2Vec embeddings. This conclusion is in line with those of Fadel et al. (2024) and the El Mekki et al (2022), who indicate that domain-specific embeddings play a critical role in low-resource languages, which further proves our hypothesis that well-trained embedding strategies can improve sentiment analysis in the Arabic hospitality discourse.

One of the distinguishable aspects of the study compared to previous studies on the use of static Arabic Sentiment-Based Recommendation System is that it had an aspect of reinforcement-learning. Even though the present report does not provide quantitative measures, including reward curves, the fact that the agent adaptively modified its strategy of recommending products as user responses to the aggregate feedback indicated successful behavioral learning. The further improvement may implement task-specific reward construction and tracking of the engagement rates in the long term, thus allowing a more detailed analysis of the DQN agent personalization effectiveness. Taken together, the results of the current research prove that the proposed architecture will provide an inclusive solution that will match between the precision of language and the adaptive action, to fill this gap that still needs to be between the existing research on the topic of recommending Arabic language. Besides, the modular structure of the model implies that it can be potentially applied in other areas and other languages where a similar problem must be solved in the context of sentiment-rich personalization tasks.

Conclusion:

In this study, a hybrid personalized content recommendation framework for Arabic hotel reviews is proposed, through the integration of Aspect-Based Sentiment Analysis (ABSA), GRU-based sequentially modeling and Deep Q-Learning (DQN) for adaptive user dynamic. The proposed architecture displayed good performance at classification of the polarity (accuracy: 86.5%; AUC: 0.91), which, in its turn, is evidence of its efficacy in handling the linguistic and dialectal complexities intrinsic to Arabic texts. Combining the granularity of the sentiment signals with the decision-making involving reinforcement learning allowed the system to generate context and user-centric recommendations, thus significantly expanding the existing state-of-the-art in the Arabic hospitality recommender systems.

Despite these promising results, two limitations merit attention. First, the absence of quantitative reinforcement learning metrics (e.g., cumulative reward, Q-value convergence) restricts full assessment of the DQN agent's adaptivity. Second, the reliance on a single annotated dataset (SemEval 2016 Task 5) limits generalizability across broader Arabic domains or regional dialects. Future research should focus on expanding to larger, multi-dialectal corpora and integrating online learning environments for real-time feedback tracking. Additionally, incorporating multilingual sentiment adaptation and user trust modeling could further enrich recommendation quality. Overall, the proposed architecture serves as a robust foundation for future personalized Arabic-language content systems across hospitality and beyond.

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