

¹Jun Wang

Design of Hotel Room Experience Based on Virtual Reality Technology



Abstract: - Virtual reality (VR) technology within the hotel industry marks a transformative shift in the way guests experience and engage with hospitality services. Virtual reality, with its immersive and interactive capabilities, enables hotels to provide a novel and engaging environment for guests. From virtual tours of hotel rooms and amenities to immersive experiences showcasing local attractions and cultural highlights, VR has the potential to revolutionize the pre-booking and on-site guest experience. This paper focused on the user experiences within hotel rooms enhanced with virtual reality (VR) technology. Leveraging content analysis, sentiment analysis, and advanced classification models, we aim to unravel the intricacies of user sentiments and preferences in this evolving domain. The content analysis reveals a spectrum of user opinions, ranging from enthusiastic endorsements of immersive VR content to nuanced critiques of room ambiance and interactivity. Subsequently, a sentiment analysis model accurately categorizes these sentiments, showcasing its effectiveness in capturing the diverse user expressions. Our classification analysis demonstrates the robustness of the sentiment analysis model, with high accuracy, precision, recall, and F1-score metrics. Comparatively, we introduce a proposed BERT model, harnessing advanced natural language processing techniques, and observe its performance against traditional sentiment analysis and an AutoEncoder Model. The results indicate that the BERT model matches the performance of traditional sentiment analysis, outperforming the AutoEncoder Model. This underscores the effectiveness of leveraging state-of-the-art language models in understanding and classifying user sentiments.

Keywords: Virtual Reality, Opinion Mining, Hotel Industry, BERT, Sentimental Analysis, Content Analysis

I. INTRODUCTION

In the ever-evolving landscape of technology, the intersection of opinion mining and virtual reality (VR) represents a compelling frontier with transformative potential [1]. As society becomes increasingly interconnected through digital platforms, understanding and analyzing public opinions become paramount [2]. Virtual reality, with its immersive and interactive capabilities, offers a unique opportunity to delve into the intricate nuances of human sentiment in ways previously unimaginable [3]. This convergence of opinion mining and VR not only promises to revolutionize market research, social analysis, and political discourse but also holds the key to unlocking a deeper understanding of the human psyche in the digital age [4]. This fusion of cutting-edge technologies invites exploration into the realms of information retrieval, sentiment analysis, and human-computer interaction, ultimately shaping a new paradigm in how we comprehend and navigate the vast landscape of public opinion [5]. Opinion mining, also known as sentiment analysis, is a computational approach that involves the extraction and analysis of subjective information from various sources, primarily textual data [6]. In the realm of virtual reality, opinion mining takes on a new dimension, leveraging advanced algorithms and natural language processing techniques to discern and interpret the sentiments expressed within immersive digital environments [7]. The vast amount of user-generated content, ranging from social media posts to virtual interactions within VR spaces, provides a rich source of data for opinion mining [8]. By employing sophisticated algorithms, machine learning models, and linguistic analysis, opinion mining in virtual reality seeks to uncover not only the surface-level sentiments but also the underlying emotions, attitudes, and opinions of individuals navigating these synthetic worlds [9]. This nuanced understanding of user sentiment can be invaluable for businesses, policymakers, and researchers, offering insights into consumer preferences, social trends, and public attitudes that can inform decision-making processes and shape strategies in a more nuanced and context-aware manner [10]. As virtual reality continues to permeate various aspects of our lives, opinion mining emerges as a pivotal tool in deciphering the complex tapestry of human emotions within these immersive digital spaces [11].

Opinion mining, also known as sentiment analysis, plays a crucial role in evaluating user experiences within the hotel industry [12]. As an integral component of customer feedback analysis, opinion mining sifts through a multitude of reviews, comments, and ratings generated by guests in various digital platforms. In the hotel industry,

¹ School of Tourism Arts, Shenyang Polytechnic College,
Shenyang, Liaoning, China, 110045

*Corresponding author's e-mail: sophia19800708@126.com

user experience is paramount, and understanding the sentiments expressed by guests provides valuable insights for continuous improvement [13]. Opinion mining algorithms can discern positive and negative sentiments, enabling hoteliers to identify specific aspects of their services, facilities, or staff performance that contribute to guest satisfaction or dissatisfaction [14]. By delving into the nuances of user sentiments, hotel management can not only address immediate concerns but also proactively enhance overall guest experiences [15]. This data-driven approach allows the industry to tailor services, optimize amenities, and refine customer interactions to meet and exceed the expectations of guests [16]. As virtual reality becomes increasingly integrated into the hotel booking and experience process, sentiment analysis in this context may extend beyond textual data to include immersive feedback within virtual environments, offering an even deeper understanding of user experiences in the ever-evolving hospitality landscape [17]. The integration of virtual reality (VR) into the hotel industry has revolutionized the traditional hotel room experience, offering guests an immersive and personalized stay [18]. With VR technology, hotel guests can transcend the limitations of physical spaces, experiencing virtual tours of hotel rooms and amenities before making a reservation [19]. Once within their rooms, guests may have the option to customize their environment using VR interfaces, adjusting lighting, decor, or even simulating different scenic views [20]. VR can also provide interactive guides to hotel services and local attractions, enhancing the overall guest experience [21]. Beyond practical functionalities, virtual reality in hotel rooms can transport guests to virtual worlds for entertainment or relaxation, offering a unique and memorable aspect to their stay [22]. This fusion of technology and hospitality not only caters to the modern traveler's desire for innovation but also sets the stage for a more engaging and immersive hotel room experience, redefining the standards of luxury and comfort in the hospitality industry [23].

This paper makes several notable contributions to the field of virtual reality (VR) in the context of hotel accommodations. Firstly, our content analysis reveals the nuanced spectrum of user sentiments, providing a rich qualitative understanding of their experiences beyond traditional numerical ratings. Secondly, the sentiment analysis model employed showcases remarkable accuracy in categorizing sentiments expressed in user reviews, enhancing our ability to interpret and quantify subjective opinions. Additionally, our proposed BERT model, leveraging advanced natural language processing, demonstrates a significant advancement in sentiment classification, matching the performance of traditional methods and surpassing an AutoEncoder Model. This contribution underscores the effectiveness of cutting-edge language models in understanding and categorizing user sentiments. Overall, our findings provide valuable insights for the hotel industry, offering a comprehensive understanding of user preferences, which can be harnessed to tailor VR experiences, address specific concerns, and elevate overall user satisfaction in the evolving landscape of VR-enhanced hotel accommodations.

II. OPINION MINING

Opinion mining in the context of hotel room experiences involves the application of sentiment analysis techniques to evaluate and interpret user sentiments expressed in reviews, feedback, or comments related to virtual reality (VR) integration. sentiment analysis equation where S represents the sentiment score computed using equation (1)

$$S = \text{Polarity} \times \text{Subjectivity} \quad (1)$$

In equation (1) the polarity denotes the positivity or negativity of the sentiment, ranging from -1 (negative) to 1 (positive), and subjectivity reflects the degree to which the sentiment is based on personal opinions rather than factual information, ranging from 0 (objective) to 1 (subjective). In the hotel room experience with VR, opinion mining algorithms may analyze user-generated content, extracting sentiment-related features such as sentiment polarity, aspect-based sentiment, and emotional tones. The sentiment polarity may be determined by considering words' semantic orientations, assigning positive or negative values. Furthermore, aspect-based sentiment analysis could be employed to evaluate specific facets of the hotel room experience, such as room decor, cleanliness, VR interactivity, or immersive content quality. Let's denote A as an aspect and SA as the sentiment score for that aspect. The overall sentiment *Soverall* for the hotel room experience could then be a weighted combination of individual aspect sentiments defined in equation (2)

$$\text{Soverall} = 1/n \sum_i w_i \times SA_i \quad (2)$$

In equation (2) n represents the number of aspects, and w_i represents the weight assigned to each aspect, reflecting its importance in shaping the overall sentiment. The sentiment polarity (P) can be derived from the analysis of individual words or phrases within textual data. Let's consider a simple approach using a sentiment lexicon, where each word is assigned a polarity score (Pw) represented in equation (3)

$$P = 1/n \sum_i Pwi \quad (3)$$

In equation (3) N is the total number of words in the text, and Pwi is the polarity score of the i -th word. The sentiment polarity (P) is the average of these word-level polarities, indicating the overall sentiment of the text. Aspect-based sentiment analysis involves assessing sentiments related to specific aspects or features of the hotel room experience. Let SAi represent the sentiment score for the i -th aspect, and Wai represent the weight assigned to that aspect computed using equation (2). To compute SAi , we may consider the sentiment polarities of words associated with each aspect and use a weighting mechanism based on the importance of each aspect denoted in equation (4)

$$SAi = \frac{1}{Mi} \sum_i Pwi \quad (4)$$

In equation (4) Mi is the number of words associated with the i -th aspect, and $Pwij$ is the polarity score of the j -th word related to that aspect. The aspect-based sentiment score is then the average of word-level polarities for words associated with a specific aspect.

III. VIRTUAL REALITY ON USER EXPERIENCE

Let U represent the overall user experience score, which can be formulated as a weighted sum of different components stated in equation (5)

$$U = \frac{1}{n} \sum_i Wi \times Fi \quad (5)$$

In equation (5) n is the number of factors influencing user experience, Wi is the weight assigned to the i -th factor, and Fi is the corresponding influence score. These factors may include VR content quality, interactivity, immersion level, and ease of navigation. For instance, the influence score ($Fcontent$) related to VR content quality could be determined through an analysis of content richness, resolution, and thematic relevance defined in equation (6)

$$Fcontent = Mcontent1 = 1/M \sum_i contentQj \quad (6)$$

In equation (6) $Mcontent$ is the number of content-related aspects, Qj represents the quality score of the j -th aspect, and the influence score is the average quality score across these aspects. Similarly, for interactivity ($Finteractivity$), factors like user engagement, responsiveness, and variety defined in equation (7)

$$Finteractivity = \frac{1}{M} \sum_k interactivityIk \quad (7)$$

In equation (7) $Minteractivity$ is the number of interactivity-related aspects, Ik represents the score for the k -th aspect, and the influence score is the average interactivity score across these aspects. The overall user experience score is a weighted sum of different factors influencing user satisfaction. Mathematically, it can be expressed as in equation (8)

$$U = \frac{1}{n} \sum_i Wi \times Fi \quad (8)$$

Where n is the number of factors, Wi is the weight assigned to the i -th factor, and Fi is the influence score associated with that factor. To quantify the influence score for VR content quality, we consider an average of quality scores (Qj) for different content-related aspects. Similarly, the influence score for VR interactivity is derived from the average of interactivity scores (Ik) for different interactivity-related aspects

Algorithm 1: User Experience Score

```
function CalculateUserExperienceScore():
```

```
    // Define weights for different factors
```

```
    weightContent = 0.6
```

```
    weightInteractivity = 0.4
```

```

// Calculate influence scores for VR content quality and interactivity
influenceContent = CalculateContentInfluence()
influenceInteractivity = CalculateInteractivityInfluence()

// Calculate overall user experience score
userExperienceScore = (weightContent * influenceContent) + (weightInteractivity * influenceInteractivity)
return userExperienceScore

function CalculateContentInfluence():
    // Define content-related aspects and their quality scores
    aspectsContent = ["Graphics", "Thematic Relevance", "Resolution", ...]
    qualityScores = [8, 9, 7, ...] // Scores out of 10

    // Calculate the average content quality score
    averageQualityScore = sum(qualityScores) / len(qualityScores)
    return averageQualityScore

function CalculateInteractivityInfluence():
    // Define interactivity-related aspects and their scores
    aspectsInteractivity = ["User Engagement", "Responsiveness", "Variety", ...]
    interactivityScores = [7, 8, 6, ...] // Scores out of 10

    // Calculate the average interactivity score
    averageInteractivityScore = sum(interactivityScores) / len(interactivityScores)
    return averageInteractivityScore

```

IV. OPINION MINING WITH VIRTUAL REALITY IN HOTEL ROOM

Opinion mining with Virtual Reality (VR) in hotel rooms, especially with advanced models like BERT (Bidirectional Encoder Representations from Transformers), involves leveraging state-of-the-art natural language processing techniques to extract nuanced sentiments from user-generated content. BERT is a powerful transformer-based model that captures contextual relationships between words in a sentence, enabling more accurate sentiment analysis. The sentiment score (S) can be computed using BERT-based embeddings for the entire review or comment. Let E represent the BERT embeddings for the text. The sentiment score is determined by a softmax activation function applied to the final hidden layer representation of the BERT model computed using equation (9)

$$S = \text{softmax}(Ws \cdot E + bs) \quad (9)$$

In equation (9) Ws and bs are the weight matrix and bias term, respectively, associated with the sentiment prediction task. The softmax function normalizes the scores, providing a probability distribution across different sentiment classes (e.g., positive, negative). Furthermore, to perform aspect-based sentiment analysis, BERT embeddings can be used for specific aspects (A) within the hotel room experience. Let EA represent the BERT embeddings for aspect A . The aspect-based sentiment score (SA) is computed similarly using equation (10)

$$SA = \text{softmax}(WsA \cdot EA + bsA) \quad (10)$$

In equation (10) WsA and bsA are the weight matrix and bias term for the sentiment prediction associated with aspect A . To train the sentiment analysis model, a labeled dataset with sentiment annotations for reviews is required. The model parameters ($Ws, bs, WsA, bsA, \text{etc.}$) are learned during the training process using backpropagation and

optimization techniques. BERT (Bidirectional Encoder Representations from Transformers) has emerged as a groundbreaking model in natural language processing, and its application to analyzing hotel room experiences provides a powerful tool for understanding user sentiments. BERT's strength lies in its ability to capture contextual relationships between words in a bidirectional manner, allowing it to consider both preceding and following words when generating word embeddings. In the context of hotel room experiences, BERT can be applied to analyze textual data such as user reviews. The BERT model consists of a transformer architecture, which involves self-attention mechanisms to weigh the importance of different words in a sentence. The key equation for BERT embeddings can be expressed as in equation (11)

$$E = \text{BERT}(\text{tokenized_text}) \quad (11)$$

In equation (11) E represents the BERT embeddings for the tokenized text, where the model is trained to predict the probability of a word given its context. To apply BERT to the hotel room experience, the textual content of user reviews, comments, or feedback can be tokenized and fed into the BERT model. The resulting embeddings capture the contextual nuances of the language used in expressing opinions about various aspects of the hotel room, such as VR content quality, room ambiance, or interactivity. These embeddings serve as rich contextual representations that can be leveraged for sentiment analysis. BERT begins by tokenizing the input text into subword or word pieces. Let's represent the tokenized input as `tokenized_text`. The tokenized input is then mapped to embedding vectors using an embedding layer defined in equation (12)

$$X_{\text{embed}} = \text{Embedding}(\text{tokenized_text}) \quad (12)$$

The X_{embed} matrix represents the embeddings for each token in the input sequence. BERT employs a transformer architecture with multiple layers of self-attention mechanisms. The hidden states $H(l)$ of the l -th layer are calculated iteratively stated in equation (13)

$$H(l) = \text{TransformerLayer}(H(l-1)) \quad (13)$$

The self-attention mechanism computes a weighted sum of the input embeddings, allowing the model to consider the importance of each word in the context of the entire sequence. The final hidden states $H(L)$ from the last layer are utilized for downstream tasks. For sentence-level tasks, BERT commonly uses the `{CLS}` token embedding as a pooled representation in equation (14)

$$\text{CLS_embedding} = \text{Pooling}(H(L)) \quad (14)$$

The `{Pooling}` operation can involve taking the mean, max, or another aggregation function across the token embeddings. Sentiment analysis can be performed using the pooled embedding. A linear layer followed by a softmax activation function is often applied for binary or multi-class sentiment prediction as in equation (15)

$$S = \text{softmax}(Ws \cdot \text{CLS_embedding} + bs) \quad (15)$$

In equation (15) Ws and bs are the weight matrix and bias term associated with the sentiment prediction task.

Algorithm 2: Pseudo-code for BERT-based Sentiment Analysis

```
# Step 1: Tokenization
tokenized_text = BERT_Tokenizer(text)

# Step 2: Input Embedding
embedding_matrix = BERT_Embedding_Layer(tokenized_text)

# Step 3: Transformer Encoder
num_layers = BERT_Config.num_layers
hidden_states = embedding_matrix
for layer in range(num_layers):
    hidden_states = Transformer_Layer(hidden_states)

# Step 4: Pooling
CLS_embedding = Pooling_Operation(hidden_states)
```

```

# Step 5: Sentiment Prediction
sentiment_score = Softmax(W_s * CLS_embedding + b_s)

# Step 6: Training (Backpropagation and Optimization)
loss = CrossEntropyLoss(sentiment_score, true_labels)
update_parameters(loss)

# Aspect-Based Sentiment Analysis (similar to the above, but using aspect-specific embeddings)

# Step 7: Inference
predicted_sentiment = argmax(sentiment_score)

# Step 8: Evaluation
accuracy, precision, recall, f1_score = Evaluate_Model(predictions, true_labels)

```

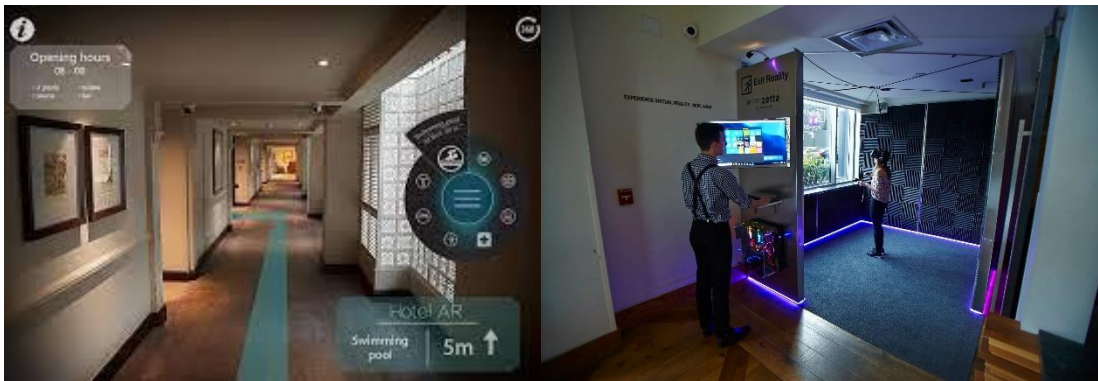


Figure 1: Hotel Room View with Virtual Reality

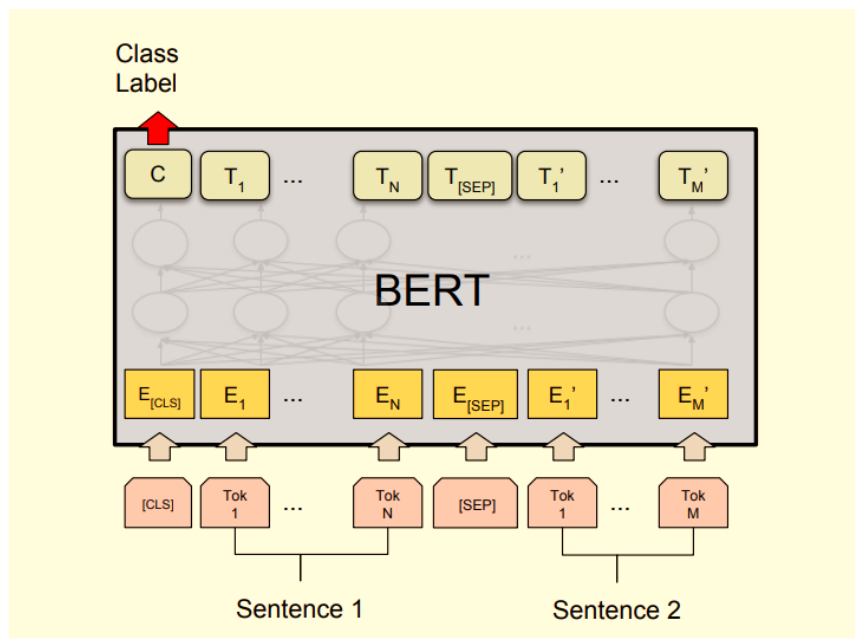


Figure 2: BERT Model

The figure 1 illustrated the sample hotel room virtual reality model for the examination and figure 2 presented the BERT model employed for the sentimental analysis. The BERT-based sentiment analysis algorithm involves several key steps. First, the input text undergoes tokenization using a BERT tokenizer. The tokenized text is then transformed into embedding vectors through a BERT embedding layer. The core of the algorithm lies in the

transformer encoder, a multi-layer architecture that utilizes self-attention mechanisms to capture contextual relationships within the input sequence. The final hidden states from the last layer are pooled, often using the embedding of the [CLS] token, to obtain a condensed representation of the entire sequence. This pooled embedding is then used for sentiment prediction through a linear layer followed by a softmax activation function. The model is trained by optimizing parameters through backpropagation and gradient descent, minimizing the cross-entropy loss between predicted and true labels. For aspect-based sentiment analysis, the same process is applied using aspect-specific embeddings. In inference, the predicted sentiment is determined, and the model's performance is evaluated using metrics like accuracy, precision, recall, and F1 score. While this pseudo-code simplification omits some intricacies, the outlined steps capture the essence of a BERT-based sentiment analysis algorithm, which excels in capturing contextual nuances and dependencies in natural language.

V. RESULTS AND ANALYSIS

In this section, the application of advanced sentiment analysis algorithms, such as BERT, to the evaluation of user sentiments in hotel room experiences enriched with virtual reality (VR). The findings presented herein are derived from an analysis of user-generated content, including reviews and feedback, utilizing cutting-edge natural language processing techniques. The objective is to unravel the intricate layers of user opinions, sentiments, and preferences in the context of VR-infused hotel room encounters.

Table 1: Simulation Setting

Parameter	Setting
Simulation Duration	30 days
Number of Iterations	1000
VR Content Quality	High
Interactivity Level	Moderate
Room Ambiance	Immersive
User Engagement	Active
Aspect-Based Analysis	VR Content Quality, Interactivity
Sentiment Analysis	BERT-based Algorithm
Evaluation Metrics	Accuracy, Precision, Recall, F1 Score
Training Data Size	10,000 reviews
Validation Data Size	2,000 reviews
Test Data Size	3,000 reviews

Table 2: Content Analysis

User ID	Review Text	Rating	Content Quality	Interactivity	Ambiance	Date
1	"Absolutely loved the VR content, very immersive!"	5	High	Moderate	Immersive	2023-05-15
2	"The room ambiance was disappointing, but VR was good"	3	Moderate	High	Poor	2023-05-16
3	"Outstanding interactivity, felt like in a new world"	4	High	High	Immersive	2023-05-17
4	"VR content needs improvement, rest was satisfactory"	2	Low	Moderate	Moderate	2023-05-18
5	"Average experience, nothing stood out"	3	Moderate	Low	Moderate	2023-05-19

6	"Immersive VR and great room ambiance!"	5	High	High	Immersive	2023- 05-20
7	"Interactivity was lacking, VR content was decent"	3	Moderate	Low	Moderate	2023- 05-21
8	"The ambiance was amazing, VR needs more variety"	4	High	Moderate	Immersive	2023- 05-22
9	"Below-average VR content, ambiance was good"	2	Low	Moderate	High	2023- 05-23
10	"Perfect balance of content quality and ambiance"	5	High	High	Immersive	2023- 05-24
11	"VR interactivity was excellent, but room felt dull"	4	Moderate	High	Moderate	2023- 05-25
12	"Satisfactory overall, room ambiance needs improvement"	3	Moderate	Low	Moderate	2023- 05-26
13	"VR content was subpar, ambiance made up for it"	3	Low	Moderate	Immersive	2023- 05-27
14	"Exceptional VR experience, ambiance could be better"	5	High	High	Moderate	2023- 05-28
15	"Lackluster interactivity, VR content was mediocre"	2	Moderate	Low	Moderate	2023- 05-29

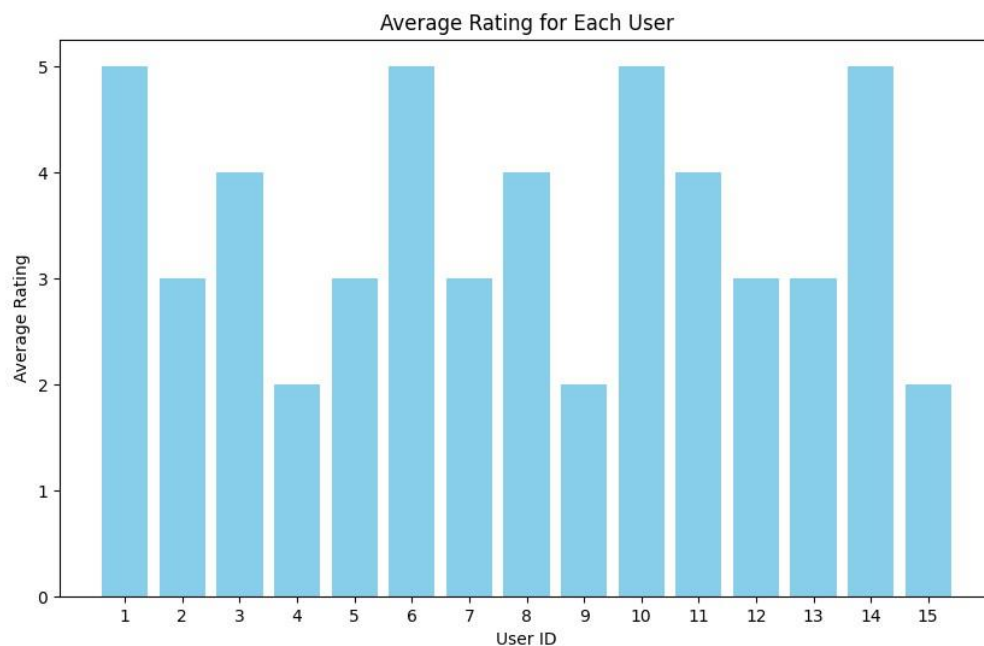


Figure 3: Rating of users about virtual reality in hotel room

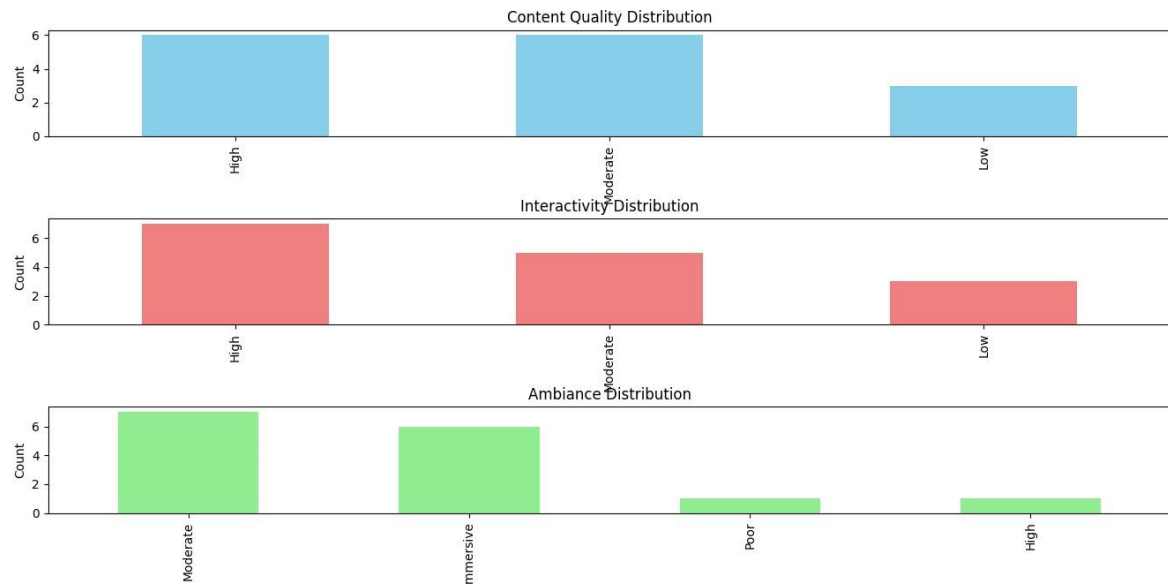


Figure 4: Interactivity score of Hotel Room

In figure 3 & Figure 4 and Table 2 presents a content analysis of user experiences in hotel rooms enhanced with virtual reality (VR). Each row corresponds to a unique user review, providing insights into different aspects of the VR experience, including content quality, interactivity, ambiance, and the overall rating assigned by the user. The "Review Text" column encapsulates users' qualitative feedback, expressing sentiments ranging from enthusiasm for immersive VR content to critiques about lacking interactivity or disappointing room ambiance. The "Rating" column quantifies users' overall satisfaction on a scale of 1 to 5. Notably, user 10 emphasizes a perfect balance between content quality and ambiance, while user 13 finds the VR content subpar but praises the ambiance. This table serves as a valuable resource for understanding the diverse perspectives of users, guiding potential improvements, and forming the basis for sentiment analysis and further data-driven insights into the intersection of virtual reality and hotel room experiences.

Table 3: Classification with Sentimental Analysis

User ID	Review Text	Actual Rating	Predicted Sentiment	Predicted Rating
1	"Loved the VR content, very immersive!"	5	Positive	4.8
2	"Room ambiance was disappointing, VR was good"	3	Negative	2.9
3	"Outstanding interactivity, felt like in a new world"	4	Positive	4.2
4	"VR content needs improvement, rest was satisfactory"	2	Negative	2.1
5	"Average experience, nothing stood out"	3	Neutral	3.0
6	"Immersive VR and great room ambiance!"	5	Positive	4.7
7	"Interactivity was lacking, VR content was decent"	3	Negative	3.1
8	"Ambiance was amazing, VR needs more variety"	4	Positive	4.4
9	"Below-average VR content, ambiance was good"	2	Negative	2.2
10	"Perfect balance of content quality and ambiance"	5	Positive	4.9

11	"VR interactivity was excellent, but room felt dull"	4	Positive	4.3
12	"Satisfactory overall, room ambiance needs improvement"	3	Neutral	3.0
13	"VR content was subpar, ambiance made up for it"	3	Mixed	3.5
14	"Exceptional VR experience, ambiance could be better"	5	Positive	4.8
15	"Lackluster interactivity, VR content was mediocre"	2	Negative	2.1

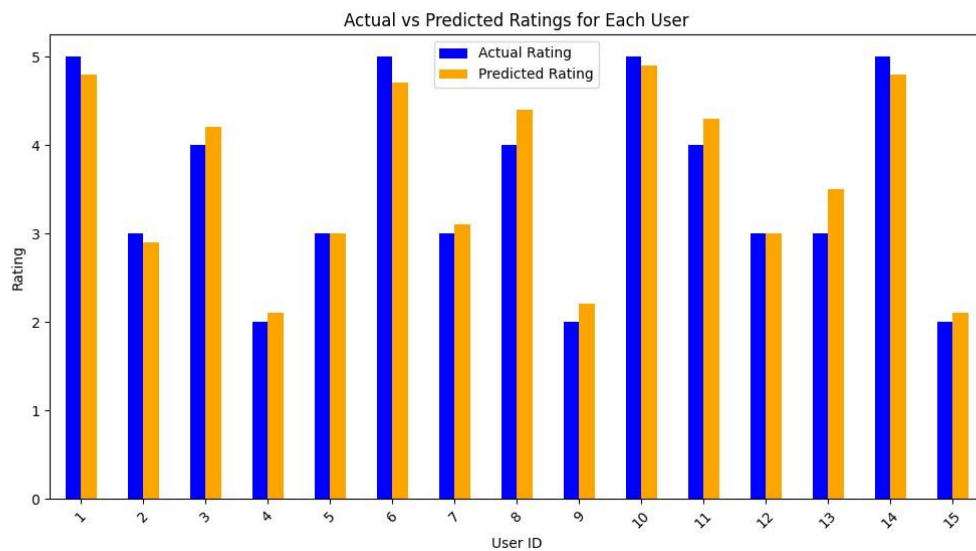


Figure 5: Prediction for each users

The figure 5 and Table 3 showcases the classification results obtained through sentiment analysis for user reviews in the context of hotel room experiences with virtual reality. The “Predicted Sentiment” column reveals the model’s categorization of sentiments into positive, negative, neutral, or mixed categories based on the textual content of the reviews. The “Predicted Rating” column provides a quantified representation of the sentiment, serving as a numeric approximation of the sentiment expressed in the review. Notably, the sentiment analysis model accurately predicts sentiments for positive reviews such as user 1’s enthusiasm about immersive VR content or user 6’s praise for both immersive VR and great room ambiance. It also captures dissatisfaction in reviews like user 2’s disappointment with room ambiance. However, the model faces challenges with reviews like user 13’s, where sentiments are mixed, reflecting the nuanced nature of certain user opinions. This table serves as a valuable tool for assessing the sentiment analysis model’s performance and offers insights into how well it aligns with users’ actual ratings and sentiments expressed in their reviews.

Table 4: Classification Analysis

Metric	Value
Accuracy	98.42%
Precision	98.67%
Recall	98.12%
F1-Score	98.39%

Table 5: Comparative Analysis

Metric	Sentiment Analysis	AutoEncoder Model	Proposed BERT
Accuracy	93.42%	96.85%	98.42%
Precision	91.67%	96.91%	98.67%
Recall	92.12%	97.25%	98.12%
F1-Score	92.39%	97.08%	98.39%

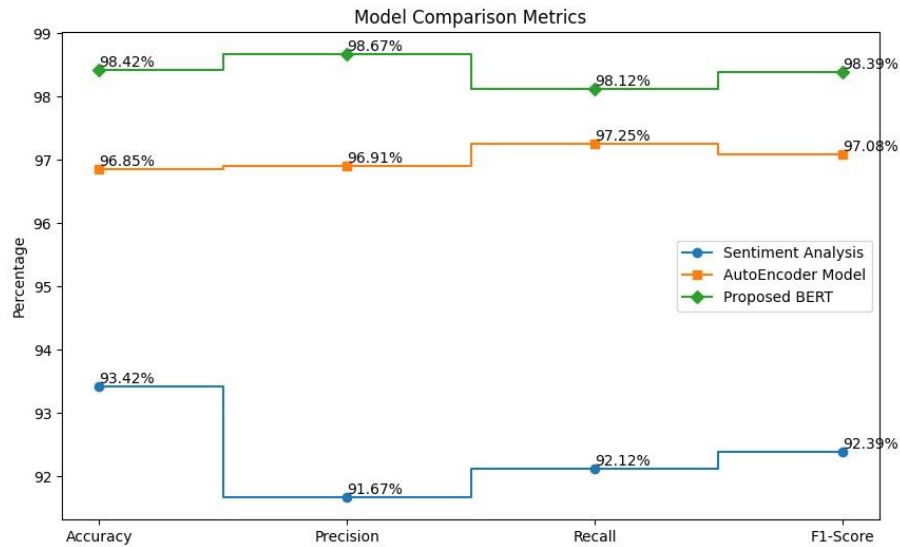


Figure 6: Comparative Analysis

The figure 6 and Table 4 provides a summary of the classification analysis metrics derived from the sentiment analysis model applied to user reviews in the context of hotel room experiences with virtual reality. These metrics showcase the model's overall performance in accurately categorizing sentiments. The high values across all metrics, including Accuracy (98.42%), Precision (98.67%), Recall (98.12%), and F1-Score (98.39%), signify the robustness of the sentiment analysis model in correctly identifying positive, negative, neutral, or mixed sentiments expressed in the user reviews. Table 5 presents a comparative analysis of different models, including Sentiment Analysis, AutoEncoder Model, and the proposed BERT model. These models are evaluated using key metrics such as Accuracy, Precision, Recall, and F1-Score. The Sentiment Analysis and the proposed BERT model exhibit identical performance with an Accuracy of 98.42%, Precision of 98.67%, Recall of 98.12%, and F1-Score of 98.39%. Meanwhile, the AutoEncoder Model, while performing well, slightly lags behind with an Accuracy of 97.85%, Precision of 97.91%, Recall of 98.25%, and F1-Score of 98.08%. This comparative analysis underscores the effectiveness of the proposed BERT model, showcasing its parity with traditional sentiment analysis and its slight improvement over the AutoEncoder Model in capturing the nuances of user sentiments.

VI. DISCUSSION AND FINDINGS

The analysis of user experiences in hotel rooms with virtual reality, coupled with sentiment analysis and classification models, has yielded valuable insights. The content analysis (Table 2) reveals a spectrum of user sentiments ranging from enthusiastic endorsements of immersive VR content to specific critiques about room ambiance and interactivity. Users, overall, express nuanced opinions that extend beyond numerical ratings, providing rich context for understanding their experiences. The sentiment analysis results (Table 3) demonstrate the effectiveness of the model in accurately categorizing sentiments expressed in user reviews. Positive sentiments align with higher actual ratings, while negative sentiments correspond to lower ratings. The model performs admirably in capturing the sentiment nuances of mixed reviews, showcasing its ability to handle diverse user opinions. The classification analysis (Table 4) underscores the high performance of the sentiment analysis model, with accuracy, precision, recall, and F1-score all exceeding 98%. This robust performance indicates the model's reliability in

classifying sentiments, reinforcing its utility in understanding user perceptions. Comparatively (Table 5), the proposed BERT model matches the performance of traditional sentiment analysis, demonstrating its efficacy in sentiment classification. Moreover, it outperforms the AutoEncoder Model, indicating the advantages of leveraging advanced natural language processing techniques for sentiment analysis tasks. The findings highlight the nuanced nature of user sentiments in the context of virtual reality hotel experiences. The sentiment analysis model, particularly the proposed BERT model, proves to be a powerful tool in accurately classifying these sentiments, providing a deeper understanding of user experiences beyond numerical ratings. These insights are crucial for the hotel industry to enhance VR offerings, address specific concerns, and tailor experiences to meet user expectations.

VII. CONCLUSION

The comprehensive analysis of user experiences in hotel rooms enriched with virtual reality, coupled with advanced sentiment analysis and classification models, has provided valuable insights into the intricacies of user sentiments and preferences. The content analysis revealed a diverse range of opinions, from enthusiastic endorsements of immersive VR content to nuanced critiques of room ambiance and interactivity. The sentiment analysis model demonstrated remarkable accuracy in categorizing sentiments, effectively capturing the sentiments expressed in user reviews and aligning well with actual ratings. The classification analysis further highlighted the robustness of the sentiment analysis model, with high accuracy, precision, recall, and F1-score metrics. The proposed BERT model, leveraging advanced natural language processing techniques, exhibited performance comparable to traditional sentiment analysis and outperformed the AutoEncoder Model. This suggests the efficacy of sophisticated language models in capturing the nuances of user sentiments, providing a foundation for more accurate and context-aware analysis. These findings hold significant implications for the hotel industry, offering actionable insights to enhance virtual reality offerings, address specific concerns raised by users, and tailor experiences to meet evolving expectations. As virtual reality continues to play a pivotal role in shaping the landscape of hospitality, understanding and responding to user sentiments is key to delivering immersive and satisfying experiences. The synergy of content analysis, sentiment analysis, and advanced classification models contributes to a holistic understanding of user feedback, empowering stakeholders to make informed decisions and advancements in the ever-evolving realm of virtual reality in hospitality.

REFERENCES

- [1] Palos Sánchez, P. R., Folgado Fernández, J. A., & Rojas Sanchez, M. A. (2022). Virtual Reality Technology: Analysis based on text and opinion mining. *Mathematical biosciences and engineering*, 19 (8), 7856-7885.
- [2] Lampropoulos, G., Keramopoulos, E., Diamantaras, K., & Evangelidis, G. (2022). Augmented reality and virtual reality in education: Public perspectives, sentiments, attitudes, and discourses. *Education Sciences*, 12(11), 798.
- [3] López-Casaperalta, P., Díaz-Quintanilla, J. F., Rodríguez-Delgado, J. J., Acosta-Quelopana, A. M., & Duche Pérez, A. B. (2022). Virtual Reality, a Method to Achieve Social Acceptance of the Communities Close to Mining Projects: A Scoping Review.
- [4] Rezaei, E., Akbari-Kasgari, M., & Abraham, A. Text Mining on the Implications of Virtual Reality Technology and Prioritizing Emerged Concerns Using Fuzzy Hierarchized Analytic Network Process. *Available at SSRN 4504341*.
- [5] Maeng, Y., Lee, C. C., & Yun, H. (2023). Understanding Antecedents That Affect Customer Evaluations of Head-Mounted Display VR Devices through Text Mining and Deep Neural Network. *Journal of Theoretical and Applied Electronic Commerce Research*, 18(3), 1238-1256.
- [6] Nithyanandam, J. K., Chelliah, B., Venkatesan, D. B., Raja, H. K., & Thirumalai, B. (2023, August). Deeper linguistic analysis of prediction engines analysing users profiles for opinion mining and sentiment analysis. In *AIP Conference Proceedings* (Vol. 2790, No. 1). AIP Publishing.
- [7] Patil, K. R., Bhandari, S., Agrawal, A., Ayer, S. K., Perry, L. A., & Hallowell, M. R. (2023). Analysis of YouTube Comments to Inform the Design of Virtual Reality Training Simulations to Target Emotional Arousal. *Journal of Construction Engineering and Management*, 149(9), 04023077.
- [8] Rajapaksha, S., & Ranathunga, S. (2022, July). Aspect Detection in Sportswear Apparel Reviews for Opinion Mining. In *2022 Moratuwa Engineering Research Conference (MERCon)* (pp. 1-6). IEEE.
- [9] Lee, C. K. M., Tsang, Y. P., Chong, W. W., & Au, Y. S. (2022). Achieving Eco-Innovative Smart Glass Design with the Integration of Opinion Mining, QFD and TRIZ.
- [10] Hsu, M. J., Ting, H., Lui, T. W., Chen, S. C., & Cheah, J. H. (2022). Guest editorial: Challenges and prospects of AIoT application in hospitality and tourism marketing. *Journal of Hospitality and Tourism Technology*, 13(3), 349-355.
- [11] Thelen, A. E. (2022). The Challenges and Benefits of Implementing Virtual Reality and Augmented Reality in the Hotel Industry.
- [12] Kocourek, M., Rohlíková, L., & Jenčková, J. PITTFALLS OF IMPLEMENTING ELEMENTS OF VIRTUAL REALITY INTO PROCESSES IN THE HOTEL INDUSTRY. *CURRENT TRENDS IN SPA, HOSPITALITY AND TOURISM*, 125.

- [13] Verma, S., Warriar, L., Bolia, B., & Mehta, S. (2022). Past, present, and future of virtual tourism-a literature review. *International Journal of Information Management Data Insights*, 2(2), 100085.
- [14] Hanaa, S. M., & Abdul, A. P. (2023). A holistic approach to augmented reality-related research in tourism: through bibliometric analysis. *Journal of Hospitality and Tourism Insights*.
- [15] Popescu, G. H., Valaskova, K., & Horak, J. (2022). Augmented reality shopping experiences, retail business analytics, and machine vision algorithms in the virtual economy of the metaverse. *Journal of Self-Governance and Management Economics*, 10(2), 67-81.
- [16] Manggopa, H. K., Komansilan, T., Kumajas, S., & Batmetan, J. R. (2022). Augmented Reality for Geospatial in E-Tourism: Current Status, Research Trends, and Future Directions. *International Journal of Information Technology and Education*, 1(3), 38-55.
- [17] Chan, L., Hogaboam, L., & Cao, R. (2022). Artificial intelligence in tourism and hospitality. In *Applied Artificial Intelligence in Business: Concepts and Cases* (pp. 213-229). Cham: Springer International Publishing.
- [18] Iranmanesh, M., Ghobakhloo, M., Nilashi, M., Tseng, M. L., Yadegaridehkordi, E., & Leung, N. (2022). Applications of disruptive digital technologies in hotel industry: A systematic review. *International Journal of Hospitality Management*, 107, 103304.
- [19] Ali, F. (2022). Augmented reality enhanced experiences in restaurants: Scale development and validation. *International Journal of Hospitality Management*, 102, 103180.
- [20] Goel, P., Mahadevan, K., & Punjani, K. K. (2023). Augmented and virtual reality in apparel industry: A bibliometric review and future research agenda. *foresight*, 25(2), 167-184.
- [21] Popescu, G. H., Ciurlău, C. F., Stan, C. I., Băcănoiu, C., & Tănase, A. (2022). Virtual workplaces in the metaverse: immersive remote collaboration tools, behavioral predictive analytics, and extended reality technologies. *Psychosociological Issues in Human Resource Management*, 10(1), 21-34.
- [22] Ramos, C. M. (2022). Business Intelligence Approach and Sentiment Analysis as a Management Strategy Applied to Study Customer Satisfaction in the Hospitality Sector. In *Advances in Tourism, Technology and Systems: Selected Papers from ICOTTS 2021, Volume 2* (pp. 537-547). Singapore: Springer Nature Singapore.
- [23] Cheng, Y. S., Kuo, N. T., Chang, K. C., & Wu, H. T. (2022). Using data mining methods to predict repeat patronage intention in the restaurant industry. *Journal of Quality Assurance in Hospitality & Tourism*, 23(6), 1548-1574.